SEARCH STRATEGY

Set No.	Searched for	Databases	Results
S3	Ai powered mental health chatbot AND alert system	ABI/INFORM Collection, Coronavirus Research Database, Education Research Index, ProQuest Dissertations & Theses Global, Publicly Available Content Database	5160
S2	Ai powered mental health chatbot AND alert system	ABI/INFORM Collection, Coronavirus Research Database, Education Research Index, ProQuest Dissertations & Theses Global, Publicly Available Content Database	5160
S1	mental health chatbot AND alert system	ABI/INFORM Collection, Coronavirus Research Database, Education Research Index, ProQuest Dissertations & Theses Global, Publicly Available Content Database	6730

Radiology AI and sustainability paradox: environmental, economic, and social dimensions

ProQuest document link

ABSTRACT (ENGLISH)

Artificial intelligence (AI) is transforming radiology by improving diagnostic accuracy, streamlining workflows, and enhancing operational efficiency. However, these advancements come with significant sustainability challenges across environmental, economic, and social dimensions. AI systems, particularly deep learning models, require substantial computational resources, leading to high energy consumption, increased carbon emissions, and hardware waste. Data storage and cloud computing further exacerbate the environmental impact. Economically, the high costs of implementing AI tools often outweigh the demonstrated clinical benefits, raising concerns about their long-term viability and equity in healthcare systems. Socially, AI risks perpetuating healthcare disparities through biases in algorithms and unequal access to technology. On the other hand, AI has the potential to improve sustainability in healthcare by reducing low-value imaging, optimizing resource allocation, and improving energy efficiency in radiology departments. This review addresses the sustainability paradox of AI from a radiological perspective, exploring its environmental footprint, economic feasibility, and social implications. Strategies to mitigate these challenges are also discussed, alongside a call for action and directions for future research.

Critical relevance statement

By adopting an informed and holistic approach, the radiology community can ensure that AI's benefits are realized responsibly, balancing innovation with sustainability. This effort is essential to align technological advancements with environmental preservation, economic sustainability, and social equity.

Key Points

AI has an ambivalent potential, capable of both exacerbating global sustainability issues and offering increased productivity and accessibility.

Addressing AI sustainability requires a broad perspective accounting for environmental impact, economic feasibility, and social implications.

By embracing the duality of AI, the radiology community can adopt informed strategies at individual, institutional, and collective levels to maximize its benefits while minimizing negative impacts.

FULL TEXT

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Multimodal AI in Biomedicine: Pioneering the Future of Biomaterials, Diagnostics, and Personalized Healthcare

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ABSTRACT (ENGLISH)

Multimodal artificial intelligence (AI) is driving a paradigm shift in modern biomedicine by seamlessly integrating heterogeneous data sources such as medical imaging, genomic information, and electronic health records. This review explores the transformative impact of multimodal AI across three pivotal areas: biomaterials science, medical diagnostics, and personalized medicine. In the realm of biomaterials, AI facilitates the design of patient-specific solutions tailored for tissue engineering, drug delivery, and regenerative therapies. Advanced tools like AlphaFold have significantly improved protein structure prediction, enabling the creation of biomaterials with enhanced biological compatibility. In diagnostics, AI systems synthesize multimodal inputs combining imaging, molecular markers, and clinical data—to improve diagnostic precision and support early disease detection. For precision medicine, AI integrates data from wearable technologies, continuous monitoring systems, and individualized health profiles to inform targeted therapeutic strategies. Despite its promise, the integration of AI into clinical practice presents challenges such as ensuring data security, meeting regulatory standards, and promoting algorithmic transparency. Addressing ethical issues including bias and equitable access remains critical. Nonetheless, the convergence of AI and biotechnology continues to shape a future where healthcare is more predictive, personalized, and responsive.

FULL TEXT

1. Introduction

1.1. Overview of Multimodal AI

Multimodal artificial intelligence (AI) is an emerging and transformative domain that combines multiple data modalities to enhance decision-making, especially in intricate fields such as healthcare and biomedical research. Unlike traditional AI systems that analyze a single data stream, like medical images or textual data, multimodal AI integrates diverse sources such as clinical imaging, genetic profiles, biosensor outputs, and electronic health records. This integrative approach enables a deeper and more unified interpretation of human biology and disease. In the context of healthcare, where the data variety is immense and complexity is high, multimodal AI offers unprecedented potential. It effectively synthesizes information from numerous biomedical sources, including high-resolution scans, genomic sequences, patient histories, and continuous physiological monitoring from wearable devices, thereby enabling more accurate and personalized medical insights [1]. Each data type, on its own, provides valuable insights into a patient's health. However, combining these datasets allows researchers and clinicians to uncover complex relationships between physiological and genetic factors, leading to more accurate diagnoses, personalized treatments, and improved outcomes [2]. Multimodal AI systems rely on advanced machine learning techniques, particularly deep learning, which can process large, complex datasets and identify patterns that would be impossible for humans to detect. For example, convolutional neural networks (CNNs) are used for analyzing medical images, while recurrent neural networks (RNNs) process time-series data such as electrocardiograms (ECGs) [3]. CNNs are advanced deep learning models specifically effective for analyzing visual data. By applying layered filters, these networks can autonomously recognize and extract intricate visual features such as edges, contours, and textures. This makes them highly suitable for medical diagnostics, where they are used to identify irregularities such as tumors in imaging techniques like MRIs and X-rays. RNNs are a distinct type of neural architecture tailored for sequential information. They excel in tasks involving temporal patterns due to their internal memory, which allows them to utilize previous inputs for current predictions. In healthcare, RNNs have been leveraged to analyze longitudinal patient data, helping forecast disease development or clinical outcomes over time. By combining diverse data sources, multimodal AI enables in-depth assessments that support early disease detection, personalized therapy recommendations, and continuous monitoring especially beneficial for managing chronic illnesses like cardiovascular disorders and diabetes [4]. Convolutional neural networks (CNNs) are frequently employed to interpret and merge various imaging techniques, such as MRI, CT, and X-ray, offering more holistic diagnostic insights. These models can be integrated with patient clinical data to assist in designing individualized treatment strategies. Meanwhile, recurrent neural networks (RNNs) are commonly applied in genomic studies to analyze DNA or RNA sequences. These models help identify genetic variations and forecast their impact on disease mechanisms, facilitating precision medicine and the development of targeted therapies.

1.2. Importance of AI in Biomedicine and Healthcare

The application of AI, especially multimodal AI, in biomedicine and healthcare is increasingly viewed as a game changer. Traditionally, healthcare systems have struggled to integrate different forms of patient data, which has led to challenges in diagnosing complex diseases, tailoring personalized treatments, and predicting outcomes. Multimodal AI overcomes traditional limitations by synthesizing data from multiple sources to construct a holistic representation of patient health. This comprehensive approach supports more accurate diagnoses and paves the way for predictive and individualized treatments [5]. A key area where multimodal AI is proving transformative is in the field of biomaterials. These materials whether synthetic or natural are engineered to interface with biological systems for medical applications such as regenerative therapies, drug delivery platforms, and tissue scaffolding [6]. The development of such materials involves evaluating a wide range of parameters, including biomechanical performance, biocompatibility, and patient-specific physiological factors. Multimodal AI enables the integration and analysis of these complex datasets, allowing for the design of highly tailored and functionally superior biomaterials [7].

AI-driven systems can synthesize diverse datasets, such as mechanical properties from materials engineering, biological responses from tissue studies, and clinical information from patient records, to develop advanced biomaterials for tissue regeneration. This integrative approach has contributed to the creation of innovative scaffolds and hydrogels that better replicate the structural and functional characteristics of native tissues, thereby enhancing the efficacy of regenerative therapies [8,9]. In addition to biomaterials, multimodal AI is transforming diagnostics and personalized medicine by merging medical images, genomic profiles, and clinical histories. Such fusion enables the predictive modeling of treatment outcomes, facilitating the selection of the most effective interventions for individual patients. This is especially impactful in cancer care, where therapeutic decisions like chemotherapy regimens can be guided by tumor genomics and radiological imaging [10,11]. Moreover, real-time health surveillance is being revolutionized through the integration of multimodal AI with wearable health technologies. Devices like fitness trackers and smartwatches continuously capture vital signs such as heart rate, body temperature, and physical activity. When combined with clinical and genomic data, this stream of information allows AI systems to deliver dynamic health assessments, early disease detection, and customized lifestyle guidance [12]. These advancements support a shift toward preventative medicine, enabling earlier interventions and contributing to reduced healthcare expenditures while improving patient outcomes [13].

1.3. Objectives of the Review

This review aims to elucidate the transformative role of multimodal artificial intelligence (AI) in reshaping the landscape of modern biomedicine, with a specific focus on biomaterials engineering, diagnostic innovations, and precision medicine. By synthesizing diverse data modalities, ranging from medical imaging and genomics to clinical and physiological data, multimodal AI offers novel avenues to enhance patient care, streamline clinical workflows, and accelerate biomedical innovation. This article provides a detailed examination of how AI technologies are being applied to facilitate data-driven decision-making and optimize biomedical interventions. In addition, we address the practical challenges associated with the clinical adoption of AI, including ethical dilemmas, regulatory constraints, data standardization, and implementation at scale [14]. Looking forward, we explore the convergence of multimodal AI with frontier biotechnologies, such as CRISPR-based gene editing and tailored therapeutics, underscoring its potential to redefine the standards of healthcare delivery [15]. Ultimately, the integration of heterogeneous biomedical data through AI holds the promise to propel the field toward more proactive, predictive, and personalized medical solutions.

1.4. Materials and Methods

1.4.1. Databases Searched

We conducted a comprehensive literature search using the following databases to cover interdisciplinary research spanning artificial intelligence, biomaterials, and healthcare:
PubMed: For peer-reviewed articles on biomedical applications of AI, biomaterials development, and clinical healthcare innovations.
IEEE Xplore: For technical research on AI algorithms such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their deployment in biomedicine.
Scopus: For a wide spectrum of research literature in materials science, biomedical engineering, and AI applications.
Web of Science: For studies on the integration of AI technologies in healthcare and biomedical research.

1.4.2. Materials and Methods for AI Model Development

In addition to literature sources, we reviewed datasets and resources essential for the development and training of AI models relevant to biomaterials and healthcare:
Protein Data Bank (PDB): A critical resource for structural biology, used in training deep learning models like AlphaFold for accurate protein structure prediction. PDB provides experimentally validated protein and macromolecular structures, forming the backbone of structure-based AI applications.
Medical Imaging Datasets: Publicly available databases such as The Cancer Imaging Archive (TCIA) and NIH Chest X-ray dataset were considered for studies utilizing AI in diagnostic imaging.
Electronic Health Records (EHRs): Studies incorporating AI in patient stratification and clinical decision-making often utilized anonymized EHR datasets like MIMIC-III.
Genomic Databases: Sources such as The Cancer Genome Atlas (TCGA) were used in multimodal AI models

combining genetic, imaging, and clinical data.

2. Role of Multimodal AI in Biomaterials Development

The integration of multimodal artificial intelligence (AI) into biomaterials development represents a transformative advancement in the biomedical sciences. Biomaterials comprising both natural and synthetic materials engineered for interactions with biological systems are fundamental to applications such as tissue engineering, drug delivery, and regenerative therapies. Historically, the design and optimization of these materials have relied heavily on trial-and-error methodologies, wherein individual materials are experimentally evaluated for attributes like biocompatibility, mechanical strength, and degradation behavior. This conventional process is often time-consuming, resource-intensive, and limited in scope.

However, this process can be slow and resource-intensive. Multimodal AI, which integrates data from various sources, like medical imaging, genomic data, and clinical information, is revolutionizing this process by accelerating material discovery, optimizing biomaterial design, and improving patient-specific applications [16,17]. Table 1 illustrates how multimodal AI is enhancing biomaterials development, offering an improved personalization, prediction accuracy, and development speed while highlighting new ethical and regulatory considerations [18,19,20,21,22,23,24,25,26].

2.1. Combining Multimodal Data (Imaging, Genomic, and Clinical Data)

A key aspect of multimodal AI in biomaterials research is the fusion of varied data types, including imaging, genomic, and clinical datasets. By analyzing the relationships between biological, mechanical, and patient-specific information, researchers gain a deeper understanding of how biomaterials perform in real-world applications. For instance, in tissue engineering, optimal material design requires balancing mechanical compatibility with host tissues while also ensuring the material supports cell adhesion, proliferation, and seamless biological integration [27]. This holistic approach enhances the development of biomaterials tailored for specific medical needs.

Leveraging Medical Imaging for Biomaterial Design

Advanced imaging techniques including MRI, CT scans, and high-resolution microscopy provide critical insights for biomaterial development. These methods enable a detailed visualization of tissue morphology, mechanical characteristics, and microstructural patterns, which are vital for designing functional tissue scaffolds. AI-driven approaches, especially convolutional neural networks (CNNs), excel at analyzing intricate imaging datasets, identifying key features such as tissue porosity, fiber alignment, and biomechanical properties. By automating feature extraction, AI enhances the precision of biomaterial optimization for regenerative medicine and tissue engineering applications [28]. By analyzing these features, multimodal AI systems can design materials with tailored mechanical properties that closely mimic those of native tissues. For instance, in cartilage tissue engineering, it is critical to design scaffolds that mimic the anisotropic mechanical properties of cartilage, such as its ability to withstand compressive forces. The AI-driven analysis of MRI scans of cartilage can help identify these properties, guiding the design of materials with comparable characteristics [29]. Similarly, in bone tissue engineering, CT scans provide detailed information about the microarchitecture of bone, which can be used to develop materials with an optimized porosity and strength.

2.2. Harnessing Genomic Data for Personalized Biomaterials

The incorporation of genomic data into biomaterial design enables a precision medicine approach, optimizing compatibility and therapeutic efficacy. By analyzing individual genetic profiles, multimodal AI can predict how a patient's immune system may react to an implant—identifying risks such as inflammation or rejection due to specific mutations or polymorphisms. Machine learning models can then recommend biomaterials that minimize adverse immune responses while promoting integration. In regenerative medicine, an AI-driven genomic analysis plays a pivotal role in material selection for stem cell therapies. By correlating genetic markers with cellular behavior, algorithms can determine which biomaterials best support differentiation and tissue regeneration. For instance, certain scaffold compositions may be prioritized based on a patient's gene expression patterns to enhance osteogenesis or angiogenesis. This tailored strategy not only improves clinical outcomes but also mitigates potential complications, advancing the frontier of patient-specific therapeutic solutions [30,31].

Clinical Data Integration for Patient-Centric Biomaterial Design

The incorporation of clinical data encompassing electronic health records, laboratory findings, and treatment responses provides a crucial context for optimizing biomaterial performance. By synthesizing this information with imaging and genomic datasets, multimodal AI enables the development of biomaterials that address both biological compatibility and individual clinical requirements. For instance, AI can evaluate comorbidities like diabetes or cardiovascular conditions to guide material selection for applications such as diabetic wound dressings or vascular implants, where healing dynamics may be significantly altered [32]. A particularly impactful application lies in smart drug delivery systems. AI models can process patient-specific variables including metabolic profiles, medication history, and treatment adherence to engineer biomaterials with tailored drug release kinetics. Such systems could adapt to individual pharmacokinetics, enhancing therapeutic efficacy while minimizing adverse effects. In oncology, for example, this approach might optimize chemotherapy-loaded scaffolds based on tumor responsiveness and patient tolerance [33]. The convergence of clinical analytics with biomaterial science thus represents a transformative step toward truly personalized medical solutions. By integrating these diverse data types, multimodal AI enables a holistic approach to biomaterials development, allowing researchers to design materials that are both biologically and mechanically suited to individual patients. Figure 1 illustrates the diverse data modalities that multimodal AI can integrate for biomedical applications, highlighting the wide-ranging opportunities this approach offers in advancing healthcare.

Modern healthcare leverages diverse data streams including medical imaging (MRI and CT), genomic profiles (DNA sequencing and transcriptomics), clinical records (EHRs and laboratory diagnostics), and wearable-derived physiological metrics to drive innovation in personalized medicine [34]. Multimodal AI synthesizes these heterogeneous datasets, revealing intricate correlations between genetic predispositions, structural abnormalities from imaging, and clinical manifestations. Such integration enhances diagnostic accuracy, enables dynamic treatment adaptations, and supports the predictive modeling of health trajectories.

This synergistic approach proves particularly transformative in three key areas:

Targeted Therapeutics: The AI-driven analysis of drug response patterns across multi-omics and clinical data informs precision drug formulation and delivery systems.

Tissue Engineering: Correlating mechanical properties from imaging with cellular behavior from genomic data facilitates scaffold customization for regenerative applications.

Proactive Care: Continuous wearable data combined with episodic clinical measurements enables early interventions through predictive analytics.

2.3. AI-Driven Biomaterial Design for Tissue Engineering

Traditional biomaterial development for tissue engineering has long depended on iterative experimental processes, involving extensive synthesis, characterization, and testing cycles. While these empirical methods have yielded valuable materials, they often prove resource-intensive and inefficient due to their reliance on trial-and-error optimization. The emergence of artificial intelligence is fundamentally reshaping this paradigm by introducing predictive, data-centric strategies that accelerate material discovery and refinement.

A critical application lies in tissue scaffold engineering, where three-dimensional architectures must precisely replicate native tissue characteristics. Key mechanical parameters including the elastic modulus, pore topology, and viscoelastic behavior require careful tuning to

. Promote cellular infiltration and nutrient diffusion through optimized porosity;

. Mimic tissue-specific mechanics (e.g., neural vs. musculoskeletal targets);

. Maintain structural integrity during dynamic remodeling processes.

AI models leverage existing experimental datasets to establish structure–property relationships, enabling an inverse design of scaffolds with predetermined performance criteria. Machine learning algorithms can predict how variations in the polymer composition, fabrication parameters, and architectural features will influence both the mechanical behavior and biological response [35]. This computational approach not only reduces development timelines but also facilitates the creation of graded or stimuli-responsive materials that adapt to evolving regenerative needs. An AI-enhanced scaffold design leverages medical imaging to create biomaterials that precisely mimic the native tissue architecture and biomechanics. Machine learning algorithms analyze CT/MRI datasets to identify critical structural patterns, enabling the data-driven fabrication of optimized tissue scaffolds. These features can then be used to guide the design of biomaterials with comparable properties. In the case of bone tissue engineering, AI can analyze CT scan data to determine the optimal porosity and strength required for scaffolds to support bone regeneration [36]. In cutaneous regeneration, artificial intelligence facilitates scaffold development by decoding skin microstructural patterns to enhance healing outcomes. Machine learning models evaluate material performance by synthesizing biological data, enabling the selection of substrates with optimal biocompatibility, cellular interaction properties, and controlled degradation kinetics [37]. A notable application involves hydrogel optimization, where AI cross-references imaging, molecular, and clinical datasets to determine formulations that best replicate natural extracellular matrix characteristics, thereby improving the regenerative potential [38]. Additionally, AI can guide the customization of these materials based on patient-specific factors, such as the location and severity of the injury. One of the most significant challenges in biomaterials development is predicting how materials will interact with cells and tissues once implanted. Multimodal AI offers a solution by enabling predictive modeling based on data from multiple sources, including in vitro experiments, imaging data, and clinical outcomes [39]. AI models can analyze these data to predict how cells will behave on different materials, including their adhesion, proliferation, and differentiation. For instance, in cartilage tissue engineering, AI-driven models can predict how chondrocytes will interact with different biomaterials, enabling the design of scaffolds that promote cartilage regeneration. Similarly, in vascular tissue engineering, AI can predict how endothelial cells will respond to specific materials, guiding the development of vascular grafts that promote blood vessel formation and reduce the risk of thrombosis [40]. Here Table 2 highlights how AI-driven approaches are revolutionizing biomaterial design by enabling data-driven optimization and patient-specific customization. Machine learning and deep learning techniques enhance scaffold properties (e.g., porosity and stiffness), while predictive modeling improves cell–material interactions for targeted tissue regeneration. The integration of multimodal data (imaging and genomics) underscores AI’s transformative role in developing precision biomaterials for diverse clinical applications, from bone repair to vascular grafts. Multimodal AI enables groundbreaking advances in patient-specific biomaterial designs by synthesizing individual imaging, genomic, and clinical profiles [41]. This precision approach proves particularly transformative for regenerative therapies, where the material–tissue compatibility directly determines therapeutic success. Sophisticated algorithms can predict individual immune reactions from genetic markers, informing the development of immune-compatible materials that reduce rejection risks. Furthermore, AI tailors biomechanical characteristics from bone scaffold rigidity to cutaneous graft flexibility to match each patient's unique physiological requirements [42].

2.4. AI in Drug Delivery Systems

Multimodal artificial intelligence (AI) is revolutionizing drug delivery systems by integrating diverse datasets, such as clinical records, imaging data, and molecular characteristics, to create more precise and effective therapies. Drug delivery systems are critical in medicine, ensuring that therapeutic agents reach their intended targets in the body in the right quantities and at the right times. Conventional drug delivery systems often suffer from inefficiencies such as poor targeting, low bioavailability, and side effects. AI can optimize these systems by predicting and modeling how different drugs interact with biological environments, leading to personalized and targeted delivery approaches [43]. Nanoparticles serve as effective drug carriers by enhancing therapeutic solubility, stability, and bioavailability. However, optimizing their design remains challenging due to multiple interdependent parameters including size, morphology, surface chemistry, and material properties [44]. Multimodal AI accelerates this optimization by synthesizing diverse datasets from clinical studies, computational simulations, and imaging analyses to predict ideal nanoparticle configurations for targeted drug delivery. For example, AI can analyze high-throughput screening data from in vitro experiments to determine how the nanoparticle size and surface chemistry affect drug release kinetics and cellular uptake. Similarly, AI models can process imaging data from animal studies to predict how nanoparticles distribute throughout the body and accumulate at specific disease sites, such as tumors. This data-driven approach enables the design of nanoparticles that are more efficient at delivering drugs to their targets while minimizing off-target effects [45]. In a study, machine learning algorithms were applied to predict the bio-distribution and pharmacokinetics of nanoparticles in drug delivery applications. By integrating imaging data and pharmacological data, the AI model could optimize the nanoparticle design, improving both the targeting efficiency and safety profile of the drug delivery system [46].

By harnessing multimodal artificial intelligence, therapeutic delivery systems can now be precisely customized to match each patient's distinct physiological profile. This AI-powered approach to individualized treatment represents a transformative advancement in modern healthcare, positioning smart drug delivery technologies as pivotal components in the emerging era of precision medicine. By integrating genomic, proteomic, and clinical data, AI models can predict how individual patients will respond to specific drugs, allowing for the design of delivery systems that maximize therapeutic efficacy while minimizing adverse effects [47]. One area where personalized drug delivery is particularly valuable is in cancer treatment. Tumors are highly heterogeneous, meaning that different patients with the same type of cancer may respond differently to the same drug. AI can integrate genomic data from tumor biopsies with imaging data and clinical histories to identify the most appropriate drug and delivery system for each patient [48]. For example, AI could analyze a patient's genetic mutations and tumor microenvironment to select nanoparticles that will effectively penetrate the tumor and release the drug at the optimal rate. This level of precision could significantly improve outcomes for cancer patients, reducing the need for trial-and-error approaches to treatment [49]. Table 3 presents a comparative analysis of various AI-driven diagnostic models in biomedicine, highlighting their methodologies, accuracy, advantages, and limitations. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) demonstrate a superior performance in medical imaging and the sequential data analysis, respectively, with CNNs excelling in tumor detection and classification, while RNNs show promise in processing genomic and electronic health record data. Transformer-based models, such as attention mechanisms in multimodal AI, have enhanced diagnostic precision by integrating heterogeneous data sources [50,51,52,53,54].

Despite achieving impressive accuracy rates, AI diagnostic systems still face significant hurdles related to data quality requirements, algorithmic transparency, and inherent biases in training datasets. While conventional machine learning approaches like Support Vector Machines (SVMs) and decision trees provide more interpretable and computationally lightweight solutions, they typically struggle with the complexity of modern biomedical data analysis. The comparative analysis highlights AI's transformative capacity in precision diagnostics while clearly identifying key areas for advancement—particularly in enhancing model generalizability, establishing robust regulatory standards, and addressing ethical implications for real-world clinical integration.

Traditional drug delivery routes, such as oral and transdermal administration, also stand to benefit from AI. Oral drug delivery is the most common route of administration but often suffers from challenges like the poor solubility and low bioavailability of drugs. Transdermal drug delivery, which involves delivering drugs through the skin, is limited by the skin's natural barrier function. AI can address these challenges by predicting the physicochemical properties that influence the drug absorption through these routes and optimizing drug formulations accordingly [55]. For example, machine learning algorithms can predict how different excipients and formulation techniques affect the solubility and dissolution rates of orally administered drugs. Similarly, AI can model how different drug formulations interact with the skin barrier, guiding the development of transdermal patches that improve drug penetration and absorption [56].

Controlled-release systems are designed to release drugs over an extended period, reducing the frequency of dosing and improving patient compliance. Targeted drug delivery systems aim to deliver drugs directly to the site of the disease, minimizing the exposure to healthy tissues. AI plays a crucial role in optimizing both controlled and targeted drug delivery by modeling how different materials and drug formulations influence the release kinetics and targeting specificity [57]. For instance, AI can integrate data from in vitro drug release studies, imaging data, and clinical outcomes to optimize the formulation of hydrogels, polymers, and nanoparticles for controlled and targeted drug release. In a study, AI models were used to predict the release profiles of drugs encapsulated in hydrogels based on the material's properties and environmental conditions. This approach enabled the design of hydrogels that released drugs at a controlled rate in response to specific physiological triggers, such as changes in pH or temperature [58]. Figure 2 demonstrates the process of the drug encapsulation and release within micelles formed by the polymeric structure Ad-(PCL-b-PDEAEMA-b-PPEGMA)4. These micelles serve as nanocarriers for Doxorubicin (DOX), a widely used chemotherapy drug. The figure highlights how the micelles are formed through the self-assembly of the block copolymers, driven by hydrophobic interactions. The system exhibits pH-responsive behavior, where the release of DOX is triggered in acidic environments, such as tumor tissues, due to the protonation of the PDEAEMA block. This pH-dependent release mechanism enhances the targeted delivery of DOX, minimizing side effects and improving the therapeutic efficacy in cancer treatments [59].

2.5. AI in Regenerative Medicine Applications

Regenerative medicine seeks to restore compromised tissues and organs by augmenting innate biological repair mechanisms or deploying bioengineered constructs and cellular interventions. The incorporation of multimodal artificial intelligence significantly enhances this field by enabling the data-driven optimization of tissue scaffolds, precision stem cell applications, and targeted genome editing approaches. Through the sophisticated analysis of integrated imaging, molecular profiling, and proteomic datasets, AI systems facilitate the creation of tailored regenerative solutions with improved therapeutic outcomes [60].

Tissue engineering scaffolds serve as essential three-dimensional frameworks that facilitate cellular adhesion, growth, and specialization. Effective scaffold development requires a careful consideration of multiple parameters, such as structural integrity, pore network characteristics, and biological compatibility. Advanced multimodal AI systems enhance this process by synthesizing information from biomaterials research, histological patterns, and cellular response data to engineer scaffolds that precisely replicate the biomechanical and functional properties of natural tissues [61]. For example, AI models can analyze imaging data from tissues to determine their mechanical properties, such as elasticity and stiffness. This data can then be used to guide the selection of scaffold materials and architectures, ensuring that the scaffold provides the appropriate mechanical environment for cell growth. In bone tissue engineering, the AI-driven analysis of CT scans can help design scaffolds with the optimal porosity and mechanical strength for promoting bone regeneration [24]. Similarly, in skin tissue engineering, AI can analyze histological data to design scaffolds that support wound healing and tissue integration [62]. Table 4 provides a comparative analysis of AI-optimized biomaterials for tissue engineering applications, emphasizing their composition, functionality, and AI-driven enhancements [22,24,36,63,64]. Artificial intelligence has revolutionized biomaterial development by enabling the predictive modeling of material characteristics, the optimization of three-dimensional scaffold geometries, and the customization of formulations to enhance both biological integration and structural performance. Notably, advanced neural networks have successfully engineered hydrogel matrices with superior cellular binding properties and programmable degradation profiles, significantly improving tissue reconstruction outcomes. AI-driven generative models have also enabled the discovery of novel polymer composites with tunable porosity and mechanical properties suited for bone and cartilage regeneration. Furthermore, reinforcement learning algorithms have optimized 3D bioprinting parameters, ensuring a precise layer deposition and vascular network formation in engineered tissues. While AI-driven biomaterials demonstrate significant advancements in regenerative medicine, challenges remain in translating computational predictions into clinically viable solutions, necessitating further validation, regulatory standardization, and large-scale experimental studies.

Stem cell therapies are a cornerstone of regenerative medicine, offering the potential to replace damaged cells and tissues. However, the success of these therapies depends on a range of factors, including the selection of the appropriate stem cell type, the differentiation potential of the cells, and their ability to integrate with host tissues. Multimodal AI can optimize stem cell-based therapies by integrating genomic, proteomic, and clinical data to predict the behavior of stem cells in different biological environments [65]. Artificial intelligence enables precision stem cell selection by analyzing individual genetic profiles to identify optimal cell sources for patient-specific therapies. Machine learning algorithms can additionally forecast cellular differentiation pathways, predicting whether stem cells will develop into neural, cardiac, or bone-forming cells by analyzing microenvironmental signals and material characteristics. Research by Chen et al. demonstrated this capability through the AI-driven prediction of the mesenchymal stem cell osteogenic differentiation potential for skeletal tissue repair applications. By integrating genomic data with imaging data from bone tissues, the AI model could optimize the selection of stem cells and biomaterials for promoting bone formation [66].

CRISPR-based gene editing represents a transformative approach in regenerative medicine, enabling precise DNA modifications to address genetic disorders. The therapeutic efficacy of these interventions relies critically on both target specificity and the minimization of unintended genomic alterations. Multimodal artificial intelligence significantly improves editing precision by synthesizing multi-omics data to identify optimal target sequences and design efficient editing protocols [67]. Machine learning algorithms process extensive genomic information to pinpoint disease-relevant targets while predicting potential off-target activity through the computational modeling of CRISPR–cas9 interactions. A recent application demonstrated AI's capability in muscular dystrophy therapy, where an integrated analysis of genomic and proteomic datasets enabled the identification of optimal editing sites while reducing off-target risks [68]. Figure 3 presents the complex organizational structure governing advanced therapy development, highlighting interdisciplinary coordination across healthcare sectors [69].

At the center of this framework is the advanced therapy medicinal products (ATMPs), surrounded by nodes that represent essential hospital units responsible for different aspects of ATMP development and application. This interconnected structure highlights the importance of interdisciplinary collaboration in successfully bringing ATMPs from conception to clinical use. Each unit, including research, regulatory affairs, and clinical applications, contributes to ensuring that these innovative therapies are effective, safe, and compliant with regulatory standards. Overall, the figure underscores the necessity of a cohesive approach to leverage the full potential of ATMPs in advancing patient care.

Multimodal AI is revolutionizing regenerative medicine through patient-specific therapeutic designs, synthesizing radiological, genomic, and clinical data to develop customized treatment solutions. This precision approach enhances therapeutic efficacy while mitigating potential adverse effects [70]. In articular cartilage repair, AI algorithms correlate MRI-derived structural data with genetic profiles to engineer biocompatible scaffolds optimized for individual tissue regeneration requirements. For myocardial repair, intelligent systems evaluate cardiac imaging and cellular biomarkers to select ideal stem cell-biomaterial combinations for targeted cardiac tissue restoration [71]. Such biologically tailored interventions mark a paradigm shift toward truly individualized medical care, where regenerative strategies are precisely adapted to each patient’s unique physiological characteristics and health profile.

2.6. Multimodal AI in Biomaterials Science

Multimodal AI, by integrating diverse biomedical data sources such as imaging, genomic sequences, and electronic health records, enables the precise engineering of biomaterials tailored to individual patient needs. This approach surpasses conventional computational techniques by uncovering complex, nonlinear relationships between biomaterial properties and biological responses. For instance, deep learning models trained on high-throughput experimental datasets can predict biomaterial–cell interactions, leading to the rational design of bioactive scaffolds that promote tissue regeneration. Similarly, AI-driven molecular simulations enhance drug delivery systems by optimizing nanoparticle formulations for controlled and targeted therapeutic release. Furthermore, multimodal AI facilitates the convergence of bioinformatics and material science, expediting the discovery of novel biomaterials with an enhanced biocompatibility and mechanical performance. This manuscript now provides a more in-depth discussion of these advancements, supported by case studies and comparative analyses of AI-based versus traditional approaches. By narrowing the scope to AI’s transformative impact on biomaterials science, our review offers a more focused and insightful contribution to the field, highlighting the practical implications, advantages, and challenges of integrating AI into biomaterials research and clinical translation.

3. AI-Powered Diagnostics and Precision Medicine

The integration of multimodal artificial intelligence has become a cornerstone of modern diagnostic and therapeutic innovation in healthcare. By synthesizing diverse biological datasets, including molecular profiles, medical imaging, and electronic health records, AI systems facilitate the creation of precise diagnostic methods and customized intervention strategies. This technological advancement represents a fundamental evolution in medical practice, where patient management is increasingly guided by the comprehensive analysis of individual pathophysiological characteristics. The following discussion examines AI’s transformative influence on both disease detection and tailored treatment development, highlighting its significant contributions to contemporary biomedical progress. Figure 4 depicts the precision medicine paradigm, emphasizing the evaluation of various cancer therapeutics, such as chemotherapy, targeted therapies, and immunotherapy [72]. By utilizing patient-derived tumor cells and advanced models like spheroids and organoids, this approach enables more accurate assessments of drug efficacy tailored to individual patient profiles. Additionally, the inclusion of orthotopic murine xenograft models further supports the translational potential of these therapies. The anticipated integration of AI-driven systems promises to accelerate this process by streamlining the data analysis and enhancing predictive accuracy, ultimately facilitating the development of personalized treatment regimens that improve patient outcomes in oncology.

3.1. Role of AI in Disease Diagnosis

Artificial intelligence is transforming clinical diagnostics by enabling a more precise identification and evaluation of complex pathologies, including malignancies, heart disease, and neurodegenerative conditions. While conventional diagnostic approaches remain valuable, their dependence on subjective assessments can result in inconsistent interpretations and therapeutic delays. Multimodal AI overcomes these challenges by synthesizing radiological, molecular, and patient history data to generate objective, evidence-based diagnostic conclusions [73].

Artificial intelligence has revolutionized medical image interpretation, with deep learning architectures demonstrating remarkable proficiency in analyzing radiological scans. Convolutional neural networks excel at processing MRI, CT, and radiographic images, detecting subtle pathological features that often elude human observation. This capability enables an earlier and more precise disease identification [74]. A prominent example is mammographic analysis, where CNNs trained on extensive labeled datasets can discern malignant patterns with an accuracy rivaling or surpassing expert radiologists [75]. Such systems provide real-time interpretation, dramatically decreasing diagnostic turnaround times. Clinical validation studies involving over 76,000 mammograms demonstrated AI's superiority in reducing both false-positive and false-negative rates compared to conventional screening methods [76]. Comparable advancements have emerged in pulmonary oncology, with AI algorithms achieving an exceptional sensitivity in identifying malignant nodules on thoracic CT imaging [77].

Histopathology, the microscopic examination of tissue samples, is another area where AI is proving invaluable. Traditionally, pathologists analyze tissue biopsies manually, which can be time-consuming and prone to variability in interpretation. AI-powered digital pathology systems can analyze histological slides with greater consistency and speed, identifying abnormalities such as cancerous cells or inflammatory processes [78]. In prostate cancer diagnosis, for example, AI models have been trained to recognize patterns of cancerous growth in tissue samples with a high accuracy. These models can assist pathologists by providing second opinions or pre-screening slides for potential malignancies, thus reducing the workload on clinicians and improving diagnostic accuracy [79]. Similarly, in gastrointestinal pathology, AI has been employed to identify dysplastic lesions in colon biopsies, aiding in the early detection of colorectal cancer [80].

Artificial intelligence serves as a powerful bridge between molecular profiling and clinical decision-making, transforming complex genomic data into actionable diagnostic insights. As next-generation sequencing becomes more cost-effective, AI systems address the analytical challenges posed by massive genomic datasets by detecting disease-relevant mutations, transcriptional patterns, and molecular biomarkers. In oncology, machine learning algorithms distinguish pathogenic driver mutations from benign variants, while integrating these findings with radiological and clinical data for a comprehensive tumor characterization [81]. Commercial platforms exemplify this approach by cross-referencing individual genomic alterations with therapeutic databases to recommend evidence-based treatment regimens. Such systems enable truly precision oncology, where anticancer therapies are selected based on each tumor's unique molecular fingerprint [82]. Artificial intelligence is increasingly valuable for detecting neurodegenerative conditions like Alzheimer's and Parkinson's diseases, where early identification remains clinically challenging due to an insidious symptom progression. Machine learning models demonstrate a particular efficacy in analyzing structural and functional neuroimaging Magnetic Resonance Imaging/Positron Emission Tomography (MRI/PET) alongside cognitive assessments to uncover preclinical indicators of neurological decline [83]. In Alzheimer's disease, AI models have been trained to recognize patterns of brain atrophy and amyloid deposition in MRI and PET scans, providing earlier and more accurate diagnoses than conventional methods. In another study, an AI system was developed to analyze PET scans for early signs of Alzheimer's disease, achieving an accuracy rate of over 90% in detecting the disease several years before clinical symptoms appeared [84]. Such advances in AI-driven diagnostics hold the promise of earlier interventions and improved outcomes for patients with neurodegenerative diseases.

The role of protein structure predictions, particularly through advancements such as AlphaFold Ref. [85], is pivotal in the field of biomedicine and biomaterials development, as highlighted in this review. AlphaFold, an AI system developed by DeepMind, has demonstrated an unprecedented ability to predict the three-dimensional structures of proteins with remarkable accuracy, which is critical for understanding protein functions, interactions, and stability. In the context of biomaterials, accurate protein structure predictions enable researchers to design materials that closely mimic biological tissues, enhancing their compatibility and performance in tissue engineering and regenerative medicine. Furthermore, AlphaFold' s predictions support drug discovery by revealing potential binding sites and interactions at the molecular level, which can accelerate the development of targeted therapies. This capability is particularly relevant for designing biomaterials that interact with specific proteins or enzymes in drug delivery systems. The integration of AlphaFold' s predictions with other multimodal AI tools enhances our ability to manipulate and design proteins and biomaterials at the molecular level, offering transformative potential in creating highly tailored biomedical solutions. Figure 5 highlights AlphaFold' s remarkable capability to predict accurate protein structures, outperforming other top entries in the CASP14 competition [85]. The figure compares AlphaFold' s performance with other models using the median and confidence intervals, showing its superior predictive power. One example is the accurate alignment of AlphaFold' s predicted structure with an experimentally determined protein structure, demonstrating the model' s reliability in reproducing complex protein folds. Additionally, AlphaFold exhibits precise side-chain predictions in a zinc-binding site, despite not explicitly predicting the metal ion. In more complex cases, such as a 2180-residue protein, AlphaFold correctly predicts the domain organization, underscoring its ability to handle large and intricate protein structures. The figure also illustrates AlphaFold' s model architecture, showcasing how information flows between sequences, residues, and channels, which contributes to its high accuracy. These examples emphasize AlphaFold' s impact on structural biology, enabling more reliable protein modeling for research applications.

3.2. AI-Driven Precision Medicine

The transition to personalized healthcare marks a fundamental evolution in medical practice, replacing generalized treatment protocols with tailored therapeutic strategies based on individual patient profiles. Artificial intelligence serves as a critical enabler of this transformation by synthesizing multidimensional biological data—including genomic variations, protein expression patterns, and clinical histories—to guide therapeutic decision-making. Through the large-scale analysis of these complex datasets, machine learning algorithms can forecast patient-specific treatment responses, empowering clinicians to optimize therapeutic regimens for enhanced effectiveness and reduced complications [86]. Precision oncology has emerged as a prime beneficiary of AI-driven personalized medicine, addressing the critical challenge of tumor heterogeneity where histologically similar cancers demonstrate divergent treatment responses. Advanced machine learning algorithms synthesize multi-omics data from tumor biopsies with clinical and imaging datasets to generate patient-specific therapeutic recommendations [87]. These systems identify predictive biomarkers—including targetable mutations and immunogenic signatures—while forecasting individual drug sensitivity patterns. A recent breakthrough application involved gene expression-based machine learning models that accurately stratified breast cancer patients by chemotherapy response, enabling risk-adapted treatment protocols [88]. AI has also been used to optimize radiation therapy for cancer patients. By integrating imaging data with genomic information, AI can predict how tumors will respond to radiation, allowing for the design of radiation plans that maximize tumor destruction while minimizing the damage to surrounding healthy tissues [89]. AI-enhanced precision oncology significantly improves therapeutic efficacy while minimizing adverse effects through pharmacogenomic optimization. By analyzing genetic polymorphisms in drug metabolism pathways (e.g., CYP450 enzymes) and therapeutic targets, machine learning algorithms predict individual pharmacokinetic profiles, enabling customized dosing strategies [90]. This approach proves particularly impactful in cardiovascular care, where AI models incorporating CYP2C9/VKORC1 variants optimize warfarin dosing, reducing hemorrhage risks while maintaining anticoagulation efficacy [91]. In cancer therapeutics, these systems demonstrate a similar value by correlating tumor genomic landscapes with drug sensitivity patterns—as evidenced by recent non-small cell lung cancer research where an AI-guided therapy selection improved outcomes through mutation-specific treatment matching [92]. Cardiovascular medicine is leveraging AI to develop patient-specific management strategies for heart disease. Advanced algorithms process multimodal cardiac data, including electrophysiological signals, imaging biomarkers, and clinical histories, to stratify the individual risk for acute coronary events or cerebrovascular incidents. These predictive insights inform tailored therapeutic approaches, optimizing medication selection, lifestyle modifications, and interventional timing [93]. Notably, machine learning applications in arrhythmia prediction demonstrate particular clinical value; by detecting subtle ECG pattern abnormalities, these systems enable prophylactic measures ranging from pharmacological management to device implantation, substantially mitigating the probability of catastrophic cardiac events while enhancing prognostic outcomes [94].

Artificial intelligence is revolutionizing mental healthcare by enabling tailored interventions for heterogeneous psychiatric conditions, including depressive disorders, anxiety syndromes, and psychotic illnesses. Machine learning systems synthesize psychometric evaluations, neuroimaging findings, and genomic markers to forecast individual treatment responses, addressing the well-documented variability in therapeutic outcomes [95]. Particularly in major depression management, predictive algorithms analyze phenotypic and genetic factors to optimize the antidepressant selection, substantially reducing the conventional trial-and-error approach and accelerating symptom remission [96]. Despite this potential, implementation barriers persist, particularly regarding data protection requirements for sensitive health information and the need for explainable AI frameworks in clinical decision-making [97]. The continued progress in computational methods and multimodal data fusion promises to enhance these systems' reliability and adoption, potentially transforming mental healthcare through precise diagnostic categorization and individualized treatment protocols [98].

3.3. Advanced Predictive Modeling in Healthcare Through Machine Learning

Machine learning has emerged as a transformative force in healthcare predictive analytics, enabling the data-driven forecasting of clinical trajectories. These computational approaches leverage historical patient data to generate probabilistic assessments of disease progression, therapeutic efficacy, and adverse event risks—facilitating proactive medical interventions. When combined with multimodal AI architectures, predictive models gain an enhanced capability to process heterogeneous datasets spanning molecular profiles, medical imaging, and electronic health records. This integration enables the development of sophisticated prognostic tools that deliver a personalized risk stratification with improved accuracy, ultimately supporting precision medicine initiatives.

Various machine learning algorithms, such as logistic regression, decision trees, Support Vector Machines (SVMs), and deep learning models, have been employed in predictive healthcare. Logistic regression, a fundamental method in medical statistics, remains popular for its simplicity and interpretability in predicting binary outcomes, such as disease presence or absence [99]. However, with the increasing complexity of available healthcare data, more sophisticated models like decision trees and SVMs, which can handle nonlinear relationships, are being adopted. Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are proving to be even more effective at making predictions when complex, high-dimensional datasets are involved. CNNs are particularly useful for analyzing medical imaging data, while RNNs are often employed for time-series data, such as monitoring patient vitals [100]. These models can learn hierarchical patterns in data, automatically identifying significant features that would be difficult for clinicians to notice manually. An example of machine learning in predictive healthcare is the prediction of patient readmission rates, a critical issue in hospital management. Predicting which patients are at risk of readmission allows healthcare providers to intervene proactively. In one study, a machine learning algorithm was able to predict 30-day hospital readmissions for heart failure patients by analyzing factors like previous admissions, medications, and vital signs, achieving a predictive accuracy significantly higher than traditional statistical methods [101]. Another example involves predicting the progression of chronic diseases, such as diabetes or kidney disease, by analyzing clinical data and lab results. ML models can identify early signs of disease progression, allowing for timely interventions to prevent complications [102].

Predicting the onset of diseases at their earliest stages is a key area where ML models have demonstrated considerable success. One of the most significant applications is in the early prediction of cancer. Using ML algorithms trained on large datasets that include clinical records, genomic data, and medical images, AI can predict the likelihood of cancer development before clinical symptoms appear. For instance, an AI system developed to analyze mammograms for breast cancer risk was able to predict the onset of cancer up to five years in advance with an accuracy higher than that of human radiologists [103]. A similar predictive model was applied to Alzheimer's disease, where machine learning algorithms analyzed brain scans and genetic markers to predict the onset of the disease before clinical symptoms became evident. A study conducted by a scientist group demonstrated that a deep learning model could predict Alzheimer's disease from PET scans up to six years before an official diagnosis, with an accuracy of over 90% [104]. Early prediction enables patients and healthcare providers to take preventive measures, potentially delaying the progression of the disease.

Despite its transformative potential, predictive analytics in healthcare faces several critical challenges that must be addressed. A fundamental limitation stems from the training data quality, as many models rely on retrospective datasets with a limited generalizability across diverse populations. When certain demographic groups are underrepresented, algorithmic biases can emerge, potentially exacerbating healthcare disparities for marginalized communities [105]. Model interpretability presents another hurdle, especially for complex deep learning systems whose decision-making processes remain opaque. While emerging techniques like SHAP and LIME offer post hoc explanations for model outputs [106], further advances are needed to meet clinical transparency requirements. Ethical considerations around data privacy and informed consent also demand careful attention, particularly regarding their compliance with international standards like GDPR [107]. Looking ahead, incorporating multimodal data streams from genomic profiles to wearable device metrics while employing privacy-preserving approaches such as federated learning [108] will be crucial for developing robust, equitable predictive systems that account for the full spectrum of health determinants.

3.4. Multimodal Data Fusion for Enhanced Diagnostic Accuracy

Multimodal AI, which integrates diverse data sources such as medical images, genomic data, and clinical records, is revolutionizing diagnostics by providing a more comprehensive and nuanced understanding of patient health. Data fusion refers to the process of combining information from different modalities to enhance the accuracy and reliability of diagnostic predictions. In biomedicine, leveraging multimodal data fusion allows AI systems to provide richer, more precise diagnostic insights than any single modality could offer on its own.

Single-modality diagnostics, where only one type of data is analyzed (e.g., medical imaging or genetic data), often suffer from limitations that can reduce diagnostic accuracy. For example, relying solely on medical images may miss underlying molecular or genetic abnormalities that contribute to disease progression. Similarly, using only genomic data may overlook anatomical or functional changes visible in imaging studies. Each modality provides only a partial view of the patient's condition, leading to potential misdiagnoses or incomplete assessments [109]. An illustrative example is the diagnosis of brain tumors. While imaging techniques such as MRI are excellent at detecting the physical presence and size of a tumor, they cannot provide information on the tumor's genetic mutations or molecular characteristics, which are crucial for determining the most effective treatment. Integrating imaging data with genomic information can significantly enhance diagnostic accuracy by providing both structural and molecular insights into the tumor [110].

Multimodal data integration combines complementary data types to enhance diagnostic precision through comprehensive analytical models. This synergistic approach in AI-based diagnostics merges radiological, molecular, and clinical datasets to minimize diagnostic errors while improving detection accuracy across various pathologies [111]. In oncological applications, the convergence of radiomic features from advanced imaging with molecular profiling data enables a more precise tumor characterization, prognostic stratification, and therapeutic personalization. The research demonstrates a superior predictive capability when combining CT-derived radiomics with transcriptomic data for forecasting treatment responses in pulmonary malignancies, outperforming single-modality analytical approaches [112].

The integration of imaging and genomic data represents a transformative frontier in precision diagnostics. By correlating radiological patterns with molecular profiles, AI systems can predict disease susceptibility, genetic mutations, and therapeutic responses with unprecedented accuracy. In breast oncology, the combined analysis of mammographic features and genomic signatures enables a reliable prediction of tumor recurrence risk, guiding critical treatment decisions regarding the chemotherapy necessity [113]. Similarly, for neurodegenerative conditions, AI models synthesizing PET imaging with APOE4 genotyping demonstrate a remarkable capability in preclinical Alzheimer's detection, facilitating early intervention opportunities [114].

Multimodal AI applications now span diverse medical specialties, demonstrating superior performances to conventional diagnostic approaches. Cardiovascular risk assessment exemplifies this advancement, where an integrated analysis of echocardiograms, electronic health records, and genetic data achieves more accurate heart failure predictions than established risk-scoring systems [115]. A landmark study in preventive cardiology showed such multimodal systems surpassing traditional metrics like the Framingham Risk Score in forecasting acute cardiovascular events [116]. Future development focuses on incorporating emerging data streams—from wearable biosensors to environmental factors—while overcoming challenges of healthcare data interoperability and maintaining rigorous ethical standards for data privacy and algorithmic transparency [117,118].

4. Wearable Technologies and Real-Time Health Monitoring

4.1. AI Integration with Wearable Devices

Modern wearable health technologies have evolved into intelligent monitoring systems through artificial intelligence integration, transitioning from basic biometric tracking to sophisticated health analysis platforms. These AI-enhanced devices process continuous physiological data streams to detect emerging health patterns, forecast potential risks, and deliver customized health recommendations, establishing a new paradigm of proactive, data-driven wellness management. Figure 6 outlines the significant milestones in the evolution of AI-assisted wearable biosensor networks (WAIBNs), highlighting the technological advancements that have facilitated their integration into healthcare [119]. The timeline showcases the transition from basic biosensors to sophisticated, AI-enhanced systems capable of real-time data analysis and interpretation. These technological advancements facilitate the uninterrupted tracking of vital health metrics, significantly improving clinical monitoring and therapeutic management. A sophisticated machine learning integration transforms raw biometric data into actionable health intelligence, enabling preemptive medical interventions tailored to individual needs. Collectively, these innovations demonstrate AI's transformative impact on wearable health technologies, driving progress in telemedicine and precision healthcare delivery.

Contemporary wearable technologies span consumer-grade fitness trackers to clinical-grade biosensors, collectively enabling the continuous tracking of vital physiological parameters. These devices capture critical health metrics, including cardiovascular function, metabolic indicators, and behavioral patterns, generating longitudinal datasets essential for identifying health trends and enabling proactive interventions [120]. Research demonstrates their particular value in chronic disease management, where real-time physiological streaming enhances clinical decision-making [121]. The incorporation of artificial intelligence transforms these devices from passive data collectors to active diagnostic assistants through advanced signal processing and pattern recognition. Modern wearables employ sophisticated machine learning architectures to derive clinically meaningful insights from continuous biometric streams. Deep learning models excel at detecting subtle pathological patterns, such as cardiac arrhythmias in ECG waveforms or early hypertension risk factors from blood pressure trends [122,123]. These systems enable truly personalized healthcare by analyzing individual health patterns to generate tailored lifestyle recommendations and medication adherence prompts [124]. In diabetes care, AI-enhanced continuous glucose monitors provide real-time glycemic feedback while analyzing behavioral data to optimize dietary and activity suggestions [125], representing a paradigm shift in chronic disease self-management. Despite their potential, AI-powered wearables face significant adoption barriers including data security vulnerabilities and a lack of standardization across device ecosystems [126,127]. Addressing these limitations requires robust encryption protocols and unified data frameworks compliant with healthcare regulations. Future advancements will focus on a multidimensional health analysis incorporating psychosocial and environmental determinants through next-generation sensors and adaptive machine learning models, promising to redefine preventive healthcare delivery through increasingly sophisticated wearable health ecosystems.

Wearable devices encompass a range of technologies, including smartwatches, fitness trackers, and medical-grade sensors. These devices can monitor various physiological parameters, such as heart rate, blood pressure, blood glucose levels, sleep patterns, and physical activity. The continuous monitoring capabilities of wearables facilitate the collection of longitudinal health data, which is critical for understanding health trends and making timely interventions [120]. For instance, a study highlighted that wearable devices could effectively monitor patients with chronic diseases, providing real-time data that helps healthcare providers make informed decisions [121]. The integration of AI into these wearables enhances their functionality by enabling a data analysis and interpretation that go beyond simple metrics.

The integration of AI algorithms allows wearables to not only collect but also analyze data in real-time. Machine learning techniques can identify patterns and anomalies in the data, offering insights that can inform healthcare decisions. For example, wearable ECG monitors use AI algorithms to detect arrhythmias, providing early warnings to both patients and healthcare providers [122]. These systems have shown high accuracy rates in identifying abnormal heart rhythms, which is crucial for preventing serious cardiovascular events. Deep learning models are particularly effective in processing the complex data generated by wearable devices. These models can learn from large datasets to improve their predictive capabilities. For instance, researchers developed a deep learning model that could predict the risk of hypertension based on data collected from wearable blood pressure monitors. The model analyzed historical data, lifestyle factors, and real-time measurements to identify individuals at high risk of developing hypertension [123].

The AI integration with wearable devices allows for personalized health management by tailoring interventions based on a real-time data analysis. For example, wearables can provide personalized feedback and recommendations for physical activity, diet, and medication adherence based on the individual’s health data. This personalization enhances patient engagement and promotes healthier lifestyles [124]. In diabetes management, wearable devices equipped with continuous glucose monitors (CGMs) and AI algorithms can provide real-time feedback on blood glucose levels. These systems can alert patients when their levels are too high or too low, enabling timely interventions. Moreover, AI can analyze dietary patterns and physical activity levels to suggest lifestyle changes that can help maintain optimal blood glucose levels [125]. Despite the promising benefits of AI integration with wearable devices, several challenges must be addressed. Data privacy is a significant concern, as continuous monitoring involves collecting sensitive health information. Ensuring the security of this data is paramount to maintaining patient trust and complying with regulations such as the Health Insurance Portability and Accountability Act (HIPAA) [126]. Another challenge is the standardization of data collected from various wearable devices. Inconsistent data formats and metrics can hinder interoperability and the ability to aggregate data from multiple sources. Standardization efforts are essential to create a unified ecosystem that enhances the effectiveness of AI algorithms [127]. Looking forward, the future of AI-integrated wearables lies in developing more sophisticated algorithms that can analyze not only physiological data but also contextual factors, such as emotional well-being and social determinants of health. The incorporation of advanced sensors and machine learning models will enable wearables to provide even deeper insights into health, ultimately transforming the way healthcare is delivered.

4.2. AI-Enhanced Remote Patient Monitoring

The adoption of remote patient monitoring (RPM) systems has accelerated significantly, driven by technological advancements and pandemic-induced healthcare transformations. These platforms utilize interconnected wearable sensors, mobile health applications, and virtual care interfaces to enable continuous physiological tracking beyond clinical environments. AI integration augments RPM capabilities through advanced data analytics, facilitating early anomaly detection and personalized care recommendations while maintaining the care quality across distances. Modern RPM architectures typically incorporate three key elements: biometric wearables for vital sign acquisition (e.g., cardiac rhythm and oxygen saturation), patient-facing applications for data transmission, and clinician portals for centralized monitoring [128]. Such systems prove particularly valuable for chronic disease management, exemplified by heart failure protocols that track dynamic parameters like daily weight fluctuations and cardiopulmonary metrics, enabling preemptive clinical interventions before acute decompensation occurs [129].

The incorporation of AI into RPM systems significantly enhances their functionality. AI algorithms can analyze data collected from wearables to identify trends and anomalies that may indicate potential health issues. For example, an AI system can monitor heart failure patients’ weight and fluid intake data to predict exacerbations, allowing healthcare providers to intervene before hospitalization is necessary [130]. A study demonstrated that AI-powered RPM systems reduced hospital readmission rates for heart failure patients by over 30%, showcasing the effectiveness of these technologies [131]. Intelligent risk stratification represents a key advantage of AI-enhanced monitoring systems, which synthesize multi-source data streams from wearables, electronic records, and patient-generated health metrics. This analytical capability allows clinicians to precisely identify vulnerable patient subgroups needing prioritized care, thereby optimizing resource allocation and enhancing healthcare system efficiency [132]. Despite these advantages, significant implementation barriers must be overcome to achieve broad clinical adoption. One significant challenge is patient engagement and adherence to using wearable devices and monitoring systems. Studies have shown that patient engagement decreases over time, which can limit the effectiveness of RPM systems [133]. Strategies to improve patient adherence include user-friendly interfaces, educational resources, and regular communication with healthcare providers. Data privacy and security concerns also pose challenges. RPM systems collect sensitive health information, making it essential to implement robust security measures to protect patient data. Ensuring compliance with regulations, such as the HIPAA, is crucial to maintaining patient trust and confidentiality [134]. Another challenge is the integration of RPM systems into existing healthcare workflows. Healthcare providers may face difficulties in adapting to new technologies and incorporating RPM data into clinical decision-making. Training and support for healthcare professionals are essential to facilitate the successful implementation of RPM systems [135]. The evolution of remote patient monitoring systems shows tremendous potential as AI algorithms and wearable technologies advance. Next-generation platforms will deliver increasingly precise predictive analytics, enabling more accurate health assessments and personalized interventions [136]. The convergence of RPM with telehealth solutions will create dynamic care ecosystems, allowing immediate clinician–patient interactions when abnormalities are detected. The expansion into diverse care settings from home-based care to rehabilitation centers promises to democratize the access to continuous monitoring while reducing healthcare expenditures [137]. This synergistic integration of AI and connected health technologies is ushering in a paradigm shift toward anticipatory, precision medicine—one that prioritizes prevention, personalization, and health system sustainability through data-driven care delivery models.

4.3. Use of Multimodal Data for Continuous Health Surveillance

Modern biosensor devices have ushered in a new era of continuous physiological tracking through sophisticated multimodal data integration. These systems capture comprehensive health metrics, including cardiopulmonary function, metabolic indicators, and movement patterns, while simultaneously recording environmental exposures and behavioral patterns [138]. This multidimensional approach enables unprecedented insights into individual health trajectories, allowing for preemptive clinical interventions before acute manifestations occur.

Multimodal data refers to information collected from various sources, providing a holistic view of an individual's health. In the context of wearable technologies, this data can include the following:

Physiological Data: Collected from devices such as smartwatches, fitness trackers, and medical sensors that monitor vital signs.

Environmental Data: Information about the patient's surroundings, such as the air quality, temperature, and humidity, which can impact health.

Behavioral Data: Insights into lifestyle factors, including physical activity levels, sleep patterns, and dietary habits.

Social Data: Contextual information regarding social interactions and support systems, which can influence mental and emotional well-being [138].

The true power of wearable technologies lies in their ability to correlate disparate health determinants. Continuous glucose monitoring systems exemplify this capability, combining biochemical measurements with activity logs and nutritional data to optimize diabetes management [139,140]. Research confirms such integrated approaches yield superior glycemic control compared to conventional monitoring methods [141]. Similarly, advanced cardiac monitors now analyze electrocardiographic signals in the context of sleep quality and exertion levels, providing nuanced cardiovascular assessments impossible through isolated measurements [142].

Machine learning transforms raw wearable data into clinically actionable intelligence through pattern recognition and predictive modeling. Deep learning architectures process complex physiological time-series to forecast adverse events like atrial fibrillation episodes or COPD exacerbations [143,144]. These systems detect subtle preclinical signatures often imperceptible to human observers, enabling truly proactive medicine. The integration of convolutional neural networks allows for the simultaneous interpretation of multiple biosignals while maintaining temporal relationships critical for an accurate diagnosis [142].

Real-world implementations demonstrate wearable technology's transformative potential. COPD management systems combining pulmonary function metrics with environmental and activity data have significantly reduced acute hospitalizations through early warning algorithms [144]. Cardiovascular studies utilizing multimodal wearables show improved arrhythmia detection rates and treatment outcomes compared to standard monitoring [145]. These successes validate the clinical value of continuous, integrated health surveillance systems in chronic disease management.

While the integration of multimodal data holds great promise for continuous health surveillance, several challenges must be addressed. One significant issue is the interoperability of devices and systems. The diverse range of wearables on the market often produces data in different formats, making it challenging to aggregate and analyze information effectively [146]. The standardization of data formats and communication protocols is essential to create a seamless ecosystem for health monitoring. Another challenge is ensuring the accuracy and reliability of the data collected by wearable devices. Variability in sensor performance and environmental factors can influence data quality. Therefore, implementing robust data validation and calibration processes is critical to ensure that the information used for health surveillance is accurate and actionable [147].

The future of continuous health surveillance through wearable technologies lies in enhancing data integration capabilities and leveraging advances in AI and machine learning. As wearable devices become more sophisticated, they will be able to collect an even wider array of data types, including biomarkers from sweat or saliva, genomic data, and mental health assessments through mobile applications [148]. Furthermore, the use of federated learning, a machine learning technique that allows models to be trained across decentralized data sources while preserving privacy, has the potential to enhance predictive analytics without compromising patient confidentiality [149]. This approach can facilitate the development of more accurate models that consider diverse patient populations and health conditions. Just above, Table 5 offers a comparison summarizing the key elements covered in this review, illustrating the advancements and challenges of multimodal AI in biomedicine and biomaterials, along with its implications for personalized healthcare. This table provides a comprehensive overview of the benefits, current limitations, and future potential of multimodal AI in transforming biomedicine and biomaterials science for personalized healthcare applications.

4.4. Impact of AI on Preventive Healthcare

Artificial intelligence is redefining preventive medicine through advanced risk prediction and early intervention capabilities. Machine learning algorithms analyze comprehensive health datasets to identify subtle patterns preceding disease onset, enabling the proactive management of chronic conditions [150]. In oncology, deep learning systems demonstrate superior accuracy in early cancer detection through a medical imaging analysis, significantly improving the diagnostic precision for breast and colorectal malignancies [151,152]. This predictive capacity shifts healthcare from reactive treatment to anticipatory care, simultaneously enhancing outcomes and reducing long-term costs.

Sophisticated AI models synthesize diverse health indicators, including genetic predispositions, lifestyle factors, and physiological metrics, to generate individualized risk assessments [152,153]. During recent public health crises, these systems proved invaluable for forecasting the infection spread by processing mobility patterns and healthcare utilization data [154]. The technology now enables personalized prevention strategies, from genomic-based screening recommendations to AI-powered health coaching applications that analyze wearable device data for real-time lifestyle interventions [155,156,157]. This granular approach to risk mitigation represents a fundamental advancement in population health management.

While promising, AI-enabled prevention faces significant hurdles in data quality and privacy protection. Incomplete or non-representative health datasets can introduce dangerous biases into predictive models, necessitating the rigorous standardization of training data [158]. Simultaneously, the sensitive nature of health information demands robust security measures and strict compliance with patient privacy regulations like the HIPAA [159]. Addressing these challenges requires a careful balance between data accessibility for AI development and the protection of individual rights.

The next frontier of AI prevention integrates emerging data streams from wearable biosensors, social determinants, and unstructured clinical narratives [158,160]. Natural language processing breakthroughs will unlock insights from physician notes and patient-reported outcomes, while federated learning approaches may resolve privacy concerns [161]. As these technologies mature, they promise to establish a new paradigm of continuous health optimization—shifting healthcare systems from episodic treatment to sustained wellness maintenance through intelligent, data-driven prevention strategies.

5. Ethical, Regulatory, and Scalability Challenges

5.1. Ethical Concerns in AI Applications

As artificial intelligence (AI) continues to permeate various sectors, including biomedicine, ethical concerns have emerged that warrant critical examination. The implementation of AI technologies in healthcare raises numerous ethical questions regarding patient autonomy, consent, bias, transparency, and accountability. Addressing these ethical concerns is essential to ensuring that AI applications enhance, rather than undermine, patient care and public trust. Figure 7 highlights the multifaceted ethical and legal challenges surrounding the implementation of artificial intelligence (AI) in healthcare [162]. Key issues include patient privacy and data security, as the use of AI often necessitates access to sensitive medical information. Additionally, there are concerns regarding algorithmic bias, which can lead to unequal treatment outcomes among diverse patient populations. The figure also underscores the need for transparent decision-making processes, as AI-driven recommendations can lack interpretability. Moreover, the regulatory landscape remains complex, necessitating a framework that addresses liability and accountability in cases of AI-related errors. Collectively, these dilemmas underscore the importance of integrating ethical considerations into the development and deployment of AI technologies in healthcare settings.

One of the most significant ethical issues in AI applications is the impact on patient autonomy. In traditional healthcare settings, patients are often involved in decision-making processes regarding their treatment options. However, with the increasing use of AI-driven diagnostic tools and treatment recommendations, there is a risk that patients may become passive recipients of care, relying on algorithms to make decisions for them [163]. This shift raises concerns about informed consent, as patients may not fully understand how AI systems work, the data being used, or the implications of AI-driven decisions. Informed consent is a foundational ethical principle in healthcare, requiring that patients are fully aware of the nature and consequences of their treatment options [164]. With the complexity of AI algorithms, ensuring that patients understand these systems is challenging. Healthcare providers must take proactive steps to educate patients about AI technologies, including how they are used in diagnosis and treatment, to ensure that patients can make informed choices regarding their care.

Bias in AI algorithms is another critical ethical concern. AI systems are trained on historical data, which may contain inherent biases that reflect societal inequalities. If these biases are not addressed, AI applications can perpetuate existing disparities in healthcare outcomes [165]. For instance, a study found that certain algorithms used in clinical settings exhibited racial bias, leading to the underdiagnosis and undertreatment of minority groups [166]. This is particularly concerning in biomedicine, where the equitable access to treatments and diagnostic tools is essential for improving patient outcomes. To combat bias, researchers and developers must prioritize diversity in training datasets, ensuring that AI algorithms are exposed to a wide range of demographic and clinical variables. Furthermore, implementing regular audits and evaluations of AI systems can help identify and mitigate biases, promoting fairness in healthcare delivery [167].

The "black-box" nature of many AI algorithms poses challenges to transparency and explainability. When AI systems generate recommendations or diagnoses, it can be difficult for healthcare providers and patients to understand the underlying reasoning behind these decisions. This lack of transparency can undermine trust in AI applications and raise ethical concerns regarding accountability [168]. To address these issues, it is crucial to develop explainable AI models that provide insights into their decision-making processes. Explainable AI allows healthcare professionals to interpret AI outputs and communicate them effectively to patients, fostering a collaborative decision-making environment [169]. Ensuring transparency not only enhances trust in AI systems but also empowers healthcare providers to critically evaluate AI recommendations, ultimately improving patient care.

The question of accountability and liability in AI applications is another ethical dilemma. When an AI system makes a mistake, such as providing an incorrect diagnosis or treatment recommendation, determining who is responsible can be complex. Is it the healthcare provider, the software developer, or the institution that deployed the AI system? This ambiguity can hinder efforts to address errors and learn from them [170]. Establishing clear guidelines for accountability in AI applications is essential. Regulatory bodies and healthcare institutions must work collaboratively to define standards for AI deployment, including protocols for error reporting and accountability mechanisms. Furthermore, incorporating human oversight in AI decision-making processes can help mitigate risks associated with erroneous outputs and clarify responsibility in case of adverse outcomes [171].

The ethical implications of data privacy and security are paramount when implementing AI in biomedicine. AI systems often rely on large datasets that contain sensitive patient information. Ensuring the confidentiality and security of this data is crucial to maintaining patient trust and complying with regulations such as the Health Insurance Portability and Accountability Act (HIPAA) [172]. Breaches in data security can have severe consequences for patients, including identity theft and the loss of confidentiality. To safeguard patient data, healthcare organizations must implement robust cybersecurity measures and establish strict protocols for data handling. Additionally, patients should be informed about how their data will be used and stored, empowering them to make informed choices about their participation in AI-driven healthcare initiatives [173]. The ethical concerns surrounding AI applications in biomedicine are multifaceted and complex. Addressing these issues requires a collaborative effort from healthcare providers, researchers, policymakers, and technology developers. By prioritizing patient autonomy, mitigating bias, ensuring transparency, clarifying accountability, and safeguarding data privacy, the healthcare sector can harness the potential of AI technologies while upholding ethical standards that prioritize patient welfare and trust.

5.2. Regulatory Frameworks for AI-Driven Systems

The integration of AI into biomedicine demands comprehensive regulatory oversight to ensure patient safety while fostering innovation. As these technologies advance, governing bodies must develop adaptive frameworks that address unique challenges in clinical validation, algorithmic transparency, and ethical implementation. Effective regulations will balance technological progress with rigorous standards for efficacy, safety, and equitable access across healthcare systems. Global regulatory approaches are emerging to govern medical AI applications, with distinct regional strategies taking shape. The U.S. FDA has implemented specialized pathways for AI-based medical devices through its Digital Health Innovation Action Plan, emphasizing rigorous premarket evaluations and ongoing performance monitoring [174]. Meanwhile, the EU's proposed Artificial Intelligence Act introduces risk-based classifications for AI systems, with stringent requirements for healthcare applications, including mandatory clinical validation, auditability, and maintained human oversight [175]. These evolving frameworks reflect the international community’s commitment to responsible AI adoption in medicine.

A risk-based regulatory approach is essential for managing AI technologies in healthcare. By classifying AI applications according to their potential risks, regulatory bodies can tailor oversight measures accordingly. For example, high-risk applications, such as AI algorithms used for diagnostic purposes, may require rigorous pre-market testing and ongoing monitoring to ensure safety and effectiveness [176]. Conversely, lower-risk applications, such as AI-driven wellness apps, may be subject to less stringent regulations. This approach enables regulatory bodies to allocate resources effectively while fostering innovation in lower-risk areas. A risk-based framework also encourages transparency in AI algorithms, enabling healthcare providers to assess their reliability and suitability for clinical use [177]. The effective governance of medical AI requires multi-stakeholder collaboration to develop balanced regulatory approaches. Involving clinicians, technologists, patients, and policymakers ensures frameworks address real-world needs while maintaining ethical standards [178]. Regulatory agencies like the FDA and EMA are pioneering inclusive consultation models that incorporate diverse perspectives into policy development, fostering transparency in AI validation and deployment processes [179]. Such participatory approaches help align technological capabilities with clinical priorities while building public confidence. Regulatory systems must maintain adaptability to keep pace with AI’s rapid evolution in healthcare. Continuous framework refinement is essential to address emerging challenges in algorithm validation, data governance, and clinical integration [180]. Robust postmarket surveillance mechanisms enable an ongoing evaluation of AI system performance, identifying potential safety issues or performance drifts in operational environments [181]. This dynamic regulatory posture ensures patient protections evolve alongside technological advancements. International regulatory harmonization presents both a challenge and opportunity for global health innovation. Divergent national standards create compliance complexities for AI developers while potentially delaying patient access to beneficial technologies [182]. Initiatives like the WHO’s digital health programs promote cross-border collaboration, working toward a consensus on core principles for medical AI evaluation and oversight [183]. Establishing universal standards for high-risk applications while allowing regional adaptations could accelerate the responsible global adoption of transformative healthcare AI solutions.

5.3. Challenges in Scaling AI Systems for Clinical Use

The widespread deployment of AI systems in healthcare faces significant technical hurdles, primarily stemming from fragmented data ecosystems. Disparate electronic health record systems with incompatible data structures create substantial obstacles for algorithm training and validation [184]. Standardization initiatives like FHIR aim to establish unified data exchange protocols, while common data models help harmonize information across platforms [185,186]. Equally critical is ensuring algorithmic robustness through rigorous testing on diverse, representative datasets to mitigate biases and enhance generalizability across patient populations [187,188,189]. A successful AI adoption requires a careful alignment with clinical operations to minimize workflow disruptions. Resistance from healthcare professionals often stems from poorly designed interfaces and inadequate training programs [190]. Developing intuitive systems with seamless EHR integration, coupled with comprehensive clinician education initiatives, can facilitate smoother transitions [191,192]. Financial constraints present another major barrier, particularly for resource-limited settings. Strategic partnerships between healthcare providers, academic centers, and technology developers can create cost-sharing models that make AI implementation more accessible [193,194,195].

Professional skepticism and patient concerns represent significant adoption barriers that demand proactive management. Clinicians require transparent demonstrations of AI’s assistive (rather than replacement) role in clinical decision-making [196]. Including healthcare providers in development cycles and showcasing validated use cases helps build confidence in these technologies [197,198]. Patient education initiatives must clearly communicate AI’s complementary role in care delivery while addressing privacy concerns and algorithmic transparency [199,200,201]. Realizing AI’s full potential in clinical settings demands coordinated strategies addressing technical, financial, and human factors. Prioritizing interoperable data infrastructure, clinician-centered design, and ongoing performance monitoring creates a foundation for successful scaling. Simultaneously, innovative funding models and stakeholder engagement initiatives can overcome resource limitations and cultural resistance. By adopting this multifaceted approach, healthcare systems can responsibly integrate AI to enhance diagnostic accuracy, therapeutic development, and patient outcomes while maintaining the human touch in medicine.

5.4. Addressing Data Privacy and Security

The implementation of multimodal AI in biomedicine raises critical data protection challenges given its reliance on sensitive health information. Maintaining data integrity while preserving patient confidentiality requires sophisticated security frameworks, particularly as healthcare systems become increasingly digitized. Breaches risk severe consequences, including medical identity theft and the erosion of public trust in medical AI systems [202]. Regulatory frameworks like the HIPAA and GDPR establish essential guidelines for data handling, mandating strict consent protocols, access controls, and security measures that organizations must rigorously implement [203].

The development of effective AI models necessitates cross-institutional data sharing, creating tension between research needs and privacy protection. Privacy-preserving computational methods offer viable solutions to this challenge. Differential privacy techniques enable an aggregate analysis while obscuring individual identities through strategic data perturbation [204,205]. Federated learning architectures allow collaborative model training across institutions without direct data exchange, maintaining information security while advancing AI capabilities [206]. These approaches demonstrate how technological innovation can balance research progress with ethical obligations.

Healthcare organizations face escalating threats from sophisticated cyberattacks targeting valuable medical data. Comprehensive defense strategies must incorporate end-to-end encryption, continuous vulnerability assessments, and staff cybersecurity training [207,208]. Proactive measures like real-time network monitoring and automated threat detection systems can identify breaches early, while detailed incident response plans ensure rapid containment [209]. Such multilayered security approaches are becoming essential infrastructure for AI-enabled healthcare delivery.

Transparent data practices form the foundation of ethical AI implementation in medicine. Patients deserve clear communication about how their information will be used, protected, and potentially shared [210]. Organizations should prioritize informed consent processes and patient education initiatives to foster trust in AI applications [211,212]. Regulatory compliance tools can automate the monitoring of data handling practices, while ongoing collaboration with legal experts ensures the alignment with evolving privacy legislation [213,214,215]. By addressing these concerns holistically, the healthcare community can responsibly harness AI’s potential while maintaining rigorous patient protections.

6. Future Opportunities for AI in Biomedicine

6.1. AI in Emerging Biotechnologies

The rapid advancement of biotechnology has opened new avenues for improving healthcare outcomes, and artificial intelligence (AI) is poised to play a transformative role in this evolving landscape. Emerging biotechnologies, such as gene editing, synthetic biology, and nanotechnology, present unique challenges and opportunities that AI can help navigate.

By integrating multimodal AI systems, researchers and clinicians can harness vast amounts of data from diverse sources to accelerate discovery, optimize processes, and personalize treatment strategies. Figure 8 illustrates the integration of various AI models (deep learning, machine learning, reinforcement learning, AlphaFold, and GANs) in biomaterials research. It highlights key data inputs, including medical imaging, genomic sequences, and material property datasets, feeding into AI-driven optimization processes [216]. The schematic also showcases AI applications in biomaterial design, tissue engineering, drug delivery, and regenerative medicine, while addressing challenges such as data bias, regulatory hurdles, and model interpretability. Moreover, these images serve as a creative prompt for discussions on ethical considerations and the integration of AI in clinical practice, encouraging stakeholders to envision a collaborative future between humans and intelligent systems. Ultimately, this figure underscores the need for continued research and development to harness AI’s full potential while addressing the challenges associated with its implementation in medical settings. Table 6 outlines the transformative future opportunities AI presents for biomedicine, highlighting how AI integration can improve precision, efficiency, and accessibility across various domains of healthcare and medical research [10,16,66,126,217,218,219,220,221,222].

The advent of CRISPR–Cas9 systems has transformed genetic manipulation, yet challenges persist in predicting editing outcomes and minimizing off-target effects. Artificial intelligence addresses these limitations through a sophisticated genomic analysis, enabling researchers to identify optimal target sequences and anticipate modification consequences with greater accuracy [223]. Machine learning models evaluate the sequence context and structural biology to forecast CRISPR activity, significantly improving the editing precision while reducing experimental iterations [224,225]. This synergy is particularly valuable for developing personalized genetic interventions, where AI algorithms analyze individual genomic profiles to design patient-specific editing strategies for monogenic disorders [226,227].

Artificial intelligence is re-engineering synthetic biology through the predictive modeling of complex biological systems. Deep learning architectures optimize microbial metabolic networks for enhanced bioproduction, identifying genetic modifications that maximize yields of therapeutic compounds and sustainable biomaterials [228,229]. Concurrently, AI-driven protein structure predictions enable the de novo design of functional biomolecules, creating novel enzymes and therapeutic proteins with tailored characteristics [230,231,232]. These computational tools are accelerating the development of next-generation biologics, from targeted drug delivery systems to innovative biologic therapies [233]. The intersection of AI and nanotechnology is pioneering new frontiers in precision medicine. Machine learning algorithms analyze structure–property relationships across nanomaterial libraries, enabling the rational design of particles with optimized characteristics for diagnostic and therapeutic applications [234,235]. Automated image analysis systems enhance nanomaterial characterization, rapidly assessing critical quality attributes while improving manufacturing consistency [236,237]. These AI-driven approaches are streamlining the translation of nanomedicines from bench to bedside, offering safer and more effective solutions for drug delivery and medical imaging [238]. Together, these technological convergences demonstrate how multimodal AI systems can overcome fundamental challenges across biotechnology domains, driving innovation in personalized therapeutics.

6.2. Integration of AI with 3D Bioprinting

The convergence of artificial intelligence with 3D bioprinting technologies is revolutionizing regenerative medicine by enabling the precise fabrication of customized biological constructs. AI-enhanced bioprinting systems leverage advanced computational modeling and data-driven optimization to improve the architectural complexity, functional performance, and clinical applicability of engineered tissues [239]. This synergistic integration addresses critical limitations in conventional bioprinting approaches while accelerating the development of patient-specific therapeutic solutions for tissue repair and organ regeneration.

The design phase of bioprinting is critical for achieving the desired structural and functional properties of bioprinted tissues. AI can significantly enhance this phase by optimizing the design process and enabling the creation of complex architectures that mimic natural tissues [240]. AI-driven computational design algorithms can analyze vast datasets of tissue characteristics, materials properties, and biological requirements to generate optimized designs for bioprinted constructs [241]. For example, machine learning models can assess the mechanical properties and biocompatibility of various biomaterials to recommend optimal combinations for specific applications [242]. By automating the design process, researchers can accelerate the development of bioprinted tissues that closely resemble their natural counterparts. AI can also be employed to predict the functional outcomes of bioprinted constructs based on their design parameters. By integrating multimodal data, such as mechanical testing results, biological assays, and imaging data, AI algorithms can identify correlations between design features and functional performance [243]. This predictive capability allows researchers to fine-tune their designs and optimize the functionality of bioprinted tissues before fabrication, reducing trial-and-error approaches [244]. The bioprinting process itself involves several parameters, including the printing speed, nozzle diameter, and material properties. AI can optimize these parameters to enhance the quality and reproducibility of bioprinted constructs [245]. Machine learning algorithms can analyze real-time data generated during the bioprinting process to identify optimal settings for various parameters. For instance, reinforcement learning techniques can be applied to adjust printing parameters dynamically based on feedback from the printing environment [246]. By optimizing these parameters, researchers can improve the fidelity of bioprinted tissues and reduce defects caused by variations in printing conditions [247]. AI can play a crucial role in quality control and assurance throughout the bioprinting process. By implementing computer vision techniques, AI systems can analyze images captured during printing to detect anomalies, such as misaligned layers or material inconsistencies [248]. Automated quality assurance processes can help ensure that bioprinted constructs meet the required specifications and standards, ultimately enhancing their reliability for clinical applications [249].

The post-processing phase of bioprinting involves additional steps to enhance the functionality and viability of bioprinted tissues. AI can aid in this phase by optimizing bioreactor conditions, assessing tissue maturation, and facilitating the functionalization of constructs [250]. AI-driven algorithms can analyze data from bioreactor systems to optimize culture conditions for bioprinted tissues. By integrating data on nutrient availability, mechanical stimulation, and cell behavior, AI can identify optimal parameters that promote tissue growth and functionality [251]. This approach allows for the development of bioprinted tissues that can better mimic the physiological conditions of native tissues [252]. AI can also assist in the functionalization of bioprinted constructs by predicting the effects of various biomolecular cues on cell behavior. By analyzing data on cell signaling pathways and molecular interactions, AI models can recommend specific growth factors or biomolecules to enhance tissue maturation and functionality [253]. This capability can lead to the development of bioprinted tissues with an improved integration into the host environment and enhanced therapeutic potential [254]. The integration of AI with 3D bioprinting represents a significant opportunity for advancing biomedicine. By enhancing the design, optimization, and functionalization of bioprinted constructs, AI can drive the innovation in tissue engineering and regenerative medicine. As researchers continue to explore the synergies between AI and bioprinting, the potential for creating patient-specific tissues and organs will expand, ultimately leading to improved healthcare outcomes and personalized treatment strategies.

6.3. Role of AI in Personalized Therapeutic Design

Contemporary medicine is undergoing a transformation through AI-enabled personalization, where treatment strategies are optimized using comprehensive patient profiles. By synthesizing multi-omics data, clinical histories, and lifestyle factors, machine learning algorithms reveal intricate biological patterns that inform tailored interventions [255]. Deep learning applications demonstrate a particular promise in correlating genomic variants with electronic health records, providing unprecedented insights into individual drug metabolism and therapeutic response patterns

[256]. This data integration enables the identification of optimal treatment pathways while minimizing adverse effects through the precision targeting of disease mechanisms.

The convergence of AI with genomic medicine has revolutionized therapeutic personalization. Advanced algorithms analyze nucleotide sequences to detect pathogenic variants and predict medication efficacy, guiding clinicians in selecting genetically compatible treatments [257]. Beyond patient care, these computational tools accelerate novel drug development by identifying population-specific therapeutic targets through a large-scale genomic analysis [258]. AI-enhanced clinical decision support systems further refine treatment selection by dynamically incorporating emerging research, historical response data, and patient-specific biomarkers to generate real-time therapeutic recommendations [259,260]. This approach proves particularly valuable in drug repurposing, where machine learning mines vast pharmacological datasets to match existing compounds with new indications based on molecular signatures and patient subgroup characteristics [261,262,263].

The implementation of intelligent monitoring systems represents the next frontier in personalized care. Connected health technologies coupled with AI analytics enable the continuous assessment of therapeutic effectiveness through physiological tracking and medication adherence monitoring [264]. Predictive models process these real-time data streams alongside historical records to forecast treatment outcomes, allowing clinicians to preemptively modify regimens [265]. This dynamic approach ensures therapy remains optimized throughout the care continuum, adjusting for evolving patient responses while maintaining safety parameters [266]. As these technologies mature, they promise to establish a new standard of responsive, patient-centered medicine powered by intelligent data integration.

6.4. Potential for AI in Drug Discovery

Artificial intelligence is transforming pharmaceutical research by addressing key inefficiencies in traditional drug discovery pipelines. By processing multimodal biological data, AI accelerates target identification through the sophisticated analysis of genomic, proteomic, and metabolic networks, revealing novel disease-associated pathways [267,268,269]. Deep learning architectures excel at mining complex molecular datasets to pinpoint therapeutic targets, while predictive models assess the target druggability and potential clinical impact—significantly reducing early-stage attrition rates [270,271,272]. This data-driven approach uncovers promising interventions that conventional methods might overlook.

AI revolutionizes lead compound development through advanced computational chemistry techniques. Virtual screening algorithms rapidly evaluate millions of compounds for optimal target binding characteristics, with convolutional neural networks predicting pharmacological properties to prioritize candidates [273,274,275]. Generative AI models create novel molecular structures with tailored bioactivity profiles, using reinforcement learning to iteratively optimize parameters like potency and safety [276,277,278]. These innovations compress years of laboratory work into computational processes, enabling rational drug design at unprecedented scales.

The AI advantage extends through clinical translation, enhancing both efficiency and safety. Predictive toxicology models identify high-risk compounds before human trials, while machine learning optimizes trial protocols through patient stratification and adaptive design [279,280,281]. Real-time analytics during clinical studies enable dynamic protocol adjustments based on emerging efficacy and safety data [282,283]. As these technologies mature, AI-driven drug discovery promises to deliver more targeted therapies faster and at lower cost, ushering in a new era of precision pharmacotherapy.

6.5. Advantages and Limitations of Multimodal AI in Biomaterials Science

Multimodal AI has become an indispensable asset in biomaterials research, demonstrating exceptional capabilities in synthesizing heterogeneous biological data to advance material design and optimization. By simultaneously processing medical imaging, genomic profiles, and clinical parameters, these systems reveal complex structure–function relationships that inform biomaterial development. Sophisticated predictive algorithms, exemplified by protein-folding models like AlphaFold, enable the precise simulation of biological interactions, facilitating the rational engineering of tissue scaffolds and targeted drug carriers. Furthermore, AI empowers personalized biomaterial design through the machine learning analysis of patient-specific genetic markers and tissue characteristics, yielding implants and regenerative matrices with an enhanced biocompatibility and therapeutic performance.

However, several critical limitations currently constrain the broader implementation of AI in biomaterials science. Data-related challenges, including dataset incompleteness, quality inconsistencies, and inherent biases, compromise the model reliability and clinical generalizability. Translational hurdles also persist, with complex regulatory requirements and the absence of standardized validation protocols slowing clinical adoption. The opaque nature of deep learning architectures (“black box” problem) raises interpretability concerns, while substantial computational resource demands create accessibility barriers for many research institutions. Overcoming these obstacles will necessitate coordinated efforts to establish robust data-sharing infrastructures, develop explainable AI frameworks, and foster cross-disciplinary partnerships between computational scientists, material engineers, and clinical researchers.

Table 7 provides a comparative analysis of AI models in biomaterials science and highlights their diverse roles in biomaterial design, optimization, and clinical translation. Deep learning (DL) models, particularly convolutional neural networks (CNNs), have demonstrated superior pattern recognition capabilities, making them highly effective for imaging-based biomaterial characterization and tissue engineering applications [22,37,284,285,286,287,288]. However, their black-box nature and dependence on large datasets pose interpretability challenges. AlphaFold has revolutionized protein–material interaction modeling, allowing the precise prediction of bioactive scaffold designs, though its scope remains limited to protein-based biomaterials. Traditional machine learning (ML) models, such as Random Forest and Support Vector Machines (SVMs), offer computational efficiency and interpretability, making them suitable for small-to-medium-scale datasets, but they lack the deep feature extraction capabilities of DL models. Reinforcement learning (RL) enables self-optimizing biomaterial formulations, while generative adversarial networks (GANs) facilitate the design of novel biomaterials with enhanced properties, though training instability remains a concern. Hybrid AI models integrating DL, ML, and statistical methods offer a promising multimodal approach, leveraging diverse datasets for precision biomaterial development in tissue engineering, drug delivery, and regenerative medicine. Despite these advancements, the data quality, computational constraints, and regulatory challenges must be addressed to fully realize AI’s potential in biomaterials science.

6.6. Emerging Trends: Federated Learning, Digital Twins, and Clinical Translation

As AI continues to evolve, several emerging technologies are poised to significantly enhance its impact on biomedicine:
Federated Learning for Privacy-Preserving AI: Federated learning is an emerging machine learning paradigm that enables model training across decentralized data sources without transferring sensitive patient data to a central server. This approach enhances data privacy and security while allowing AI models to learn from diverse healthcare datasets across institutions. It holds particular promise for collaborative biomaterials research and multi-center clinical studies, addressing data ownership concerns and complying with stringent privacy regulations.
Integration with Digital Twins and 3D-Printed Biomaterials: Digital twins—virtual replicas of biological systems or

patient-specific conditions—offer a powerful platform for simulating and optimizing biomaterial interactions, treatment responses, and implant integration. When combined with AI and 3D printing technologies, this integration enables the design of customized biomaterials tailored to individual patients' anatomical and physiological profiles. AI-enhanced digital twins can predict outcomes of regenerative therapies or surgical implants, accelerating design iterations and improving therapeutic precision.
Multimodal AI in Clinical Translation and Regulatory Approval: Multimodal AI systems that integrate clinical, molecular, and imaging data can streamline the clinical validation of new biomaterials and therapeutic devices. By providing more comprehensive and interpretable evidence of efficacy and safety, these systems can support regulatory submissions and facilitate approval pathways. Furthermore, explainable AI (XAI) techniques are increasingly being explored to meet transparency and accountability requirements in regulatory frameworks.

7. Conclusions

The incorporation of multimodal artificial intelligence into biomedical research and clinical practice marks a revolutionary shift in healthcare innovation, particularly for biomaterial development and advanced therapeutics. This analysis reveals several critical insights demonstrating AI's capacity to redefine medical approaches. A primary advantage lies in AI's proficiency at synthesizing heterogeneous biological data—encompassing molecular profiles, medical imaging, and clinical records—to generate holistic health assessments. Such an integrative analysis supports earlier disease detection, more precise prognostic evaluations, and customized treatment strategies. Within biomaterial science, an AI-driven computational design enables the fabrication of personalized constructs with optimized properties for tissue regeneration and implant applications. AI-enhanced diagnostic systems and precision treatment protocols are revolutionizing clinical care through the sophisticated analysis of complex medical datasets. These intelligent systems facilitate data-informed therapeutic decisions while enabling proactive healthcare through continuous monitoring and predictive capabilities. The convergence of AI with wearable biosensors and remote monitoring platforms creates unprecedented opportunities for real-time health tracking and patient-centered care models that emphasize prevention and early intervention. Nevertheless, significant implementation hurdles persist, including ethical dilemmas regarding data security, algorithmic transparency, and equitable access. Developing appropriate regulatory guidelines and ensuring scalable deployment across diverse healthcare settings remain essential for the responsible adoption of these transformative technologies.
Future Prospects for AI in Healthcare and Biomaterials

The horizon of multimodal AI in biomedical applications appears exceptionally bright, with emerging synergies between artificial intelligence and cutting-edge biotechnologies like CRISPR-based genome engineering and precision biomanufacturing. These convergences will enable the unprecedented customization of medical interventions, accounting for both genotypic and phenotypic patient variability. Particularly transformative is AI's capacity to streamline pharmaceutical innovation through the rapid analysis of multidimensional biological data, identifying promising drug candidates and biomarkers with remarkable efficiency. Realizing this potential fully will demand sustained, cross-disciplinary partnerships that bridge computational science, clinical expertise, and fundamental research to translate technological advances into tangible global health benefits.
Final Thoughts on Multimodal AI's Impact

Multimodal AI represents a revolutionary force in modern medicine, enabling the unprecedented integration of diverse biological datasets to drive precision healthcare solutions. This technological convergence facilitates a deeper understanding of disease mechanisms while creating opportunities for tailored therapeutic interventions. As research advances, these systems promise to transform biomaterial development and treatment paradigms, fostering more equitable and efficient healthcare delivery. Realizing this potential will require sustained interdisciplinary collaboration to address existing limitations and maximize the clinical impact of AI-driven innovations.

Conflicts of Interest

The authors declare no conflicts of interest.

Footnotes

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Figures and Tables

Figure 1 Various data modalities and potential applications of multimodal AI in biomedicine.

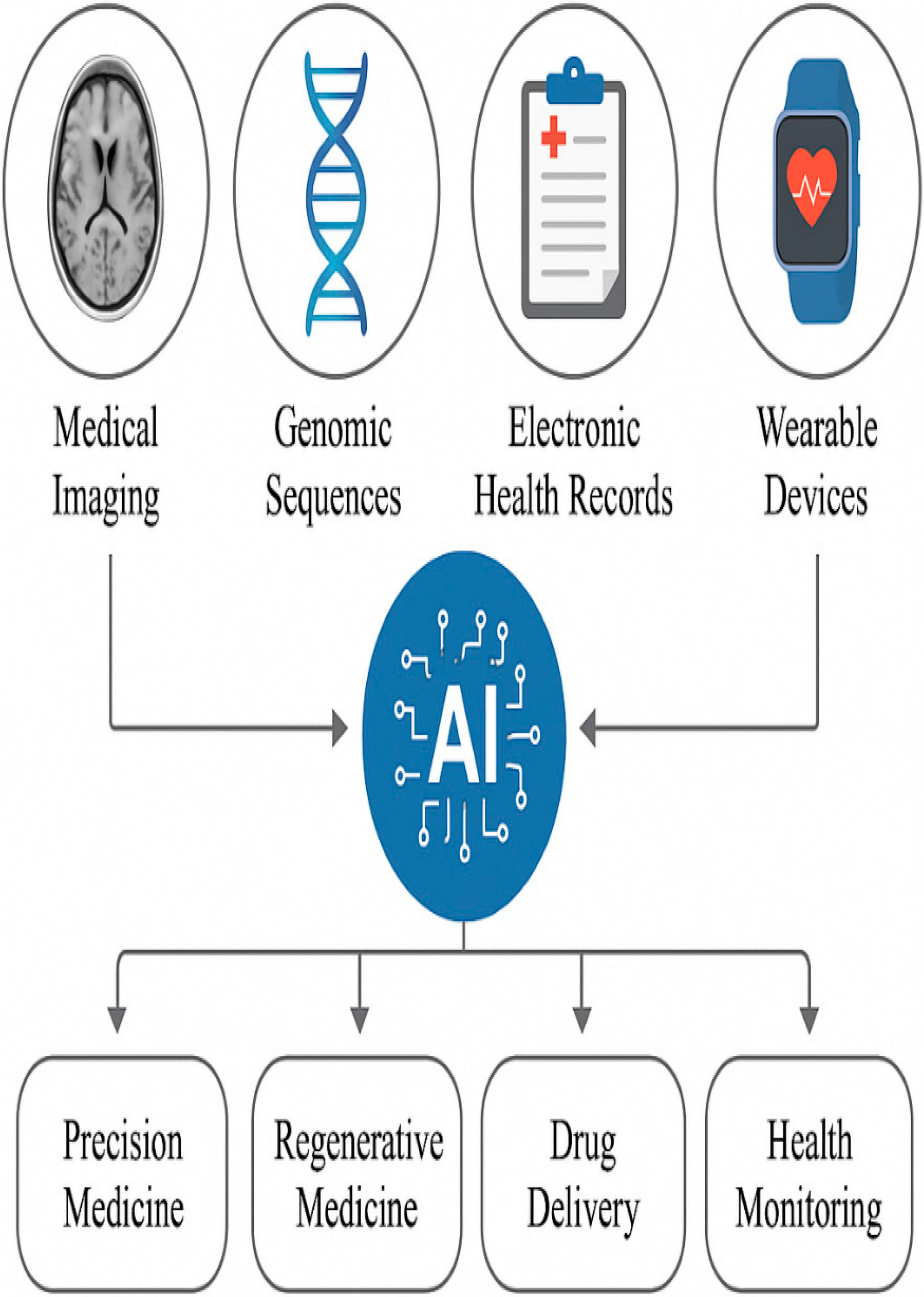

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Figure 2 Illustration of pH-sensitive drug delivery micelles formed by adamantane-terminated [poly(ε-caprolactone)-block-poly(2-(diethylamino)ethyl methacrylate)-block-poly(poly(ethylene glycol) methyl ether methacrylate)]$_4$ (Ad-

(PCL-b-PDEAEMA-b-PPEGMA)$_4$) triblock copolymers, demonstrating their Doxorubicin (DOX) encapsulation and controlled release mechanism in response to acidic environments. Reprinted with permission from Ref. [5]. cc by 4.0, https://doi.org/10.3390/polym10040443.

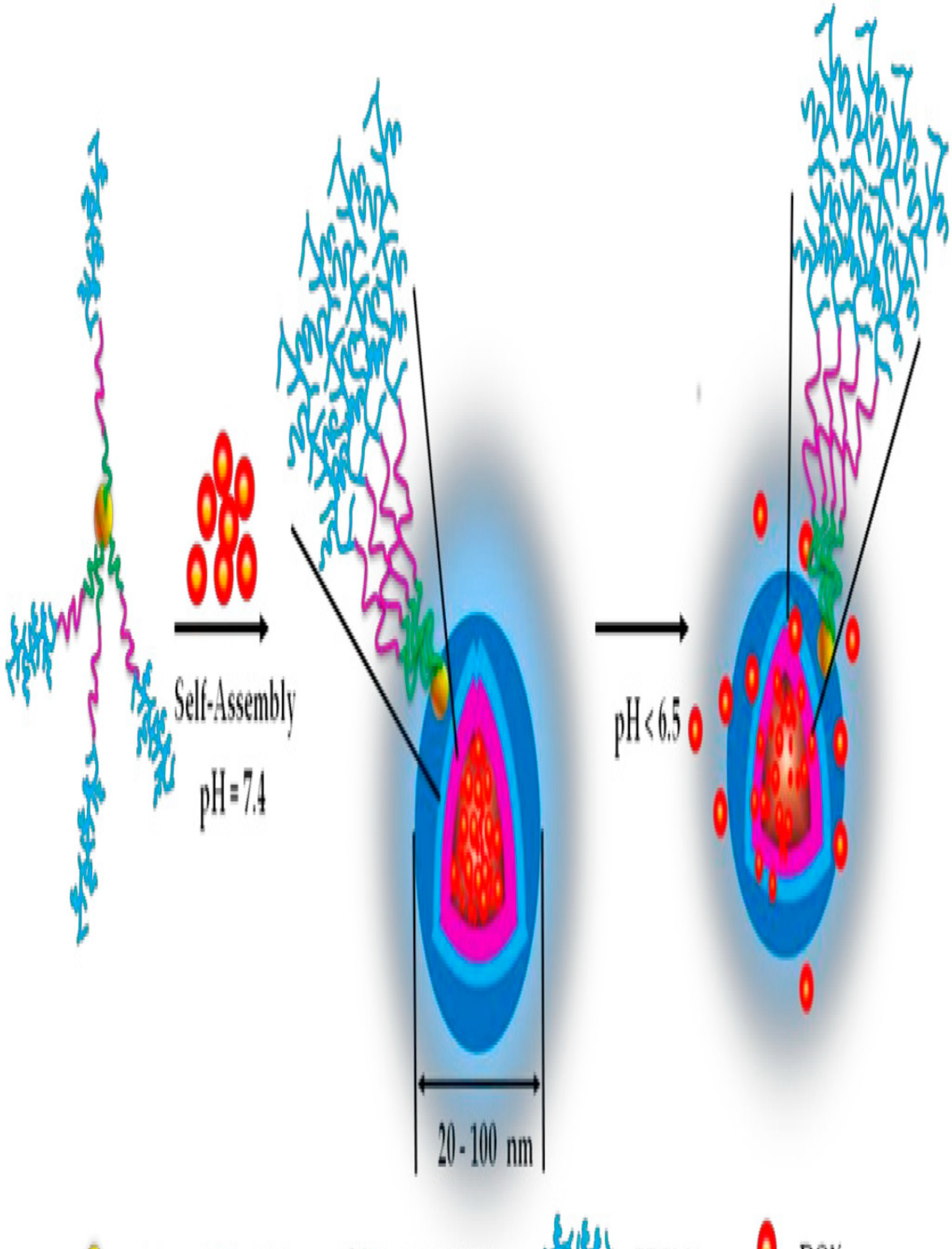

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Figure 3 Visualizes the integrated workflow for advanced therapy medicinal products (ATMPs), highlighting their central position within a network of specialized clinical and research units. The schematic demonstrates how *multidisciplinary hospital departments collectively contribute to ATMP development, manufacturing, and therapeutic implementation, underscoring the coordinated nature of these cutting-edge medical interventions.*

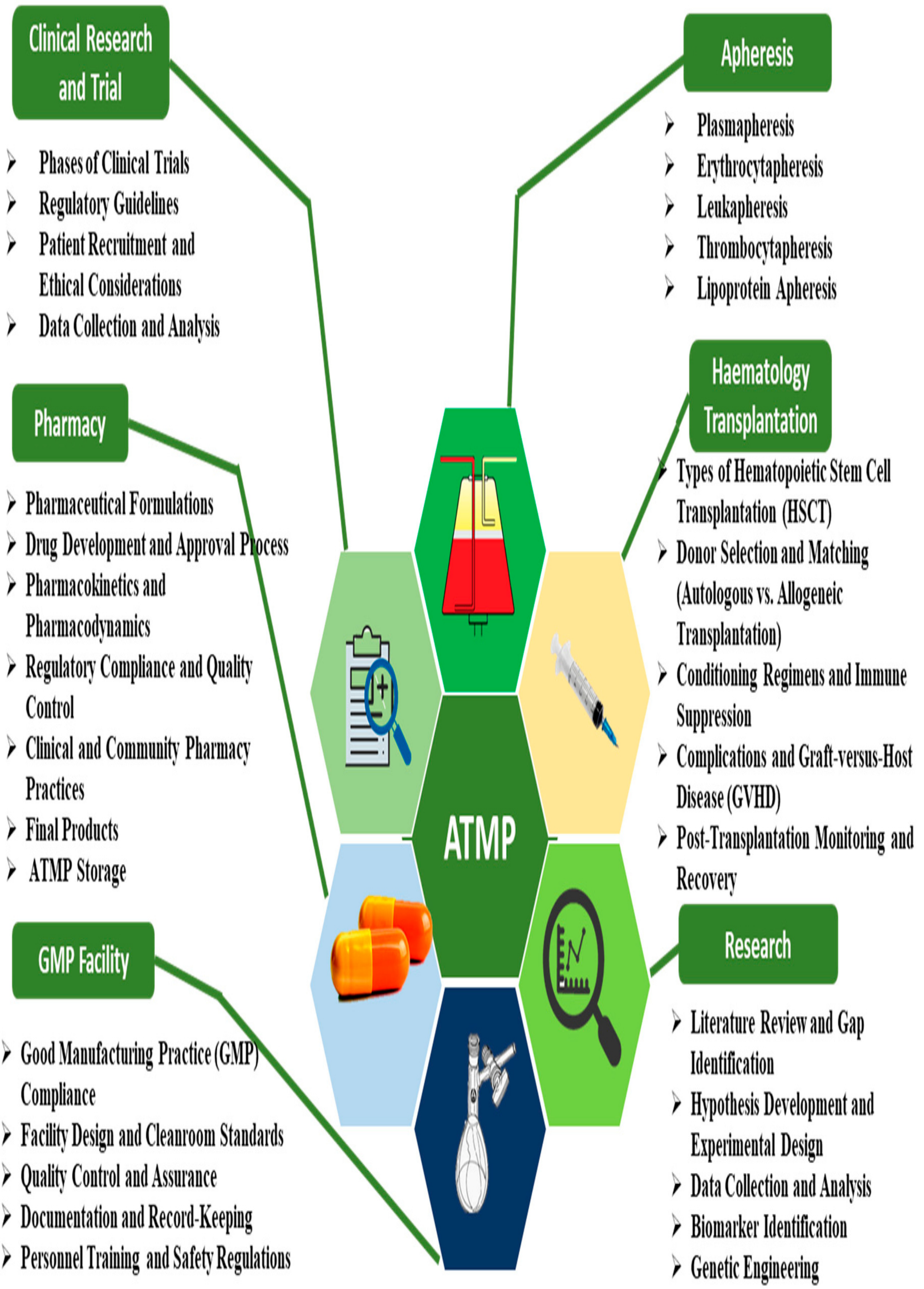

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Figure 4 Illustrates the paradigm of precision medicine, showcasing contemporary strategies that involve evaluating different cancer treatment options, including chemotherapy, targeted therapies, and immunotherapies. These assessments typically utilize patient-derived cancer cells or models, such as spheroids and organoids, along with orthotopic murine xenograft models. The integration of AI-driven systems and technological platforms is expected to streamline and enhance this evaluation process, potentially leading to more rapid and personalized treatment strategies for cancer patients.

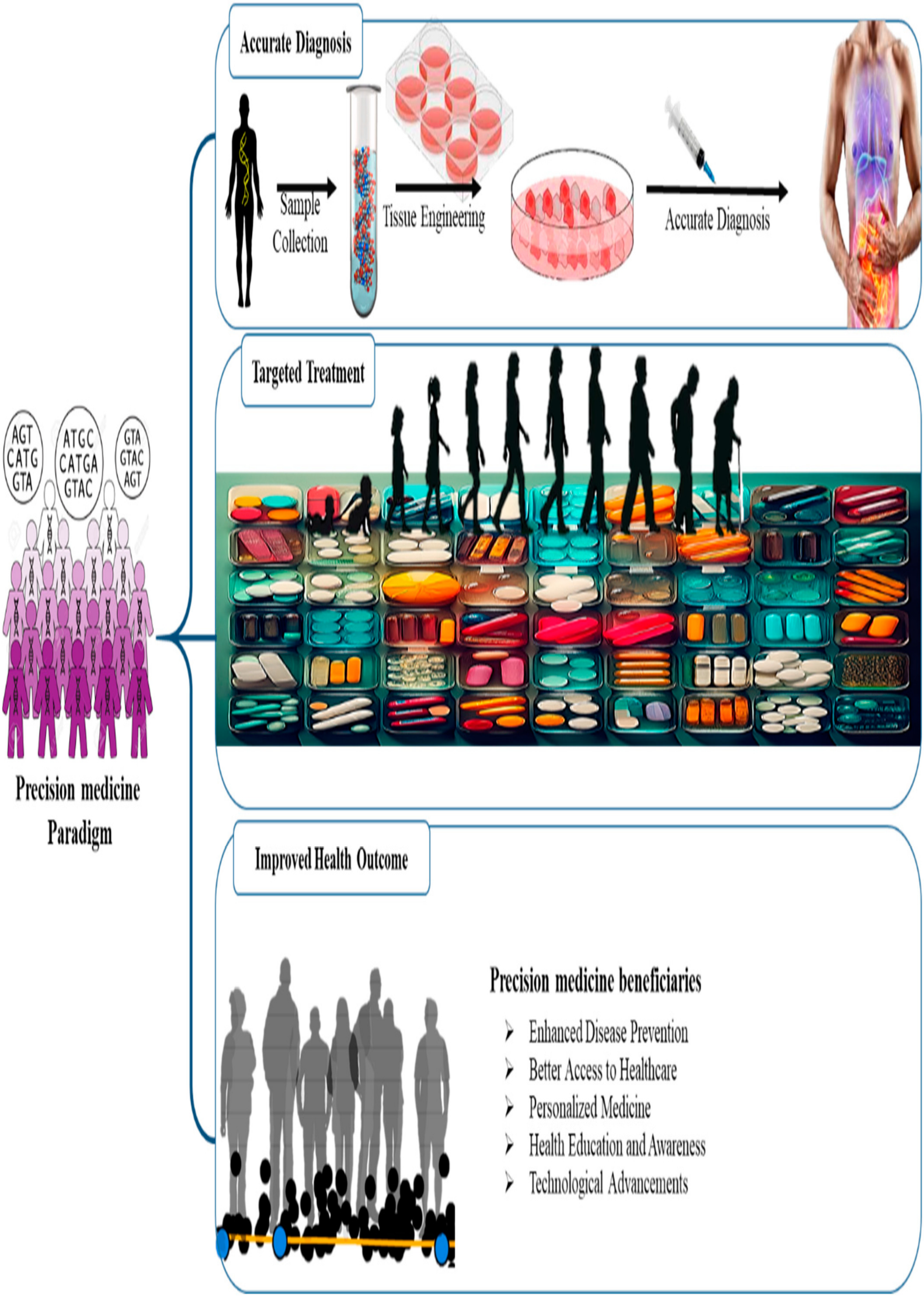

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Figure 5 Demonstrates AlphaFold' s breakthrough protein structure prediction capabilities: (a) Benchmarking against CASP14 competitors (n = 87 domains) shows superior accuracy, with box plots representing median values *and 95% confidence intervals across 10,000 bootstrap samples. (**b**) Structural alignment of prediction (blue) versus experimental determination (green) for target T1049 (6Y4F), excluding disordered C-terminal residues. (**c**) Precise modeling of zinc-coordination geometry in target T1056 (6YJ1), including correct side-chain placement despite omitting metal ions. (**d**) Accurate domain organization prediction for massive 2180-residue target T1044 (6VR4) achieved fully autonomously. (**e**) Schematic of AlphaFold's neural network architecture, detailing dimensional parameters (Nseq = s, Nres = r, feature channels = c) and component interactions. Adapted from [85] under CC BY 4.0.*

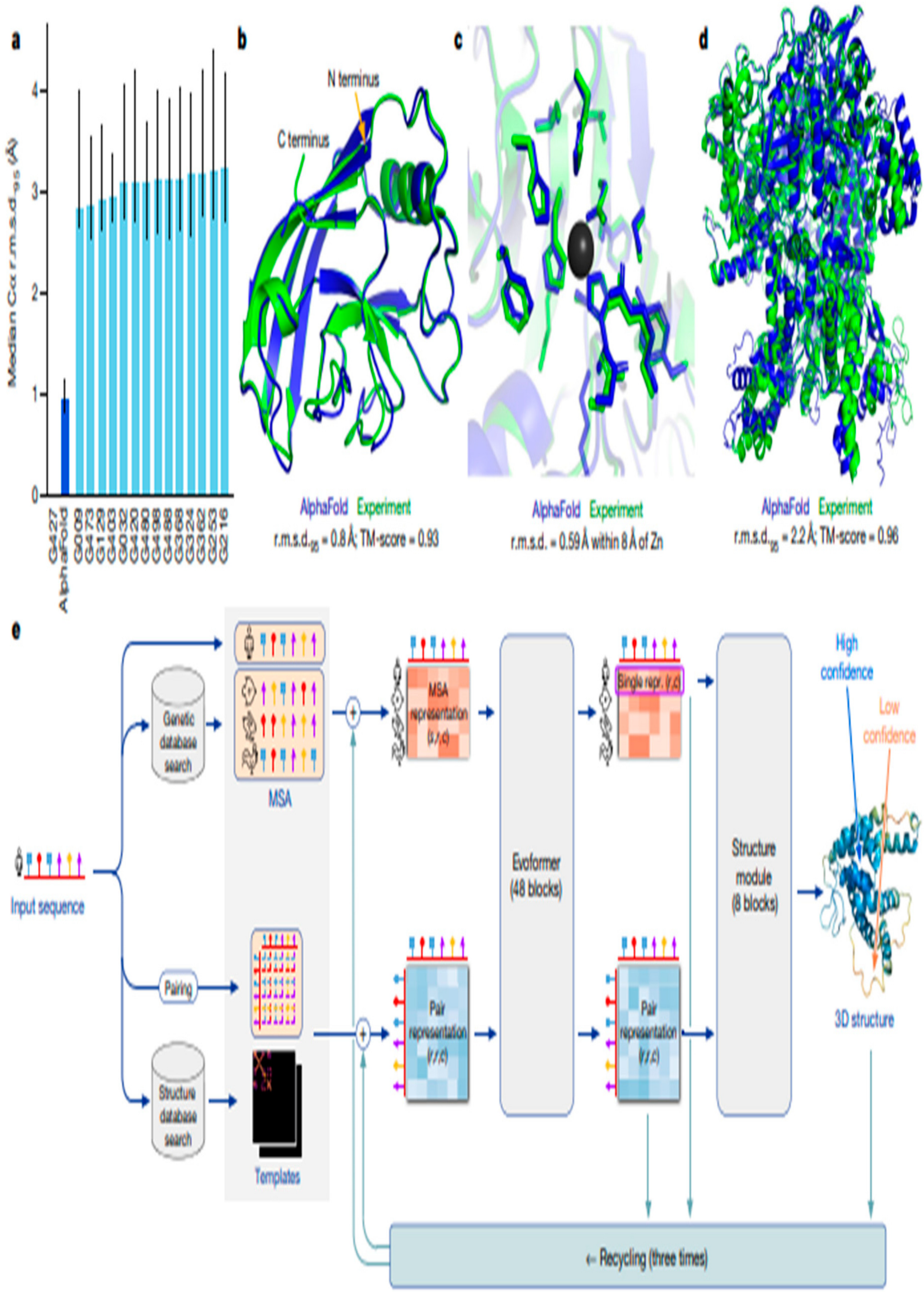

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Figure 6 Chronological progression of AI-enhanced wearable biosensor networks (WAIBNs).

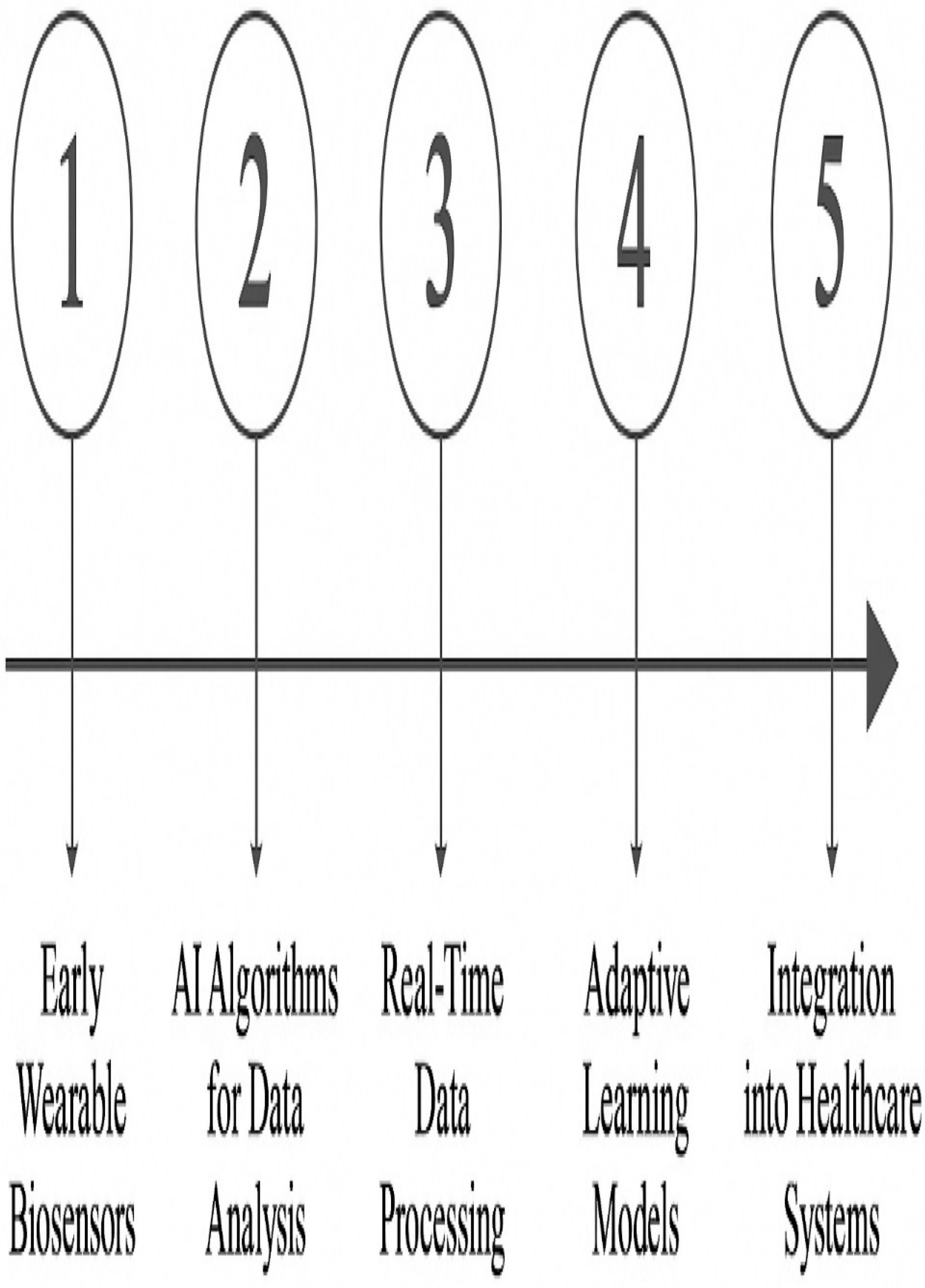

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Figure 7 Ethical and legal dilemmas in AI for healthcare.

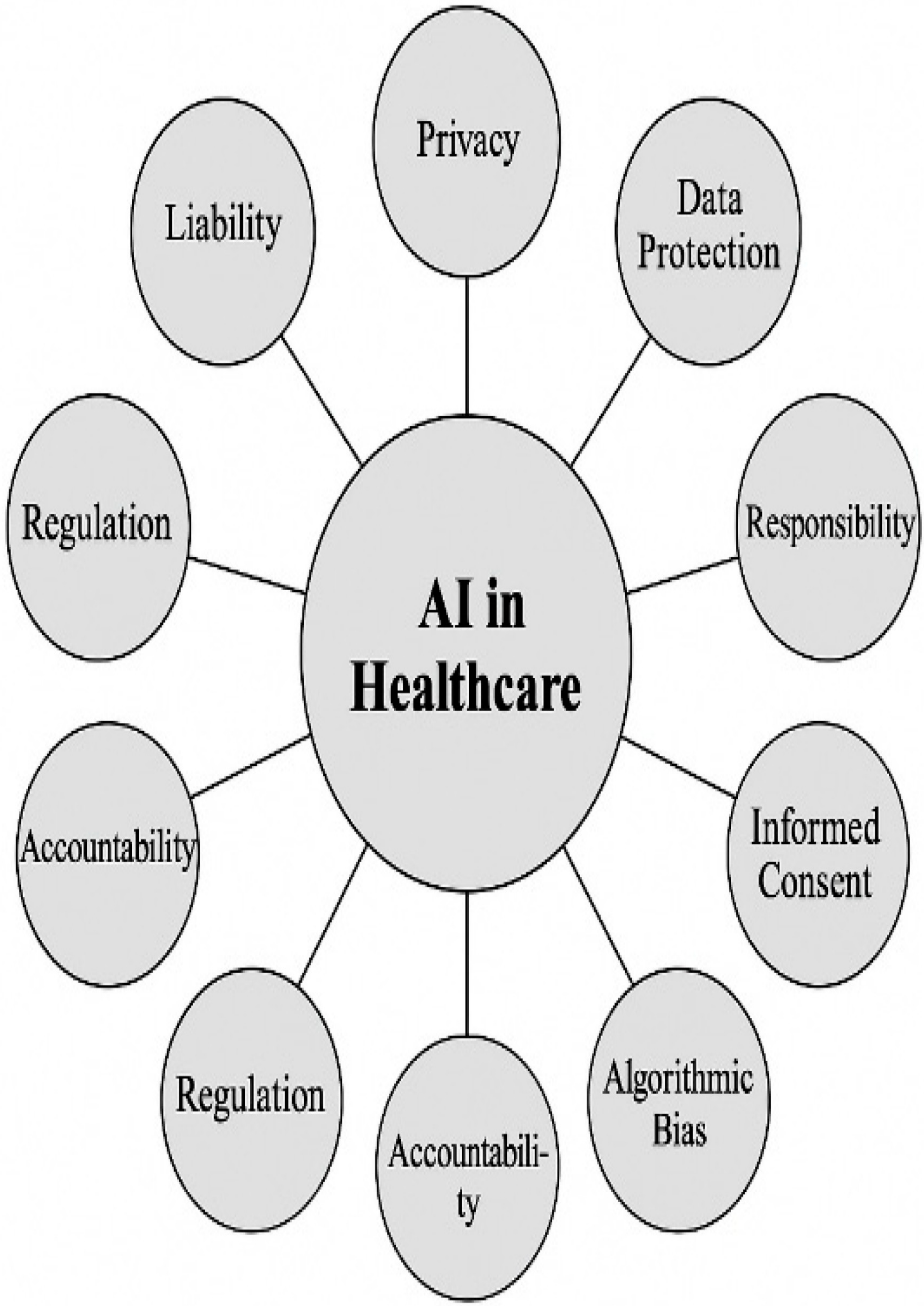

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Figure 8 Schematic representation of multimodal AI in biomaterials science.

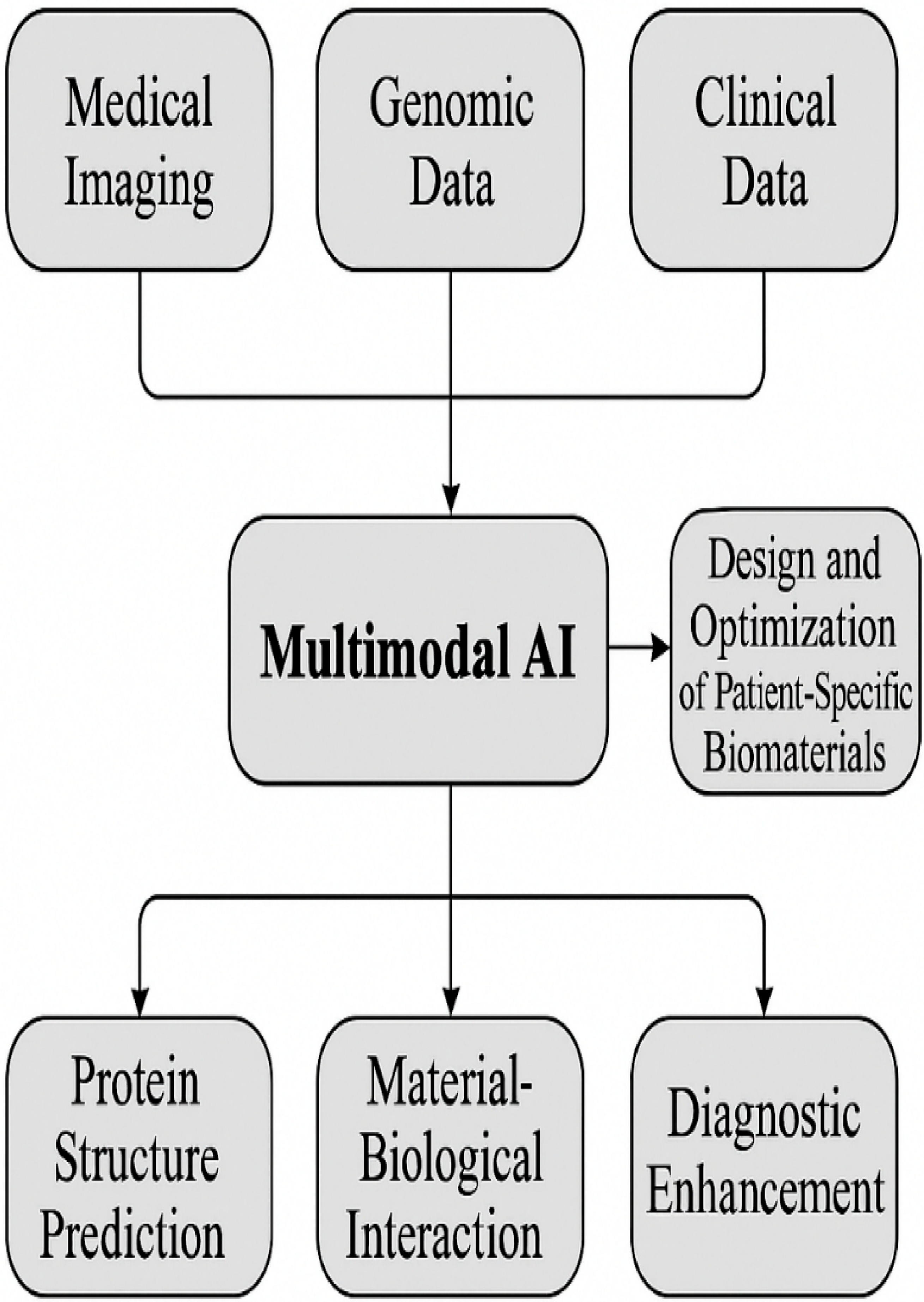

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Table 1

A comparative overview of the role of multimodal AI in biomaterials development.

Aspect	Traditional Biomaterials Development	Multimodal AI-Enhanced Biomaterials Development	Advantages of AI Integration	Ref
Data Utilization	Primarily relies on single-source data (e.g., biological assays)	Integrates diverse data sources (imaging, genomics, clinical data)	Provides holistic insights, improving biomaterial specificity and efficacy	[18]
Material Design Approach	Generalized designs based on population data or trial-and-error methods	Patient-specific designs based on individual health data	Enables precision and personalization in biomaterial properties	[19]
Predictive Modeling	Limited predictive capability, often requiring extensive experimentation	Advanced AI-driven modeling (e.g., AlphaFold for protein structures)	Reduces time and cost by predicting outcomes accurately before physical testing	[20]
Optimization of Properties	Based on empirical adjustments and physical testing iterations	AI analyzes complex relationships for optimal property tuning	Achieves targeted material properties efficiently for specific medical applications	[21]
Interaction with Biological Systems	Determined through iterative biocompatibility testing	AI predicts compatibility with biological systems using multi-omics data	Enhances biocompatibility and reduces adverse reactions	[22]
Speed of Development	Slower due to reliance on experimental validation	Accelerated through rapid AI-driven simulations and predictions	Shortens time-to-market for new biomaterials	[23]
Application in Regenerative Medicine	Limited personalization in grafts and scaffolds	AI customizes biomaterials to patient-specific regenerative needs	Promotes individualized tissue regeneration with higher success rates	[24]
Scalability and Adaptability	Challenging to scale personalized solutions	AI streamlines scalability by optimizing designs for diverse needs	Facilitates adaptable, scalable solutions for diverse patient populations	[25]

Ethical and Regulatory Challenges	Established guidelines for biomaterial safety	Emerging concerns over AI transparency, data privacy	Calls for updated regulatory frameworks and ethical standards	[26]

Table 2
AI-driven biomaterial design for tissue engineering.

Material Type	AI Tools/Methods Used	Biomedical Applications	Ref
Polymeric Scaffolds	Machine learning (ML) for structure–property prediction; Inverse design algorithms	Optimizing porosity, stiffness, and degradation rates for tissue-specific scaffolds (e.g., bone, neural, and musculoskeletal)	[35]
Hydrogels	Multimodal AI (imaging + molecular + clinical data fusion); Deep learning for ECM replication	Skin regeneration, wound healing, and extracellular matrix (ECM)-mimicking hydrogels	[37, 38]
Bone Scaffolds	CT/MRI-based AI analysis (CNNs); Predictive modeling for porosity and mechanical strength	Patient-specific bone grafts with optimized pore architecture for osteogenesis	[36]
Cartilage Scaffolds	AI-driven cell-material interaction modeling; Predictive algorithms for chondrocyte behavior	Cartilage repair with enhanced cell adhesion and differentiation	[39, 40]
Vascular Grafts	AI-based endothelial cell response prediction; Genetic algorithm-driven material optimization	Blood vessel regeneration with reduced thrombosis risk	[40]
Immunocompatible Biomaterials	Genomic data integration with ML; Immune response prediction models	Personalized implants with minimized rejection risks (e.g., skin grafts, and bone scaffolds)	[41, 42]

Table 3
Comparative analysis of AI-driven diagnostic models in biomedicine.

AI Model	Medical Application	Accuracy (%)	Precision (%)	Recall (%)	Reference
CNN (ResNet-50)	Cancer Detection (Histopathology)	94.5	93.8	92.7	[50]

Deep Neural Network (DNN)	Cardiovascular Disease Prediction	89.2	87.5	88.3	[51]
Transformer-Based Model (BERT)	Medical Text Analysis (EHR Processing)	96.1	95.3	94.9	[52]
Generative Adversarial Networks (GANs) (CycleGAN)	Medical Image Enhancement	92.8	91.2	90.7	[53]
AlphaFold	Protein Structure Prediction	>92.4	N/A	N/A	[54]

N/A: Not Available.

Table 4

AI-optimized biomaterials for tissue engineering applications.

AI Model	Biomaterial Type	Application	Predicted Property (Accuracy %)	Biocompatibility (%)	Reference
ML-Based Model (SVM)	Hydrogel Scaffolds	Cartilage Regeneration	91.7	95.2	[24]
Deep Learning (CNN)	Nanocomposites	Bone Tissue Engineering	88.4	93.8	[36]
Bayesian Optimization	3D-Printed Biomaterials	Patient-Specific Implants	94.5	97.1	[22]
Reinforcement Learning	Bioactive Coatings	Antimicrobial Surfaces	90.3	92.6	[63]
AI-Guided GANs	Polymer-Based Biomaterials	Drug Delivery Systems	87.9	91.3	[64]

Table 5

Comparative overview of multimodal AI advancements and challenges in biomaterials science and personalized healthcare.

Aspect	Current State	Advancements with Multimodal AI	Challenges and Considerations	Future Implications
Data Integration	Data often remains siloed across imaging, genomics, and health records	AI combines diverse data sources, allowing holistic analysis for personalized material design	Ensuring data privacy, interoperability, and regulatory compliance	Enables comprehensive patient profiles for precision medicine

Biomaterial Design	Traditional biomaterials are designed based on generalized requirements	AI optimizes patient-specific biomaterials for drug delivery, tissue engineering, and regenerative applications	Complexity in validating AI-driven designs and achieving regulatory approvals	Patient-specific biomaterials that interact optimally with biological systems
AI Tools (e.g., AlphaFold)	Limited predictive accuracy for complex protein structures and interactions	High-accuracy prediction of protein folding and interactions	Algorithmic limitations in handling diverse biological contexts and data complexities	Accelerates biomaterial development tailored for biological compatibility
Diagnostic Precision	Diagnostic tools often rely on isolated data sources, limiting precision	AI-enhanced diagnostics integrate imaging, molecular, and clinical data for higher accuracy	Potential bias in algorithms and difficulty in validating AI-driven diagnostics	More accurate, personalized diagnoses supporting tailored treatments
Wearable Health Monitoring	Basic health tracking with limited data analysis capabilities	AI enhances real-time health monitoring for proactive interventions	Data privacy risks and lack of regulatory frameworks for wearable health data	Personalized health insights and early intervention possibilities
Ethical and Regulatory Issues	Emerging ethical standards; limited regulation for AI in healthcare	AI demands transparent and ethical algorithmic decisions for responsible healthcare use	Addressing algorithmic bias, data handling, and ensuring informed consent	Ethical and regulatory frameworks evolve, supporting AI integration in healthcare
Potential for Personalized Medicine	Limited precision and scalability in current treatments	AI enables tailored approaches, enhancing treatment efficacy and patient outcomes	Scalability, cost, and access barriers for AI-driven healthcare solutions	Transformative shift to data-driven, patient-centered healthcare systems

Table 6

Future opportunities for AI in biomedicine.

Opportunity Area	Current State	Future Potential with AI Integration	Impact on Biomedicine	Ref
Personalized Medicine	Limited to general population models	AI enables individualized treatments based on genetic, clinical, and lifestyle data	Enhances treatment efficacy and minimizes adverse reactions	[10]
Drug Discovery and Development	Time-intensive, costly with high attrition rates	AI accelerates drug discovery through predictive modeling and molecule screening	Reduces development time and cost, improving drug accessibility	[217]

Predictive Diagnostics	Diagnostics primarily based on isolated tests	Multimodal AI integrates diverse data for highly accurate, early diagnosis	Supports early intervention and improves prognosis	[16]
Tissue Engineering and Regenerative Medicine	Largely dependent on generalized biomaterials	AI designs patient-specific biomaterials for enhanced tissue compatibility	Improves patient outcomes and supports complex tissue repair	[66]
Wearable Health Monitoring	Limited to basic tracking (e.g., heart rate, steps)	AI-powered wearables analyze real-time data for personalized health insights	Facilitates proactive health management and early detection	[218]
Genomic Analysis and Precision Genomics	Analysis focused on specific genes or markers	AI analyzes entire genomes, identifying complex genetic interactions	Enables precise identification of genetic risk factors and mutations	[219]
Remote and Telemedicine Applications	Limited real-time patient analysis	AI enables real-time remote monitoring, diagnostic support, and patient triaging	Expands healthcare access, especially in underserved areas	[220]
Ethical and Regulatory Frameworks	Initial standards in place	AI-driven healthcare prompts the development of advanced ethical and regulatory models	Ensures responsible use, transparency, and patient trust	[126]
AI-Augmented Surgical Procedures	Limited AI assistance, primarily robotic arms	Future AI systems can assist in complex surgeries through real-time guidance	Enhances surgical precision and reduces risk of complications	[221]
Health Data Management	Fragmented data management across systems	AI consolidates data for seamless integration and patient care continuity	Improves care coordination and data-driven decision-making	[222]

Table 7

Comparative analysis of key AI models in biomaterials science.

AI Model	Application in Biomaterials Science	Strengths	Limitations	
Deep Learning (DL) (CNNs, RNNs)	Predicting biomaterial properties, image-based tissue analysis	High accuracy in feature extraction and pattern recognition	Requires large datasets; potential overfitting; lack of interpretability	[37]

AlphaFold (Deep Learning-Based Structural Prediction)	Protein-material interaction modeling, bioactive scaffold design	Highly accurate protein structure prediction; aids in rational biomaterial design	Computationally intensive; limited to protein-centric applications	[284]
Machine Learning (ML) (Random Forest, SVM, Decision Trees)	Biomaterial classification, mechanical property prediction	Efficient with small datasets; interpretable models	Performance depends on dataset quality; may lack deep feature extraction	[285]
Reinforcement Learning (RL)	Self-optimizing biomaterial formulations, drug delivery system design	Learns from trial-and-error; adaptive optimization	Requires extensive computational resources; long training times	[286]
Natural Language Processing (NLP)	Literature-based discovery of novel biomaterials	Automates knowledge extraction from vast scientific data	Limited understanding of contextual nuances in biomedical data	[287]
Bayesian Networks	Risk assessment in biomaterial biocompatibility and toxicity prediction	Handles uncertainty well; suitable for probabilistic modeling	Requires prior domain knowledge for accurate results	[22]
Generative Adversarial Networks (GANs)	Designing new biomaterials with optimized properties	Generates novel materials with desired characteristics	Training instability; potential for generating unrealistic structures	[288]
Hybrid AI Models (Combining DL, ML, and Statistical Methods)	Multimodal AI for patient-specific biomaterial optimization	Integrates diverse data sources for better decision-making	Complexity in integration; challenges in model validation	[22]

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DETAILS

Subject:	Medical electronics; Artificial intelligence; Precision medicine; Chemical synthesis; Biotechnology; Health care; Medical imaging; Wearable technology; Biomaterials; Tissue engineering; Ethical standards; Disease detection; Electronic medical records; Customization; Electronic health records; Biomedical materials; Decision making; Neural networks; Biocompatibility; Protein structure; Drug delivery
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The Mental Health Impacts of Internet Scams

Balcombe Luke . Balcombe Luke.

ABSTRACT (ENGLISH)

Internet scams have become more sophisticated and prevalent in countries such as Canada, the US, the UK, and Australia. Australia has made some progress in effective scam intervention strategies and seen possible growth in public awareness. However, there is a lack of insight into factors associated with profound shame and embarrassment, emotional distress such as anxiety and depression, and trauma and suicide in scam victims. To fill this gap, this perspective paper aimed to provide insight into the factors associated with the negative mental health impacts of internet scams by integrating a narrative literature review with a victim case study detailing a group' s experience of an investment scam in Australia. It found that internet scams cause emotional and social issues like depression, anxiety, trauma, and isolation, mostly prolonged upon substantial loss. The author' s insight into the intensely negative mental health impacts of an investment scam allows for the presentation of a group who struggled to access adequate support and mental health care in their response to insidious organized crime. Better education, resilience-building, and support systems are needed. These shortcomings call for strategies for tailored digital mental health services such as emotionally attuned, trauma-informed digital companionship through human-like artificial intelligence (AI) applications.

FULL TEXT

1. Introduction

Scams are a common and sophisticated issue in today' s digital age, with scenarios involving the internet, as well as telephone calls and text messages [1,2,3]. The damage to financial well-being in scam victims has been examined more than the profound psychological impact [4,5,6,7]. The global increase in internet scams since the COVID-19 pandemic led to a call for mental health professionals to provide trusted sources of education on cybersecurity [8]. While Canada, the US, and the UK have seen rising scam losses, Australia saw a significant drop in average losses in early 2025 compared to previous quarters, indicating effective intervention strategies and possible growth in public awareness [9]. The need for insight into factors associated with individuals' experiences called for research into the profound and hidden mental health impacts of internet scams manifesting as emotional distress, including depression, anxiety, shame, and embarrassment [10].

The aim of this perspective is to provide insight into current findings on internet scams by reviewing the literature and media articles and comparing them with an intrinsic case study of individuals' negative mental health impacts from an investment scam in Australia. Additionally, it discusses the potential of tailored digital mental health services to effectively deploy human-like artificial intelligence (AI) applications to increase moderation, accessibility, and help-seeking as well as reduce emotional distress and trauma in scam victims.

2. Methodology

This perspective integrates (1) a narrative literature review (i.e., purposive sample of media articles and journal articles) with (2) a case study involving the author embedded in a scam victim group.

The narrative literature review is adapted from the four steps outlined by Demiris et al. [11]: (1) conduct a search of numerous databases and search engines; (2) identify and use pertinent keywords from relevant articles; (3) review the abstracts and text of relevant articles and include those that address the research aim; and (4) document results by summarizing and synthesizing the findings and integrating them into the review.

A preliminary online search found that there are not enough studies that meet the strict criteria of a systematic review. Therefore, a purposive sample of articles was applied to demonstrate an educational approach to the novel topic. By selectively choosing relevant articles and reviewing them thoroughly, valuable insights were compiled into a coherent narrative literature review. This method enabled flexibility in considering diverse perspectives, providing a more comprehensive understanding of the topic.

Peer-reviewed journal articles and media articles were obtained through systematic searches of computerized databases and targeted online searches. The databases searched were Scopus, ScienceDirect, Sage, and the Association for Computing Machinery (ACM) Digital Library. The search engines used were PubMed, Google Scholar, and IEEE Xplore. The search terms used were "internet scams" OR "cybercrime OR "investment scams" AND "mental health impact" OR "psychological impact".

The following selection criteria were used:

Inclusion criteria:
Studies that have been published in peer-reviewed journals and media articles;
Studies that have been published in the English language;
Studies that have been published between 2010 and 2025;
Studies that have investigated the mental health impact of internet scams;
Studies that have reported on internet scams, how they operate, current issues, and their financial and mental health impact on victims.

Exclusion criteria:
Studies that have not been published in peer-reviewed journals and media articles;
Studies that have not been published in the English language;
Studies that were published before 2010;
Studies that have investigated the mental health impact of internet scams;
Studies that have not reported on internet scams, how they operate, current issues, and their financial and mental health impact on victims.

Relevant articles and their reference lists were explored based on (1) relevance to the guiding research aim (2) the inclusion of examples of theoretical and empirical research and (3) the highlighting of issues and possible solutions. These articles were used for a thorough and unbiased analysis of current knowledge, utilizing a systematic approach to minimize bias through comprehensive searches and relevant article focus. Despite this, bias in the literature was critically assessed, and any limitations were noted.

This perspective also applies an intrinsic case study approach as designed by Stake because it is inherently interesting [12]. It focuses on qualitative inquiry and interpretive analysis within a real-world context to understand unique perspectives in a specific investment scam of which the researcher was also a victim [12]. Five steps—case selection, data collection, data analysis, narrative development, and reflexivity with ethical considerations—guide the detailed exploration and presentation of a unique case study.

The lead author led the case study with member checks by a fellow scam victim to delve deeply into individual and collective experiences of an investment scam in Australia. The case study started with archival research; the author examined historical records, including media articles, witness statements, and conversations with police detectives and significant others (e.g., investigators and informants), and examined financial/legal documents, to trace the evolution of scam tactics as well as financial/mental health impacts on victims.

Data collection involved a questionnaire with scam victims ($n = 25$) and detailed interviews ($n = 3$) to capture the financial and emotional toll of the investment scam. The case study was structured around adult Australian resident scam victims. The group' s interactions with the scam were scrutinized, revealing patterns in mental health impacts, vulnerability, and trust dynamics, as well as coping mechanisms. This included personal narratives to paint a comprehensive picture of the phenomenon.

The questionnaire was collated through email (addresses of scam victims were supplied by a police detective). The questions asked about the financial and mental health impacts of the scam experienced by individuals. In-depth interviews via phone calls with scam victims helped identify emotional triggers and psychological consequences. Thematic coding was employed to uncover recurring themes in the investment scam narratives. Since the lead author was involved as a scam victim and researcher, participants were informed that their participation was voluntary and on a victim-to-victim/researcher basis. Contact details for mental health support and crisis services were supplied to participants.

3. Literature Review Findings

3.1. The Global Epidemic of Internet Scams

Scams, involving deceptive practices to defraud individuals, cost victims over USD 1 trillion in 2023 [13]. The Global State of Scams Report in 2022 revealed that only 7% of scams are reported, highlighting the issue' s vast scale [14]. Internet scams have become a global epidemic, with the digital economy' s growth making scams the most reported crime in many countries, including developing nations where mobile scams are rampant. Investment scams, especially those involving imposters using the internet, money mule accounts, and cryptocurrencies have surged due to economic pressures, causing significant losses [15,16,17,18,19,20,21]. The rise in scams reflects the dark side of a digitalized world economy during global crises [22], weakening trust in digital platforms due to cybersecurity threats from malicious internet provider (IP) addresses and unsafe browsing [23].

3.2. The Growing Sophistication of Internet Scams

Scammers use tactics like impersonating banks, businesses, and authorities, phishing for personal information, setting up fake websites, offering deceptive investment schemes, creating urgency, and false lottery notifications, as well as tech support and romance scams [24,25].

People fall for scams due to financial desperation, promises of quick wealth, social engineering, false legitimacy, a lack of awareness about sophisticated scam tactics, emotional triggers, exploited trust, and busy lifestyles leading to missed red flags and insufficient verification [26,27,28]. Scams have become more sophisticated with AI for voice-cloning, deepfakes, chatbots [29,30], phishing schemes [31,32,33], data tracking/sharing, targeted ads, and cloned investments [34,35,36,37]. Psychological tactics include impersonation and fake 'social proof,' as well as deceptive authorized push payments and payment redirections [38,39,40,41,42,43]. There is also a lack of awareness about technological solutions like server-side tracking, Virtual Private Networks (VPNs), and AI chatbots to counter these issues [44,45,46,47,48].

Big tech companies play a crucial role in preventing scams and raising awareness [49]. However, United States (US) laws' opacity has hindered an understanding of how these companies profit from scam ads on their platforms [50]. Collaboration among US government agencies, law enforcement, financial institutions, telecommunications companies (telcos), consumer organizations, the private sector, and individuals is essential for combating scams [48,49,50,51,52]. In Australia, a federal scam protection campaign aims to fine tech giants, banks, and telcos penalties up to AUD 50 million and compensate victims, differing from the UK model, which forces banks to reimburse customers unless they acted fraudulently or with gross negligence [52,53,54,55,56,57]. The proposed Australian framework introduces obligations for companies to detect, report, disrupt, and respond to scams.

3.3. The Targeting of Internet Scam Victims

Internet scams can affect anyone, anywhere [58,59,60]. The warnings of a real risk to older people (specifically for financial cybercrime) [61] came before findings that they are less vulnerable to being scammed online than in general [62]. A systematic review found that older adults are susceptible to being online fraud victims [63]. While there is less prevalence than other age groups, they are vulnerable because of their cognition, trust, and reduced internet experience and awareness of how the internet is used to deceive them.

Media reports show how the internet enables scams. For example, foreign call center workers target Americans and Australians with investment scams from South-East Asia, the Middle East, and Eastern Europe [64,65]. One in four Australian teenagers fall victim to social media scams, including sextortion, fake websites, and illegitimate online marketplace trading [66]. Constant cyber-attacks on Australian banks and scams by overseas actors necessitate practical steps for financial services and customers to counter these risks [67,68,69].

Experts share tips on scam protection [70,71], aligning with police efforts on scam detection and disruption. However, scammers adapt their tactics based on available feedback, exploiting psychological vulnerabilities, cognitive biases, and overconfidence through manipulative communication, urgency, and rapport-building [72,73].

3.4. The Literature on the Psychological Impacts of Scams

The psychological impacts on scam victims is severe, leading to distress, anxiety, depression, post-traumatic stress disorder (PTSD), and suicidality [74,75,76,77]. Victims often feel shame, guilt, anger, helplessness, and fear as they deal with the financial and emotional fallout [78]. Awareness and vigilance are crucial in preventing scams [79,80], helping victims avoid self-blame, encouraging reporting, and learning from experiences to prevent future scams. There is a need for greater use of psychological approaches in the prevention of cybercrime as well as empowering resilience against scams [81].

The literature to date includes understanding how scams work from a financial crime or technology perspective. The focus has been on detecting and analyzing scam sites [82], while other studies have shown scammer or victim behavior before or during the fraud [83,84,85,86]. However, a systematic review of the psychology of internet fraud victimization showed susceptibility in those who respond to time-limited communications [27]. There was a call for investigating how mood and emotion affect engagement with internet scams.

Romance scams are the most studied of the internet scam genre. However, recent reviews indicate that online romance scams are under-researched despite a rise in studies [87,88]. The persistent low reporting rates of romance scams is due to embarrassment or fear of disapproval. The isolating experience of being a romance scam victim can lead to individuals finding ways to cope without understanding from family and friends [89]. Such victims tend to be middle-aged, well-educated women who are impulsive, less kind, and more trustworthy and have an addictive disposition [90]. They feel marginalized by victimization and experience persistent deep emotional shifts hindering their ability to self-regulate potential suicidality [91].

A cross-sectional study on internet scams found negative mental health impacts and that individuals with poor mental health may be more susceptible to becoming victims [92]. However, no causal relationship was established, and it is unknown for how long the impacts of an internet scam experience on mental health may last. Financial losses from internet scams may worsen mental health issues or trigger new ones. The limited findings on internet scams require developing an evidence base from narration.

3.5. Case Study of an Internet Scam

In 2023–2024, a group of Australian investors ($n = 25$) fell victim to an elaborate internet scam. The investment scam, operated by a global syndicate, preyed on internet users who conducted an online search for term deposits or bonds. This digital footprint led to fake websites on Google or Facebook advertisements. The victims' contact details were provided to 'investment advisors' who subsequently contacted them by phone and email, impersonating a legitimate business with an Australian financial services license. The scam involved developing rapport over time, authentic-looking investment guides, online portals, and payment instructions to an 'escrow account' used by money mules to forward money to other individuals and companies as well as currency exchange and cryptocurrency platforms.

The unique perspective brought by the author being part of the scam victim group became clear after a police detective tracked down 25 victims throughout Australia. This detective connected them in 2024–2025 with emails and phone calls, and assisted them in fighting back and reaching out to share personal insights into the financial and mental health impacts.

Some victims lost substantial sums, and others lost more modest sums, while a few avoided substantial financial losses after canceling the payment and/or successful bank recalls. A few months after the group connected, some victims (including the author) thereafter followed up with emails and phone calls to collate a summary of the financial aspects of the scam. The dissatisfaction with the banks and the Australian Financial Complaints Authority (AFCA)'s handling of investigations/complaints was the impetus for a spreadsheet summary. It was overall critical of the response of banks and AFCA, highlighting a perceived lack of genuine consideration, assistance, accountability, or empathy from these institutions.

In terms of the mental health impacts of the scam, the group reported significant psychological distress manifesting as insomnia, anxiety, depression, and trauma (notably, post-traumatic stress disorder). Insomnia was noted as temporary while awaiting the decision of bank recalls (1–2 months). The experience of anxiety and depression was prolonged in those who suffered major financial loss. It was compounded by a perception of not being adequately served by banks and AFCA as well as unproductive and/or slow police inquiries (up to 2 years if investigated). Those who were satisfied with bank recalls had temporary anxiety and depression (1–2 months). PTSD was commonly still present long after the scam (1–2 years), regardless of whether the financial loss was significant.

In the months after the victims learned about the scam, there were reports of persistent sadness, loss of interest, feelings of panic, and excessive worry, typical symptoms of depression and anxiety. Some scam victims were taking anti-depressive or other psychotropic medications to help them cope 1–2 years after a substantial loss. As a result of the shame of having been scammed, some withdrew from social interactions, felt isolated, and experienced loneliness and despair as well as a relationship breakup. This occurred up to 1–2 years after the scam for some victims. Constant rumination over the incident exacerbated these feelings, complicating daily life. Financial security and personal information became sources of heightened worry and anxiety. Some of the group consulted their doctor to access mental health care in the first months of realizing they were scammed, while most did not. A few found solace in sharing their experience with fellow victims, and some of this sharing occurred 1–2 years after being scammed. Overall, there were various negative mental health impacts and emotions; for some victims there were short-lived effects, while for others they were long-term.

4. Discussion

4.1. The Fight Against Internet Scams

Research and media reports highlight the widespread impact of internet scams, exploiting global loopholes such as through search engines and social media. Vulnerable groups include older adults, due to trust and limited digital literacy, and teenagers, targeted on social platforms. Scammers cause significant financial and psychological harm, underscoring the need for systemic reforms.

Australia provided a timely perspective as financial impacts from scams showed signs of decline for the first time since 2015, as noted in AFCA's 2023–2024 annual review [93]. In September 2024, the Australian Government's Treasury introduced anti-scam codes mandating businesses to implement strong measures, enforceable with penalties up to AUD 50 million, and victim compensation provisions if the business fails to meet the standards [94]. These efforts align with the creation of Australia's National Anti-Scam Centre (NASC).

Australia's recent anti-scam measures show progress in detecting and disrupting scams, yet the response to victims' financial and mental health impacts remains inadequate. The case study highlights dissatisfaction with the care from banks and financial complaints groups, along with gaps in educational resources for recovery and suicide prevention. Media reports and the literature emphasize the urgent need for stronger victim support, empowerment, and tools to rebuild trust, as victims often face isolation and emotional distress. While some efforts exist to combat scams, resilience and faster preventive measures are still under-explored.

4.2. Comparison of Findings on the Mental Health Impacts of Internet Scams

An online survey conducted in 2025 sought insight into the profound and hidden mental health impacts of internet scams, showing that victims suffer from depression, anxiety, shame, and embarrassment. This perspective also aimed to provide insight into the negative mental health impacts by comparing literature review and case study findings to address the lack of research on these effects.

Literature Review Findings:
Scam victims often experience severe emotional distress, including depression, anxiety, shame, embarrassment, and PTSD.
Romance scams are highlighted as particularly emotionally damaging, with victims reporting feelings of marginalization and deep emotional shifts that hinder self-regulation, occasionally leading to suicidality.
Victims frequently deal with persistent sadness, anger, guilt, fear, and helplessness, which exacerbate their psychological struggles.
Despite the significant psychological toll, scams are under-studied in terms of their mental health impacts compared to financial losses.
There is limited exploration of resilience and coping mechanisms among scam victims, as well as insufficient educational resources for mental health recovery and suicide prevention.

Case Study Findings:
Victims of the investment scam in Australia reported psychological distress manifesting as temporary insomnia, ongoing anxiety and depression (associated with substantial financial loss), and prolonged trauma, notably PTSD.
Symptoms typically present over months included persistent sadness, loss of interest in activities, feelings of panic, excessive worry, and rumination over the incident.
Social withdrawal, isolation, loneliness, and relationship breakups were common among victims for long periods due to the shame associated with being scammed.
Heightened anxiety surrounding financial security and personal information became prominent after the scam.
Though some victims sought medical help or mental health care, most did not, highlighting barriers to accessing support and recovery resources.

Comparison of Findings:
Both the literature review findings and case study emphasize the significant emotional distress caused by internet scams, including persistent depression, anxiety, shame, and PTSD (most prolonged).
The literature review provides broader insight into psychological impacts across different types of internet scams globally, while the case study offers a focused perspective on the mental health toll of a specific investment scam in Australia.
Victims in the case study reported similar symptoms to those outlined in the literature, but their experiences also revealed additional social and relational impacts, such as withdrawal and relationship breakups.
The literature review highlights the need for resilience-building and educational resources, while the case study underscores the inadequacies of current support systems and the isolation felt by victims.

4.3. Digital Mental Health and AI Solutions for Internet Scam Responses

Digital mental health (DMH) services complement traditional support [95], empowering internet scam victims to overcome shame and embarrassment in private with practical strategies for emotional regulation and recovery.

Although digital mental health services may connect victims to traditional support, conventional methods often fail to meet their needs effectively. For example, there is a need for new approaches to move beyond the limited effectiveness of psychotropic drugs [96] and fill the gap left by the scarcity of mental health professionals [97,98].

A help-seeking solution is to use AI-driven mental health applications, such as Wysa, Youper, and Woebot [99,100,101]. AI chatbots offer (cost)-effective treatment mainly for anxiety and/or depression [102], usually with positive engagement outcomes [103].

Conversational AI, such as AI chatbots, offers accessible and convenient mental health care, allowing individuals to receive therapy regardless of location, cost, stigma, or schedule [104,105]. The availability of AI can help overcome the persistent low reporting rates for scams. While available 24/7, DMH services lack the empathetic human touch of in-person therapy and face challenges like privacy concerns, data security, and algorithmic biases, along with limitations in addressing complex emotions. The randomized controlled trial (RCT) for Therabot—a generative AI therapy chatbot—shows promising preliminary effectiveness [106].

More research and development are required to increase the safety, usability, and effectiveness of AI chatbots [104]. While human intervention may be necessary in crisis situations, there is also the issue of AI chatbot hallucinations, and the need to address biases or errors. For example, AI chatbots can be a problem if the app crashes and a conversation is lost. Memory-enabled sessions provide personalized interactions, while clean sessions treat each as new. Combining both ensures efficiency and avoids biases, offering flexibility to users.

AI integration in scam prevention includes fraud protection in banks and monitoring online platforms to flag suspicious activities, reducing victimization and psychological harm. AI can also educate individuals on scam tactics and provide real-time alerts. However, tailored digital mental health services like lived experience-guided, emotionally attuned, trauma-informed AI companions are lacking [107].

Human-like AI chatbots with emotional intelligence, informed by lived experiences, could address dissatisfaction with systemic support by offering ethical, culturally sensitive assistance. These applications should prioritize co-regulation to help scam victims manage trauma and emotional distress effectively.

5. Conclusions

Scams have significant negative mental health impacts, leading to stress, anxiety, depression, and isolation. In the months after, victims often experience shame and embarrassment, exacerbated by financial insecurity and a lack of support. Severe cases may even trigger suicidal thoughts. Recognizing these impacts is essential for providing effective preventive measures and recovery support, some of which may be required years later.

A case study on an investment scam in Australia revealed victims' struggles with temporary insomnia and ongoing trauma, anxiety and depression, as well as social withdrawal. While some found solace in shared experiences, dissatisfaction with systemic responses was common. The study underscores the importance of innovative solutions like human-like AI chatbots, which could offer scalable, accessible, and empathetic emotional support.

Internet scams highlight the need for resilience-building resources, improved educational outreach, and integrated mental health systems. By leveraging advancements such as AI-driven emotional intelligence tools, recovery pathways can be enhanced, bridging gaps left by traditional systems and addressing the profound emotional distress associated with scams.

Finally, there is a need for strategies aimed at combining prevention and intervention with victim support, emphasizing the importance of education and technological interventions. In sum, this perspective has shed light on the intricate ways in which scams operate and affect individuals, paving the way for more targeted preventive measures and support systems.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest

The author declares that they have no conflicts of interest.

Abbreviations

ACM	Association for Computing Machinery
AFCA	Australian Financial Complaints Authority
AI	Artificial intelligence
DMH	Digital mental health
IEEE	The Institute of Electrical and Electronics Engineers
IP	Internet provider
NASC	National Anti-Scam Centre
RCT	Randomized controlled trial
PTSD	Post-traumatic stress disorder
UK	United Kingdom
US	United States
VPNs	Virtual private networks

Footnotes

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DETAILS

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Digital Mental Health Interventions for Adolescents: An Integrative Review Based on the Behavior Change Approach

Hong Sun Hwa ; Chun, Tae Kyung; Nam You Jin; Wi, Kim Tae; Cho, Yong Hyuk; Son, Sang Joon ; Roh, Hyun Woong; Hong Chang Hyung . Hong Sun Hwa; Chun, Tae Kyung; Nam You Jin; Wi, Kim Tae; Cho, Yong Hyuk; et al.

ABSTRACT (ENGLISH)

Background: Adolescents are at a critical developmental stage marked by rapid cognitive, emotional, and social changes, making them highly susceptible to mental health issues. Recently, digital health interventions (DHIs) have emerged as innovative and scalable tools for promoting mental well-being in this population. Methods: This integrative review was conducted based on comprehensive literature searches of major academic databases, including PubMed, Scopus, Web of Science, and PsycINFO. Studies published between January 2010 and December 2024 were identified using keywords such as "adolescent mental health," "digital health intervention," "behavior change model," "e-health," "mobile mental health," and "digital therapeutics." The inclusion criteria comprised peer-reviewed studies on digital mental health interventions for adolescents that applied, fully or partially, a behavior change approach. Studies targeting adults, interventions without digital technology, the gray literature, and duplicate publications were excluded. Results: We examined intervention strategies based on developmental stage prevention, early intervention, and recovery and highlighted key digital components such as accessibility, anonymity, personalization, and continuous monitoring. Furthermore, we analyzed case studies from various countries, including Korea, the United Kingdom, Australia, and Japan, to identify best practices and contextual challenges. Conclusions: DHIs rooted in sound psychological theory and ethical design can complement school- and community-based interventions by offering effective personalized support. The practical implications and future directions are discussed.

FULL TEXT

1. Introduction

Adolescence is a critical developmental stage characterized by rapid cognitive, emotional, and social changes during which mental health problems frequently emerge for the first time. According to the World Health Organization [1],

the onset of approximately 50% of all mental disorders is before the age of 14 years, and 75% emerge before the age of 24 years. Adolescents exhibit high rates of self-harm, and suicide remains one of the leading causes of adolescent death. Mental health challenges in adolescence are closely associated with a range of adverse outcomes, including poor academic achievement, substance use and abuse, violence, and issues related to sexual and reproductive health [2].
If left unaddressed, the mental health problems arising during adolescence may become chronic and exert lasting negative effects throughout adulthood and old age. Therefore, proactive and preventive interventions during adolescence are essential, and a shift toward prevention-oriented strategies is urgently needed [3,4]. However, adolescent mental health care has traditionally relied heavily on treatment-focused and reactive approaches, in which psychiatric diagnoses, pharmacotherapy, and counseling are typically provided only after symptoms become clinically evident [4]. In addition to a lack of early interventions, stigma and limited accessibility contribute to the low rate at which adolescents receive mental health support. Consequently, there is a growing call for a paradigm shift toward delaying the onset of mental illness, preventing its occurrence, and strengthening adolescents’ psychological resources [5]. This shift necessitates moving beyond a treatment-centered model toward an integrated approach that emphasizes mental health promotion and enhancement of psychological resilience [6].
To address adolescent mental health from a preventive perspective, interventions should be grounded in a developmental framework that reflects adolescents’ emotional, cognitive, motivational, and behavioral characteristics, referred to as the emotional–cognitive–motivational–behavioral change model. This approach extends beyond symptom relief by fostering self-awareness of emotions (emotional), interpretation of situations (cognitive), reinforcement of internal motivation toward positive change (motivational), and development of the capacity to act on such change (behavioral) [7]. These four psychological domains are highly interconnected during adolescence and play critical roles in mental health development and change. Therefore, an integrated framework that addresses these issues in a unified manner is essential.

Recent advances in digital technology have marked a pivotal shift in the delivery of mental health interventions to adolescents. Adolescents are digital natives and benefit from the anonymity and accessibility offered by mobile applications, online counseling platforms, and AI-based emotional analysis tools [8]. Digital interventions effectively reduce barriers to accessing mental health services and promote voluntary engagement among youth [9]. In particular, the rapid expansion of remote psychological support services following the COVID-19 pandemic has positioned digital interventions at the core of the “new mental health care ecosystem.” Moreover, digital technologies and digital mental health interventions are being increasingly recognized for their scalability and potential to address the rising demand, improve accessibility, and enhance mental health outcomes. The advantages of digital interventions include increased acceptability, enhanced access, efficiency, clinical effectiveness, and the potential for personalized care [10]. Eysenbach [11] was the first to conceptualize the term “e-health,” referring to health services delivered via the Internet and computer-based platforms. Since then, digital mental health interventions have become increasingly prominent [10,11]. An example of a digital health intervention (DHI) is computerized cognitive behavioral therapy (cCBT), which emulates traditional face-to-face CBT sessions through a series of self-paced sequential modules. Recent advancements in programming technologies have enabled the incorporation of gamification and “serious games” into cCBT, enhancing its interactivity and rendering it more suitable for adolescents [12,13,14]. Technological innovations can increase engagement and immersion among adolescents, thereby improving intervention outcomes. Furthermore, the global proliferation of digital devices and rapid expansion in technology use have significantly transformed the landscape of mental health service delivery. Digital platforms now allow for self-monitoring and self-management without temporal or spatial constraints, emerging not just as auxiliary tools but as central media for both assessment and intervention. Given the current communication preferences of adolescents, who often favor social media over face-to-face interactions, digital platforms offer a comfortable and familiar means of expressing psychological distress [15,16]. These changes are increasingly reflected in mental health policies, as digital platforms facilitate self-directed care and real-time

monitoring, offering potential advantages in terms of accessibility, efficiency, cost reduction, and effectiveness. User-generated and shared data also open up new possibilities for innovative diagnostic and intervention strategies in clinical settings. When used appropriately, digital mental health platforms that ensure anonymity and accessibility can facilitate rapid responses for adolescents in need of early intervention and prevent chronicity.
However, to maximize the utility of digital interventions, critical issues must be addressed, including the empirical validation of their effectiveness, protection of personal data, ethical considerations, and applicability across diverse settings. In response to the current adolescent mental health crisis, it is essential to adopt preventive and integrative strategies aligned with contemporary technological and societal shifts. This review explores the structural factors underlying the challenges to adolescent mental health care from the perspective of an integrated behavioral change approach. It also analyzes the theoretical foundations of digital interventions and examines international best practices, thereby offering insights into the applicability and future directions of digital mental health strategies for youth.

To comprehensively explore the existing body of research on digital mental health interventions for adolescents, this study applied an integrative review methodology. Through this approach, diverse research findings were systematically analyzed within a theoretical framework, aiming to derive practical implications for clinical application and future intervention development.

2. Main Discussion

2.1. Developmental Characteristics of Adolescence

Adolescence is a transitional phase from childhood to adulthood, marked by rapid physical development, cognitive maturation, emotional turbulence, and expanding social relationships. It is generally defined as spanning from around the age of 10 to the early 20s and is characterized by profound psychological instability and multidimensional changes [17]. Four key domains of development are particularly relevant to adolescents' mental health.
The first is neurobiological development. During adolescence, the limbic system, which is responsible for emotion and reward processing, undergoes accelerated maturation, whereas, the prefrontal cortex, which governs impulse control, planning, and decision making, matures gradually [18]. According to Casey et al. [19], this imbalance in brain development contributes to impulsive behavior, increased susceptibility to risky actions, and heightened vulnerability to mental health problems.

The second is cognitive development. Adolescents acquire the capacity for abstract and hypothetical thinking along with a growing understanding of themselves and others [20]. However, cognitive flexibility remains incomplete, often resulting in egocentric thought patterns such as the "imaginary audience" and "personal fable" [21]. These tendencies may cause adolescents to become overly sensitive to peer evaluation and social scrutiny, contributing to their emotional instability.

The third is emotional development. Identity formation emerges as a central task in adolescence [22]. The exploration of self-identity can give rise to episodes of depression, anxiety, and confusion as adolescents encounter psychosocial conflict. Emotional distress may be intensified by challenges in peer relationships, the process of separation from parental figures, and navigation of gender and sexual identity [23].

Fourth, social relationships are reconfigured. Adolescents gradually shift from family-centered to peer-centered and socially oriented networks. Peer groups play a critical role in shaping identity, and experiences of peer acceptance or rejection significantly affect emotional well-being [24]. This developmental stage is also marked by an increased desire for social approval and comparison, which is closely linked to adolescents' social interactions within digital environments such as social media.

2.2. Key Components of Mental Health Interventions

Effective adolescent mental health interventions require systematic integration of several core components. In particular, when utilizing digital environments for intervention delivery, four key elements serve as foundations (Table 1).

Accessibility refers to the provision of mental health services that adolescents can utilize without time or location constraints. Given the structured demands of school and daily life, adolescents often face challenges in maintaining consistent access to traditional face-to-face counseling. Digital resources, such as mobile applications, web-based counseling platforms, and 24/7 chatbot services, significantly enhance accessibility. These tools not only allow for more flexible engagement but also facilitate earlier intervention and help reduce treatment avoidance [25]. Second, the provision of a nonjudgmental and safe environment enables adolescents to freely express their emotions and personal challenges. Given their heightened sensitivity to social stigma surrounding mental illness and peer evaluation, adolescents greatly benefit from platforms that ensure anonymity and emotional safety. Digital spaces such as anonymous online communities and emotion diary applications offer a psychologically secure setting, fostering emotional openness and self-expression [26]. Third, person-centered engagement refers to intervention strategies designed to respect adolescents' autonomy and capacity for self-determination. This approach is operationalized through personalized content recommendations, self-guided therapy modules, and interactive game-based learning systems. Such features position adolescents as active participants, rather than passive recipients, in the intervention process. This shift in role enhances engagement and adherence, ultimately contributing to improved intervention outcomes [27]. Fourth, continuity and monitoring involve the systematic tracking of adolescents' emotional states and behavioral changes over time, enabling timely detection and response to emerging risks. Tools such as AI-based emotion analysis, regular self-assessment reminders, and visualized emotional dashboards facilitate this function by enhancing intervention consistency and predictability [28].

Collectively, the elements of accessibility, nonjudgmental environment, person-centered engagement, and continuity and monitoring constitute critical pillars for determining the effectiveness and acceptability of adolescent mental health interventions. The integration of digital technologies allows these components to be implemented in practical, sophisticated, and individualized ways. Such a comprehensive framework not only supports short-term intervention success but also provides a foundational structure for long-term emotional stability and self-reliance in youth.

2.3. Types and Strategies of Adolescent Mental Health Interventions by Stage

Adolescent mental health interventions require a continuous and structured framework that spans from pre-onset prevention to early detection and response, and finally to recovery and support for self-reliance. In particular, from the perspective of the integrated behavioral change approach, such interventions should not merely aim to reduce symptoms but empower adolescents to recognize their own psychological state, regulate their emotions and behaviors, and ultimately reclaim a sense of autonomy.
As shown in Table 2, adolescent mental health interventions can be categorized into three main types according to their timing and purpose. Preventive interventions focus on enhancing emotional resilience, increasing mental health literacy, and improving self-management skills prior to the onset of clinically significant symptoms. Representative programs include stress management education, emotion regulation training, and psychoeducational sessions to promote an understanding of mental health.

In recent years, digital tools such as smartphone applications, gamified cognitive behavioral therapy content, and

self-assessment tools have been utilized to deliver these interventions in more engaging and scalable formats [29]. For example, Kooth, a UK-based digital platform, offers adolescents opportunities for emotional self-assessment, web-based expressive writing, and peer support through anonymous community forums. It is an integrated preventive tool that enables early engagement and emotional support before clinical treatment becomes necessary [30]. When mental health problems begin to emerge, timely intervention is crucial to prevent symptom escalation and ensure that appropriate treatment and support are delivered at the right time. Early interventions typically involve strategies such as screening at-risk individuals, monitoring emotional states, and linking users to personalized digital counseling services. Recent advances in mobile-based CBT content and AI-powered emotion analysis have significantly improved the efficiency and scalability of early interventions [31]. A representative example in the Republic of Korea is the Maeum-Kkumteo mobile application, which analyzes emotional data from adolescents to recommend professional counseling, and delivers self-regulation content along with automated notifications. This supports rapid and tailored responses during the early stages of distress [32]. Recovery-oriented interventions are essential for adolescents experiencing mental health difficulties. These interventions move beyond symptom management and support adolescents to restore their functional capacity, reintegrate socially, and rebuild their self-esteem. The core components of this approach include strengthening self-management skills, engaging with peer-support networks, exploring career interests, and enhancing self-expression abilities. Recently, digital therapeutics (DTx), which embodies recovery-oriented philosophies, has gained attention as an innovative tool in adolescent mental health care [33].
In the United States, reSET-A is a digital therapeutic platform that supports treatment adherence and recovery in adolescents with substance use disorders. In the Republic of Korea, the MARO service provides emotion diary functions, anonymous counseling, and empathy-based community features. It is utilized as a digital resource not only for adolescents in the recovery phase but also for the general public, promoting emotional stability and self-reliance. These examples underscore the importance of stage-specific and individualized approaches in adolescent mental health interventions, from prevention to early response, recovery, and reintegration. In particular, digital interventions are highly effective in minimizing time and space constraints and are designed based on the principles of self-awareness and self-regulation. Therefore, the effectiveness of these interventions depends on their appropriate application, according to the specific needs and developmental stages of adolescents.

2.4. Types of Adolescent Mental Health Interventions by Setting

To effectively enhance adolescent mental health, it is essential to implement intervention strategies suited to diverse environments and modes of access. In particular, the school setting, where adolescents spend most of their time; the community setting, which encompasses adolescents and their families; and the digital setting, which is deeply embedded in the everyday lives of the youth, each present unique strengths and limitations. These settings can be used complementarily to maximize the reach, engagement, and effectiveness of mental health interventions (Table 3).

School-based interventions represent the primary setting for adolescent mental health care as schools are where adolescents spend most of their daily lives and form key social relationships with their peers and adults. School settings provide unique opportunities to identify and address emotional and behavioral issues early by leveraging human resources such as teachers, peer groups, and school counselors [34]. Core intervention strategies in this setting include emotion regulation training, social skills development programs, mental health literacy education, and crisis response protocols [35]. These interventions may be integrated into the formal curriculum or delivered through extracurricular activities, group counseling, and special programs. At the preventive level, school-wide mental health education is commonly implemented, whereas early intervention efforts typically involve regular mental health screening to identify high-risk students and refer them to specialized counseling services [36]. School-based interventions are characterized by high accessibility and direct observability of student behaviors and emotional states. However, they also face limitations, including concerns about privacy, the potential for mental health stigma, and limited mental health expertise among school personnel [34,35,36]. Community-based interventions support adolescent mental health through various public and private institutions outside the school system. Key providers include public health centers, mental health welfare centers, youth counseling and welfare centers, and youth shelters. These settings enable a multidisciplinary approach by addressing the ecological context of adolescents, including their families, peers, and community environments [37]. Common strategies include family counseling, crisis intervention, mental health awareness campaigns, peer-led self-help groups, and the development of community-based care networks.

One major advantage of community-based interventions is their ability to reach vulnerable populations such as out-of-school youths, adolescents from low-income families, and those from multicultural backgrounds. However, this model relies heavily on adolescents' awareness of and voluntary engagement with available services. Additionally, disparities in local resources may lead to unequal access to and inconsistent quality of care across regions. In recent years, the rapid advancement of digital technology has opened new avenues for mental health interventions among adolescents. Adolescents are now accustomed to digital environments and frequently use smartphones, social media, and mobile applications. Consequently, digital-based interventions offer a highly accessible and acceptable strategy for delivering mental health support, particularly for youth who may not otherwise engage with traditional in-person services [38].

Digital interventions can be applied across the continuum of adolescent mental health care, including prevention, early intervention, and recovery. Representative modalities include self-assessment tools, AI-based emotion analysis, chatbot counseling, digital CBT content, mood diary applications, and certified digital therapeutics (DTx). In the Republic of Korea, the Maeum-Kkumteo app analyzes adolescents' emotional states and provides personalized content, along with connections to professional counseling services. In the United Kingdom, Kooth offers a platform for digital expressive writing therapy and peer support communities to foster emotional expression and self-awareness [30]. The key strengths of digital interventions include autonomy, anonymity, and immediate accessibility, which make them particularly valuable for adolescents who may be reluctant to engage in face-to-face care. Digital tools also align well with the digital habits of today's youth, enhancing acceptability and engagement. However, challenges remain regarding sustained user engagement, data privacy protection, and the need for robust evidence of long-term clinical effectiveness.

2.5. Current Landscape of Digital Adolescent Mental Health Services and Analysis from a Behavioral Change Perspective

In this section, the digital adolescent mental health interventions implemented across various countries are analyzed using the integrated behavior change (IBC) framework. For each intervention, we examine how its operational components correspond to the psychological domains of emotional, cognitive, motivational, and behavioral change, as well as how they align with the system-level determinants of the COM-B model (Capability, Opportunity, and Motivation). This integrated mapping allows for a more comprehensive evaluation of both the internal mechanisms and contextual factors influencing each intervention's design and effectiveness. Digital mental health interventions are being increasingly developed and implemented worldwide, leveraging their natural integration into the everyday lives of adolescents. These interventions are uniquely positioned to align with the routines, preferences, and digital behaviors of the youth. This section examines how digital mental health services are currently designed and operated, and evaluates their effectiveness and limitations through selected representative cases. By analyzing these interventions from a behavioral change perspective, this section seeks to identify the key mechanisms driving user engagement, emotion regulation, and self-management. In doing so, we propose future directions for the development of more adaptive evidence-based digital mental health models tailored to the needs of adolescents.

Recently, digital services for adolescent mental health have garnered increasing attention as a means of overcoming the limitations of traditional offline counseling systems. These platforms offer enhanced accessibility, improved cost-effectiveness, and greater sustainability [39]. Consequently, countries such as the Republic of Korea, the United Kingdom, the United States, Japan, and Germany have developed a range of digital mental health services targeting adolescents and the general public. However, the core functions and approaches of these services vary significantly by country.

Table 4 compares the major national digital mental health services, highlighting differences in aspects such as cost-free availability, online counseling features, AI chatbot-based emotional support, community engagement, and behavior change-focused interventions. To enhance the analytic clarity, Table 4 has been revised to explicitly map the key intervention components of each digital service to both the psychological domains of the IBC model (Emotional, Cognitive, Motivational, and Behavioral) and the system-level components of the COM-B framework (Capability, Opportunity, and Motivation). This mapping allows for a more precise comparative analysis across interventions. In the Republic of Korea, platforms such as MARO, Lime, Mindling, and Mind Café demonstrate a high level of integration by offering free counseling, community-based emotional support, and self-management tools for a wide range of users, including adolescents and high-risk groups [32,40].

The UK’s Kooth, which is integrated with the National Health Service (NHS), provides free mental health services to adolescents, including self-help tools and emotional support. However, the overemphasis on counselor anonymity has raised concerns about the continuity of care and therapeutic trust [41].

From the perspective of the IBC framework, Kooth’s intervention components can be mapped as follows: its self-assessment and journaling functions primarily enhance emotional self-awareness (Emotional domain), while the provision of psychoeducational content supports cognitive restructuring (Cognitive domain). The peer-support forums foster motivation for behavioral change (Motivational domain), while the platform’s 24/7 accessibility, anonymity, and low-barrier entry reflect the Opportunity component within the COM-B model. In the United States, reSET-A focused on behavioral change through simplified digital interventions and initially showed strong accessibility in the growing digital health market. However, operational challenges such as financial instability and limited reach led to its eventual discontinuation [42].
In line with the IBC framework, reSET-A functions as a recovery-oriented digital therapeutic (DTx), primarily targeting substance use behaviors via cognitive–behavioral therapy (CBT) modules that directly address both cognitive and behavioral change domains. Personalized feedback mechanisms support the Motivational domain, while the integration of app-based reminders, self-monitoring tools, and structured therapeutic adherence features enhance both the Capability and Opportunity components within the COM-B model. Unlike more preventive interventions such as Kooth or Maeum-Kkumteo, reSET-A focuses on clinically indicated recovery and relapse prevention in adolescents with active substance use disorders. Japan’s KOKOROBO-J is a pilot program focused on suicide prevention using AI-based chatbots. While it represents a progressive initiative within Japan’s hospital-centered mental health system, the limited infrastructure for digital mental health services and lack of preventive intervention mechanisms have restricted its long-term viability [43].

In particular, AI-chatbot services show strong potential in terms of cost-efficiency and accessibility. However, if not integrated with appropriate escalation protocols, they pose risks, particularly when users express severe mental health symptoms. For example, cases in which chatbots respond inappropriately to suicide-related disclosures underscore the need for these tools to operate within collaborative frameworks involving human professionals and be embedded with ethical safeguards and emergency response mechanisms [44]. While many currently operating digital mental health services incorporate key components of the integrated behavioral change approach, such as emotional stabilization, self-awareness, and behavioral activation, gaps remain. These include insufficient tailoring to specific user groups, limited empirical validation, and absence of robust emergency support systems. These limitations, as revealed through the comparative analysis in Table 4, underscore the need for sophisticated digital mental health intervention designs that account for developmental specificity and crisis response capacity in adolescent populations.

To explicitly illustrate the application of the integrated behavior change (IBC) model to the digital mental health interventions discussed in this review, Table 5 summarizes the mapping of intervention components to the three domains of the IBC framework.

The figure illustrates the hierarchical integration of the integrated behavior change (IBC) framework, which synthesizes psychological domains (emotional, cognitive, motivational, and behavioral), system-level COM-B components (capability, opportunity, motivation), and their corresponding digital intervention components (e.g., self-assessment, CBT apps, AI emotion analysis, chatbots). This structure provides a comprehensive framework for understanding digital interventions targeting adolescent mental health.

3. Study Limitations and Future Directions

This study conducted a multidimensional analysis of digital mental health interventions for adolescents using an integrative review methodology; however, certain limitations exist. Non-English articles and the gray literature were not included in the search process, and a quantitative meta-analysis could not be performed.

While this review aimed to provide a comprehensive integrative analysis of digital adolescent mental health interventions based on the integrated behavior change (IBC) framework, it is not a fully systematic review. Although multiple major databases were searched, the search process may not have captured all relevant studies, particularly the unpublished gray literature or non-English publications. The inclusion of illustrative national case studies was based on the available literature and expert familiarity, which may introduce potential selection bias and limit generalizability. Moreover, the narrative synthesis approach, while suitable for exploring complex theoretical frameworks, may inherently carry subjective interpretations in mapping interventions to the IBC and COM-B models. Future systematic reviews and meta-analyses may further validate and extend these findings. In this review, while many digital mental health intervention platforms demonstrate promising user acceptance and practical applicability at an early stage, robust empirical validation through randomized controlled trials (RCTs) and large-scale longitudinal studies remains limited, except for Kooth. In particular, for domestic platforms such as MARO and Maeum-Kkumteo, although their implementation is expanding in real-world settings, well-designed clinical trials and comprehensive effectiveness evaluations are still needed. This limitation should be taken into account when interpreting the findings of the present study.

Future research should incorporate a broader range of data sources and consider combining qualitative synthesis with quantitative integration.

4. Conclusions

Contemporary adolescents grow up in a digitally mediated environment, where both risk and protective factors for mental health manifest in ways differing from those of previous generations. In response to this shifting landscape, this review sought to establish a framework for adolescent mental health interventions based on the integrated behavior change (IBC) approach. We examined the core components, phase-specific strategies, and implementation settings of adolescent mental health interventions, with an emphasis on digital modalities and representative service models.

Our analysis suggests that digital interventions align well with adolescents' developmental characteristics and digital lifestyles, demonstrating their potential across the full continuum of care, from prevention to recovery (Figure 1). Various digital tools, including self-assessment platforms, AI-driven emotion recognition, chatbot counseling, mood journaling apps, and digital therapeutics (DTx), serve as effective mechanisms for activating the core elements of the Capability, Opportunity, Motivation–Behavior (COM-B) model. These functions reflect a theoretically coherent and practically adaptable direction for digital intervention design. Case studies from Republic of Korea, the United Kingdom, and Japan further highlight the potential of integrative models that combine digital interventions with school- and community-based approaches. Platforms such as Kooth (UK), KOKOROBO-J (Japan), and Lime (Republic of Korea) illustrate how digital tools extend beyond basic information delivery to provide support for self-understanding, peer support, and professional linkages, thus exemplifying the real-world application of the IBC framework in digital service design. However, several challenges remain to be resolved. Many services lack robust scientific evaluation, and content designed to sustain long-term user engagement and motivation is underdeveloped. To advance digital mental health services as sustainable and effective platforms for adolescent care, there is a need for stronger empirical validation, personalized and interactive content design, and integration into broader support systems that reflect both clinical rigor and user-centered innovation (Figure 2).

Thus, digital interventions for adolescent mental health should not be viewed as standalone solutions but rather as behavior-change mechanisms designed based on sound scientific theory. To serve this function effectively, digital tools must go beyond technological implementation to incorporate developmental understanding, a structured framework of intervention components, and the integration of evidence-based practices. This review demonstrates that this integrated approach is theoretically feasible and practically applicable. These findings may serve as a foundational reference for the development of digitally enabled public mental health strategies targeting youth.

Author Contributions

Conceptualization, S.H.H., Y.H.C. and C.H.H.; methodology, S.H.H., Y.H.C., T.W.K., H.W.R., S.J.S. and C.H.H.; formal analysis, T.K.C. and Y.J.N.; investigation, T.K.C.; writing—review and editing, S.H.H. and C.H.H.; supervision, S.H.H. and C.H.H. All authors have read and agreed to the published version of the manuscript.

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The original contributions presented in this study are included in the article.

Conflicts of Interest

The authors declare no conflicts of interest. The funders had no role in the study design; collection, analyses, or interpretation of data; writing of the manuscript; or decision to publish the results.

Abbreviations

The following abbreviations are used in this manuscript:

DHI	Digital health intervention
CBT	Cognitive behavior therapy
cCBT	Computerized cognitive behavior therapy
DTx	Digital therapeutics

Footnotes

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Figures and Tables

Figure 1 Application of integrated behavior change (IBC) model to digital adolescent mental health interventions.

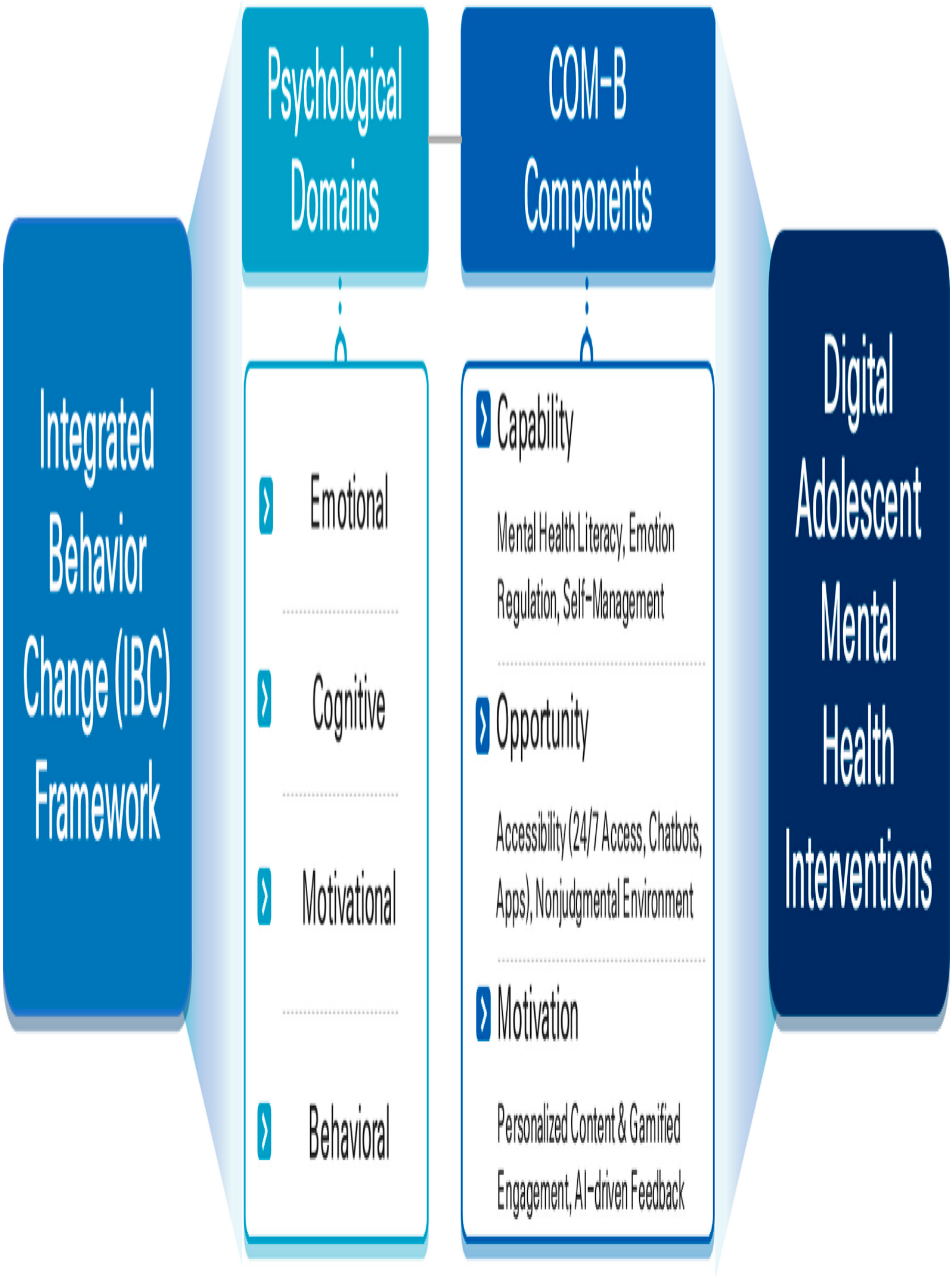

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Figure 2 Key components and strategies for digital youth mental health interventions.

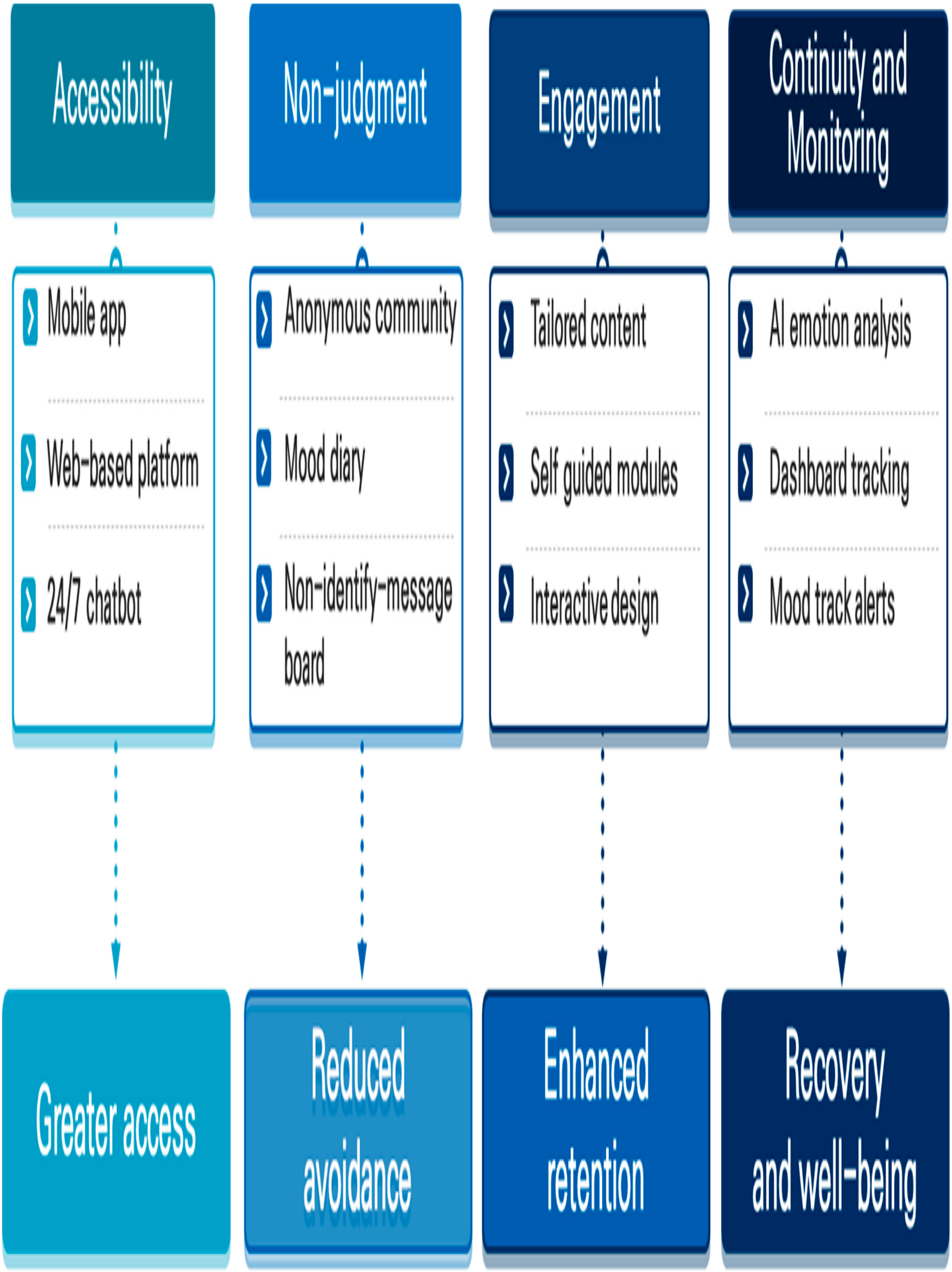

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Table 1

Core components of mental health interventions and their digital applications.

Component	Description	Example of Digital Application
Accessibility	Providing access to interventions regardless of time and location	Mobile apps, web-based counseling, 24/7 chatbot services
Nonjudgmental environment	Offering a safe space where users can express emotions without fear of stigma or evaluation	Anonymous online communities, emotion diary applications
Person-centered engagement	Designing interventions that emphasize autonomy and self-direction for adolescents	Personalized content recommendations, self-guided therapy modules
Continuity and monitoring	Enabling long-term tracking of emotional states and timely responses to changes	AI-based emotion analysis, automated alerts, risk detection system

Table 2
Stage-based approaches to adolescent mental health and representative applications.

Type(Stage)	Objective	Strategic Approach	Applied Technology	Representative Example
Preventive(Pre-onset)	Minimizing risk factors and enhancing protective factors	- Mental health literacy education- Emotion regulation training- Stress management strategies	- Mobile applications- Self-assessment tools- CBT-based digital content	Kooth (UK), MindMatters (Australia)
Early	Prevention of symptom worsening, early detection, and timely intervention	- Risk group screening- Emotion monitoring- Tailored counseling connection	- AI-based emotion analysis- App-based screening tools- Digital CBT	Maeum-Kkumteo (Republic of Korea), FOCUS (Finland)
Recovery &Empowerment-focused	Functional recovery, autonomy enhancement, and social reintegration	- Self-management training- Peer support- Restoration of self-esteem	- DTx platforms- Emotion diary- Online counseling/communities	reSET-A (USA)MARO (Republic of Korea)

Table 3
Strengths and limitations of adolescent mental health interventions by setting.

	School	Community	Digital
Environment	In-school education and counseling systems	Public health centers, mental health centers, local welfare institutions	Smartphone applications, web-based platforms

Strategies	Mental health literacy education, emotion regulation training, screening	Family counseling, crisis intervention, community-based networking	Self-assessment tools, chatbots, AI-based emotion analysis, CBT apps, digital therapeutics (DTx)
Target	General student population, high-risk youth within the school system	Vulnerable youth, out-of-school adolescents, families included	All adolescents with access to digital devices
Strengths	High accessibility, early identification through educators	Ecological approach, family engagement, multidisciplinary intervention possible	No time or location constraints, anonymity, high autonomy
Limitations	Risk of stigma, limited mental health expertise among teachers	Regional disparities in resources, low voluntary engagement	Privacy concerns, difficulty sustaining engagement
Examples	School-based mental health education programs, school counseling rooms	Youth counseling centers, regional mental health and welfare programs	Kooth (UK), Maeum-Kkumteo (Republic of Korea), reSET-A (USA)

Table 4
Application of the integrated behavior change (IBC) model and COM-B framework to representative digital adolescent mental health services.

Service	Country	Psychological Domains (IBC)	COM-B Components	Evidence Level
Kooth	UK	Emotional (self-awareness via journaling), Cognitive (psychoeducation), Motivational (peer support)	Capability (self-guided modules), Opportunity (24/7 access, anonymity), Motivation (peer engagement)	Pilot evaluation (Stevens et al., 2022 [30])
Maeum-Kkumteo	Korea	Emotional (emotion diary), Cognitive (self-assessment feedback), Motivational (automated coaching)	Capability (self-assessment), Opportunity (mobile platform access), Motivation (personalized reminders)	Early service reports, no published RCT
MARO	Korea	Emotional (emotion tracking), Cognitive (self-expression via emotion diary), Motivational (empathy-based community)	Capability (emotion monitoring), Opportunity (anonymous community), Motivation (personalized coaching)	Internal reports, no published RCT
reSET-A	USA	Cognitive (CBT modules), Behavioral (relapse prevention training), Motivational (adherence feedback)	Capability (skills training), Opportunity (app-based monitoring), Motivation (personalized feedback)	Approved DTx, clinical trials available

Table 5
Adolescent digital mental health interventions mapped to IBC components.

IBC Component	Intervention Focus	Digital Examples
Capability	Mental health literacy, emotion regulation training, self-management skills	Online psychoeducation, CBT-based mobile apps, emotion diary tools
Opportunity	Accessibility, anonymity, nonjudgmental environments	24/7 chatbot services, mobile apps, anonymous peer communities
Motivation	Personalized content, self-directed engagement, gamification	AI-based emotion analysis, personalized feedback, gamified CBT modules

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DETAILS

Subject:	Child development; Behavior; Mental health care; Intervention; Social networks; Computer platforms; Mental disorders; Identity; Integrated approach; Emotions; Adolescence; Health services; Counseling; Child &adolescent mental health
Business indexing term:	Subject: Social networks
Identifier / keyword:	adolescent mental health; digital health intervention; behavior change model; prevention; e-health; mobile mental health; digital therapeutics; youth resilience
Publication title:	Children; Basel
Volume:	12
Issue:	6
First page:	770
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Database:	Publicly Available Content Database,Coronavirus Research Database

AI Applications for Chronic Condition Self-Management: Scoping Review

Hwang, Misun ; Zheng, Yaguang ; Cho, Youmin ; Jiang, Yun . Hwang, Misun; Zheng, Yaguang; Cho, Youmin; Jiang, Yun.

ABSTRACT (ENGLISH)

Background: Artificial intelligence (AI) has potential in promoting and supporting self-management in patients with chronic conditions. However, the development and application of current AI technologies to meet patients' needs and improve their performance in chronic condition self-management tasks remain poorly understood. It is crucial to gather comprehensive information to guide the development and selection of effective AI solutions tailored for self-management in patients with chronic conditions.

Objective: This scoping review aimed to provide a comprehensive overview of AI applications for chronic condition self-management based on 3 essential self-management tasks, medical, behavioral, and emotional self-management, and to identify the current developmental stages and knowledge gaps of AI applications for chronic condition self-management.

Methods: A literature review was conducted for studies published in English between January 2011 and October 2024. In total, 4 databases, including PubMed, Web of Science, CINAHL, and PsycINFO, were searched using combined terms related to self-management and AI. The inclusion criteria included studies focused on the adult population with any type of chronic condition and AI technologies supporting self-management. This review was conducted following the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews) guidelines.
Results: Of the 1873 articles retrieved from the search, 66 (3.5%) were eligible and included in this review. The most studied chronic condition was diabetes (20/66, 30%). Regarding self-management tasks, most studies aimed to support medical (45/66, 68%) or behavioral self-management (27/66, 41%), and fewer studies focused on emotional self-management (14/66, 21%). Conversational AI (21/66, 32%) and multiple machine learning algorithms (16/66, 24%) were the most used AI technologies. However, most AI technologies remained in the algorithm development (25/66, 38%) or early feasibility testing stages (25/66, 38%).
Conclusions: A variety of AI technologies have been developed and applied in chronic condition self-management, primarily for medication, symptoms, and lifestyle self-management. Fewer AI technologies were developed for emotional self-management tasks, and most AIs remained in the early developmental stages. More research is needed to generate evidence for integrating AI into chronic condition self-management to obtain optimal health outcomes.

FULL TEXT

Introduction

Background

Chronic conditions, such as cardiovascular disease, diabetes, cancer, and chronic respiratory disease, are leading causes of death and disabilities [1]. With an aging population worldwide and increased comorbidities and complexity of care, the global burden of chronic condition management is rapidly growing [2,3]. In the United States alone, chronic conditions affected over 50% of adults in 2016, accounting for 86% of health care spending and at least 7 of the 10 leading causes of death [4]. Chronic conditions are often long term and uncertain, and patients need to take extensive responsibility for better managing their conditions [5]. It is widely accepted that self-management is essential to improve health outcomes for individuals with chronic conditions [6]. For policy makers and health care providers, self-management initiatives are increasingly recognized as an effective way to enhance health and well-being while simultaneously reducing the burdens on health care resources [7].

Patients living with chronic conditions commonly alternate exacerbations and remissions, and medical, behavioral, and emotional management are essential tasks integrated into disease self-management [8]. Medical self-management refers to adhering to prescribed medications and taking appropriate actions to manage symptoms, whereas behavioral management can involve modifying lifestyle behaviors (eg, healthy diets and physical activity). Emotional management is to cope with emotions and feelings regarding long-term chronic conditions [8]. Successful self-management, including those tasks, requires sufficient knowledge and necessary skills to manage the diseases and relevant consequences, which can be particularly challenging for most individuals [9,10].

Artificial intelligence (AI) and machine learning (ML) techniques hold the potential to overcome self-management challenges for individuals with chronic conditions. AI is defined as the technology with the ability of machines to understand, think, learn, infer, and make decisions in a similar way to human beings. ML is a subfield of AI focusing on developing algorithms and models capable of learning from data [11-13]. AI is helpful in improving the quality and access to care, reducing cost, and optimizing daily self-management when integrating with clinical information systems and patient-facing technologies [2]. AI technologies have also been reported to support chronic condition management by enabling early disease detection, improving diagnostic accuracy, and providing patient-centered care [14,15]. Multiple studies have assessed the efficacy of AI in contributing to positive health outcomes, including weight loss, controlling blood glucose, pain management, psychosocial well-being, and the quality of life by enhancing self-management of chronic conditions [16-19].

However, while AI technologies are progressing toward tailoring support for specific types of chronic conditions [20], there is a lack of understanding of the current levels of AI applications to support chronic condition self-management systematically and how AI is integrated into self-management processes and specific tasks, such as medical, behavioral, and emotional self-management. Existing literature reviews focused on developing a specific type of AI technology for certain chronic condition management outcomes (eg, glucose level prediction for managing diabetes, improving diagnostic tools for liver diseases, or severity classification of respiratory disease) [20-23]. One recent study reviewed AI applications for chronic disease management but did not focus on how AI can support patients' needs and performance in self-management [24].

Objectives

Thus, the objectives of this study were to provide a comprehensive overview of AI applications for chronic condition self-management, with self-management components supported by AI technologies based on tasks of medical, behavioral, and emotional self-management, and to identify the current developmental stages and knowledge gaps of AI applications for self-management of chronic conditions.

Methods

Study Design

This study is a scoping review of the literature conducted following the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews) guidelines [25]. The completed PRISMA-ScR checklist is described in Multimedia Appendix 1.

Search Strategy

In total, 4 databases, including PubMed, Web of Science, CINAHL, and PsycINFO, were used to search articles published between January 2011 and October 2024 to obtain a comprehensive list of studies relevant to our research topic. The search strategies were developed based on consultation with a health sciences librarian. Two groups of search terms—*self-management* and *artificial intelligence* were used in combination with their Medical Subject Headings (MeSH) terms, keywords, and synonyms. The details of the search strategy are presented in Multimedia Appendix 2.

Eligibility Criteria

The eligibility criteria for this scoping review are described in Textbox 1. In this review, chronic conditions are defined as those lasting >1 year and requiring ongoing medical attention or limiting activities of daily life, following the definition provided by the Centers for Disease Control and Prevention [26].

Research team members worked with a health sciences librarian on the literature search and the initial title and abstract screening. All authors (MH, YC, YZ, and YJ) evaluated the selected full texts and determined the data extraction strategies. The desired level of screening agreement among raters was set at 80% and achieved 100% after group discussion.

Textbox 1. Eligibility criteria for scoping review.

Inclusion criteria

DETAILS

Subject:	Health care access; Diabetes; Databases; Application; Selfmanagement; Chronic illnesses; Health status; Task performance; Health sciences; Chronic obstructive pulmonary disease; Technology; Field study; Artificial intelligence; Algorithms; Patients; Feasibility; Systematic review; Drugs; Multimedia; Chronic pain; Cardiovascular disease; Librarians; Respiratory diseases; Literature reviews
Business indexing term:	Subject: Artificial intelligence
Identifier / keyword:	artificial intelligence; chronic disease; self-management; generative AI; emotional self-management

Publication title:	Journal of Medical Internet Research; Toronto
Volume:	27
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Section:	Digital Health Reviews
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Design and Evolution of Conversational AI for Healthcare: From Structured Data Collection to Culturally Sensitive and Adaptive Support for Chronic Disease Management and ADRD Care

Hasan, Wordh Ul . Hasan, Wordh Ul.

ABSTRACT (ENGLISH)

The growing need for personalized healthcare solutions and caregiver support has driven the development of advanced conversational AI systems. This study presents a multi-phase approach to designing and implementing conversational agents for diabetes management, Alzheimer’s Disease and Related Dementias (ADRD) care, and caregiver assistance. For diabetes patients, an intelligent monitoring system was developed to track and analyze daily activities such as eating habits, mood, and demographics. This system provides personalized health insights and actionable recommendations, empowering patients to make informed lifestyle choices and supporting them in achieving better health outcomes.For ADRD patients, we designed a cognitive engagement assistant to enhance memory recall and support cognitive function. The system retrieves personal images from the user’s albums and initiates interactive conversations by asking patients if they remember the context of the image. If the patient does not recall, the assistant provides corrective guidance, fostering memory stimulation through personalized interactions. This approach leverages previously collected patient data to ensure relevance and contextual accuracy, addressing the cognitive challenges commonly faced by ADRD patients.Recognizing the unique challenges faced by ADRD caregivers, we personalized the conversational assistant to deliver targeted solutions to their concerns. The system employs an iterative questioning approach to explore problems in depth and uses Retrieval-Augmented Generation (RAG) and Knowledge Graphs (KGs) to provide accurate, real-time guidance. Voice recognition capabilities and integration with advanced large language models (LLMs), including a transition from ChatGPT-3.5 to the latest models, enhanced precision, contextual understanding, and conversational quality. The assistant significantly reduces the time caregivers spend searching for answers on forums like Reddit by offering immediate, personalized responses.This study followed an iterative, user-centered design methodology, integrating multimodal interactions and leveraging cutting-edge AI technologies. To address the limitations of single-agent systems and scale these capabilities, we further developed a multi-agent LLM framework where specialized agents—such as medical advisors, appointment schedulers, grocery planners, and proactive reminder agents—operate collaboratively under a central orchestrator. This modular architecture enhances task specialization, enables real-time proactive support, and integrates structured health data, smart device APIs, and caregiver preferences into the conversation flow. By combining personalized monitoring, cognitive engagement, and caregiver support through a multi-agent design, this research demonstrates the transformative potential of conversational AI in chronic disease management, cognitive care, and caregiver assistance, offering an adaptive, ethical, and scalable solution for real-world healthcare contexts.

FULL TEXT

TVM:UNDEFINED

DETAILS

Business indexing term:	Subject: Artificial intelligence
Subject:	Computer science; Health sciences; Artificial intelligence
Classification:	0984: Computer science; 0566: Health sciences; 0800: Artificial intelligence
Identifier / keyword:	Alzheimer's disease; Chronic disease management; Healthcare chatbots; Multi-agent systems; Retrieval-Augmented Generation
Number of pages:	214
Publication year:	2025
Degree date:	2025
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Committee member:	Kong, Jun; Magel, Kenneth; Dey, Shuvashis
University/institution:	North Dakota State University
Department:	Computer Science
University location:	United States -- North Dakota
Degree:	Ph.D.
Source type:	Dissertation or Thesis
Language:	English
Document type:	Dissertation/Thesis
Dissertation/thesis number:	31940092
ProQuest document ID:	3217827267
Document URL:	https://www.proquest.com/dissertations-theses/design-evolution-conversational-ai-healthcare/docview/3217827267/se-2?accountid=199502

The Cybersecurity of an Ethical AI-Based Smart Grid Through Data Poisoning Countermeasure Automation

Manzueta, Victor D. . Manzueta, Victor D.

ABSTRACT (ENGLISH)

The integration of smart grids into modern society has marked a paradigm shift in the power sector, offering unparalleled efficiency in energy management. However, this technological leap comes with a significant challenge—smart grids' reliance on digital systems renders them vulnerable to a wide range of cybersecurity threats and attacks. In response to these challenges, the following chapters delve into the critical intersection of cybersecurity, ethical Artificial Intelligence, and smart grid technology. The following is an endeavor to offer novel insights and solutions to combat a specific emerging cyber threat against these critical technologies. This research explores automation as a key method for safeguarding smart grids against data poisoning attacks, ensuring the integrity and security of these transformative energy management systems.

Defending against all cyber-attacks is a complicated affair. Specificity impacts complication, however. The more specific you get, the less complicated things become. Considering the myriad of cyber threats that may or may not be applicable to smart-grid AI systems, focusing on the most critical and applicable threats and vulnerabilities should be priority. To that end, data poisoning has risen as a critical threat against smart grid AI. Data poisoning involves the insertion of inaccurate or mislabeled data into the AI's dataset. It stands as one of the most direct ways to undermine AI, as the integrity of its knowledge hinges solely on the quality of its data. Should this data become tainted, the resulting model will be compromised, potentially leading to erroneous conclusions or actions.

To fully understand the impacts of data poisoning, one must comprehend the historical trajectory of AI, its contemporary significance, juxtaposed against the looming specter of threats and vulnerabilities, as well as the diverse landscape of global players in AI development and their varied objectives. These concepts provide context for the evolving challenges faced by modern society. AI plays an indispensable role in smart grid technology through resource optimization and infrastructure protection. Despite its transformative potential, the smart grid AI is vulnerable to malicious attacks. Notable vulnerabilities, include AI bias and architectural weaknesses, which can be exploited to facilitate data poisoning attacks.

Various defense strategies against malicious targeting of smart grid AI systems include data science, cybersecurity, ethics-based, and management-based approaches. These holistic defense strategies aim to mitigate risks and bolster resilience against sophisticated adversaries. There exists a tremendous amount of research contributions in cybersecurity, machine learning security, and smart grid security, providing valuable insights to inform original conclusions. Key takeaways from this research synthesis underscore the importance of proactive defense measures and innovative approaches in safeguarding smart grid AI systems.

Smart Grids that integrate AI and Machine Learning models to enhance power distribution efficiency are vulnerable to

data poisoning attacks, which can have various effects and objectives. One significant impact of data poisoning is the potential manipulation of energy prices. Attackers might inject false data into the system, indicating a power shortage, thus causing prices to skyrocket. This not only leads to increased costs for consumers but also risks causing power outages. To counter such attacks, robust security measures must be implemented in smart grid systems to detect and neutralize malicious data.
This research focuses on incorporating automation as a security measure for data poisoning defense, utilizing Infrastructure as Code to define the desired state of cloud-based infrastructure components such as virtual machines, networks, and storage. IaC automates the configuration of system dependencies and the provisioning of local and remote instances, streamlining the management and scalability of computing infrastructure [104]. The following original research automated the generation of over 70 cloud resources and configurations including VPC and subnet setup, security groups, AWS DB subnet group, RDS implementation, IAM policies, and CloudWatch audit logs. Through three original validation scenarios, the research demonstrated how automation positively impacts the security architecture of AI-powered smart grid systems, providing tangible evidence of its effectiveness in defending against data poisoning attacks. The study also tracked the time and complexity involved in generating automated environments compared to manual setups, highlighting the efficiency and reliability of automated security measures.
The integration of smart grids with AI and ML models has revolutionized energy management but has also exposed these systems to significant cybersecurity risks, particularly data poisoning attacks. This research delves into the critical intersection of cybersecurity, ethical AI, and smart grid technology to provide insights and solutions to combat this emerging threat. By focusing on automation as a key defense strategy, the study demonstrated the effectiveness of IaC in safeguarding smart grids against data poisoning attacks. The automation of cloud resources and configurations, coupled with validation scenarios, highlights the efficiency and reliability of automated security measures in defending against malicious targeting of smart grid AI systems. This research underscores the importance of proactive defense measures and innovative approaches in securing transformative energy management systems against sophisticated adversaries, contributing to the ongoing discourse in cybersecurity, machine learning security, and smart grid security.

FULL TEXT

TVM:UNDEFINED

DETAILS

Business indexing term:	Subject: Artificial intelligence
Subject:	Computer science; Information technology; Artificial intelligence
Classification:	0984: Computer science; 0489: Information Technology; 0800: Artificial intelligence
Identifier / keyword:	Automation; Countermeasure; Cybersecurity; Data poisoning; Smart grid technology
Number of pages:	198
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University/institution:	The Catholic University of America
Department:	Electrical Engineering and Computer Science
University location:	United States -- District of Columbia
Degree:	D.Phil.
Source type:	Dissertation or Thesis
Language:	English
Document type:	Dissertation/Thesis
Dissertation/thesis number:	31933304
ProQuest document ID:	3213119635
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Effectiveness of AI-Powered Advertising on Generation Z’ s Trust, Attitude, and Purchasing Behavior

Clark, Taylor M. . Clark, Taylor M.

ProQuest document link

ABSTRACT (ENGLISH)

As artificial intelligence (AI) becomes an increasingly integrated innovation in the digital world, its impact on the consumer perception and behavior has drawn interest, academically and in industry. This thesis investigates the effectiveness of AI-powered advertising on Generation Z’ s trust, attitudes, and purchasing intentions. This study will use the Technology Acceptance Model (TAM) with a few additions, such as: AI literacy, perceived AI accuracy, and perceived AI reliability. These variables are put in place to examine their level of influence on functional and emotional perception in AI on Generation Z. By exploring how AI-powered advertising affects the consumer-brand relationship within this demographic, this study will contribute to the academic understanding of technology acceptance and guide marketers in leveraging this new technology without hurting their relationship with these new and upcoming consumers.

FULL TEXT

TVM:UNDEFINED

DETAILS

Business indexing term:	Subject: Marketing Artificial intelligence
Subject:	Marketing; Computer science; Artificial intelligence
Classification:	0338: Marketing; 0984: Computer science; 0800: Artificial intelligence
Identifier / keyword:	Advertising perception; AI perception; Consumer trust; Technology acceptance model
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Committee member:	Fisher, Nate; McCoy, Armand
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Department:	Gaylord College of JMC: Journalism &Mass Communication
University location:	United States -- Oklahoma, US
Degree:	M.A.
Source type:	Dissertation or Thesis
Language:	English
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Dissertation/thesis number:	32001483
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Demand analysis of transitional care for patients undergoing minimally invasive cardiac interventions with AI-driven solutions: a mixed-methods approach

Liu, Yuwen; Li, Sijia; Yu, Jie; Cao, Jingjing; Ma, Qiao; Li, Min; Zheng, Yanqin; You, Yali; Lv, Wanqing; Li, Qiutong; Zhang, Chen; Piao, Meihua . Liu, Yuwen; Li, Sijia; Yu, Jie; Cao, Jingjing; Ma, Qiao; et al.

ABSTRACT (ENGLISH)

Aims

Minimally invasive cardiac intervention (MICI) patients remain at high risk of readmission and mortality during their post-discharge phase, with 30-day readmission rates of up to 10%. Although technological innovations, especially AI-driven solutions, hold promise for improving outcomes, there is a pressing need to clarify the full spectrum of patient demands during the transition from hospital to home. This study aimed to systematically identify these demands to guide the development of AI-driven solutions that reduce readmission rates and improve clinical outcomes.

Methods and results

A convergent parallel mixed-methods design was employed to systematically identify patient demands and inform the development of AI-driven interventions in transitional care. Quantitative and qualitative data were collected from 137 MICI patients recruited from four hospitals (June–August 2024). Quantitatively, a 23-item survey was analyzed using the Kano model, revealing no "must-be" demands—indicating that patients were accustomed to a lack of guidance post-discharge. However, health monitoring, medication guidance, symptom management, and personalized exercise plans were identified as "one-dimensional" demands that significantly impact patient satisfaction. Additionally, continuous exercise monitoring and dietary planning emerged as "attractive" features that could enhance care quality without negatively affecting satisfaction if absent. Qualitative interviews uncovered the importance of comorbidity management, psychological support and financial transparency, which were not fully captured in the survey data. The integration of these findings underscores the need for AI-driven personalized health monitoring systems and knowledge-based AI tools to revolutionize the transitional care process for MICI patients.

Conclusion

This integrated analysis highlights the significant care demands of MICI patients during the transition from hospital to home. Key recommendations include: (1) deploying AI-driven health monitoring, medication guidance, and symptom

management systems, (2) designing personalized exercise and dietary tools, and (3) creating accessible, knowledge-based platforms for reliable medical information. In addition, comorbidity management, psychological support and financial transparency are areas that call for our attention. By aligning with these patient-centered demands and leveraging AI's capabilities, future transitional care interventions—particularly in China have the potential to address healthcare staffing constraints and improve patient outcomes. However, due to the limitations of our study, these insights require further validation and exploration.

FULL TEXT

Introduction

Cardiovascular disease (CVD) is the leading cause of morbidity and mortality worldwide, contributing to a significant economic burden on healthcare systems [1]. Minimally invasive cardiac interventions (MICI) are advanced techniques for treating CVD, characterized by reduced risk and smaller incisions [2]. These interventions include cardiac catheterization-based procedures such as percutaneous coronary intervention (PCI), radiofrequency ablation, and pacemaker placement [3]. PCI, a representative of minimally invasive cardiac interventions, was performed on 1.421 million patients in China in 2022 alone [4]. With the increased popularity of MICI leading to shorter hospital stays and earlier discharges, some patients may be discharged from the hospital before they have fully recovered [5,6,7]. Research shows that approximately 10% of patients experience adverse events, including readmission or emergency department visits, within 30 days of discharge [8, 9]. This highlights a critical gap between hospital-based acute care and home-based recovery that transitional care aims to address [6, 10].

Transitional care is defined as a series of actions designed to ensure the coordination and continuity of health care received by patients as they transfer between different locations (e.g. from hospital to home) or levels of care [11]. Adequate transitional care not only reduces unplanned hospital readmissions and wastage of medical resources but also significantly improves patients' quality of life [12, 13]. Despite strong evidence supporting transitional care's effectiveness in western healthcare systems, its implementation in China remains limited [6]. A key barrier is the shortage of nursing staff relative to China's large population [14, 15]. However, the rapid advancement of information technology, the widespread use of mobile phones, and the emergence of artificial intelligence, present potential solutions to overcome these staffing constraints [16, 17]. This presents a critical opportunity to implement transitional care in China, given the rapid advancements in technology and the urgent need to address care gaps.

To develop effective AI-enhanced transitional care interventions, a comprehensive understanding of MICI patients' needs during the hospital-to-home transition is essential. Previous research has largely focused on general transitional care needs or specific cardiac conditions, leaving a knowledge gap regarding the unique demands of MICI patients. Additionally, few studies have examined how these needs might be addressed through AI-based solutions [18].

This study employs the Kano model to quantitatively assess the relative importance of various transitional care demands [19, 20]. The Kano model, developed in 1984, provides a framework for categorizing service preferences into five categories: must-be, one-dimensional, attractive, indifferent, and reverse qualities. To ensure comprehensive demand identification, we complement this quantitative approach with qualitative interviews [21, 22].

Our primary research objective is to understand the comprehensive transitional care demands of MICI patients during their hospital-to-home transition in the context of emerging AI capabilities. Specifically, we aim to: (1) identify and categorize key transitional care demands using the Kano model, (2) explore patients' lived experiences and unmet needs through qualitative inquiry, (3) generate insights to guide the development of AI-enhanced transitional care solutions.

Methods

Study design

The study adopted a convergent parallel mixed-method study design to comprehensively investigate the transitional care needs of MICI patients [23]. A cross-sectional quantitative survey identified generalizable care demands, while semi-structured qualitative interviews explored patient experiences and uncovered latent needs that structured survey items may not capture. This mixed-methods approach integrated both quantifiable trends and nuanced patient-reported needs, ensuring a comprehensive foundation for AI-driven interventions. By collecting and analyzing both quantitative and qualitative data independently but complementarily, we reduced methodological biases associated with single-method approaches, such as over-reliance on predesigned survey items in quantitative research or subjective interpretation in qualitative results.

Setting and participants

MICI patients were consecutively recruited through convenience sampling from June to August 2024 in the cardiology departments of four hospitals in southern and northern China. At each hospital, the head nurse (J.J.C., Q.M., M.L., Y.Q.Z., and Y.L.Y.) organized and supervised nurses in collecting questionnaires. When patients met the eligibility criteria, nurses invited them to scan a QR code and complete the demand survey online. The survey was discontinued once the required sample size was reached. The inclusion criteria for patients were as follows: (1) those who had undergone MICI, including cardiac stent operation, cardiac radiofrequency ablation, cardiac pacemaker implantation, cardiac occlusion and cardiac valve repair or replacement; (2) age⩾18 years old; (3) volunteered to participate in the study and signed the informed consent form. The exclusion criteria for patients were as follows: (1) participants with severe cognitive impairment or mental disorders who were unable to understand the study content or answer the questionnaire; (2) participants with severe complications (e.g., respiratory, circulatory, and renal diseases).

Data collection for quantitative study

Quantitative data were collected using Wenjuanxing, a widely used online survey platform in China. The questionnaire in this study consisted of two parts. The first part was a self-designed social-demographic questionnaire, including items such as age, gender, education level, income level, operation type, etc. The second part was a demand survey assessing the needs of MICI patients during the transition from hospital to home, and it includes 10 dimensions such as health monitoring service, exercise guidance service, diet guidance service, and medication guidance service, and 23 demands (Table 1).

[IMAGE OMITTED: SEE PDF]

The development of this questionnaire is as follows. First, we referred to the Expert Consensus on Home-Based Rehabilitation for Cardiovascular Disease Patients in China, where mentioned 10 key dimensions of cardiac rehabilitation [24]. Based on these dimensions, our research team conducted a brainstorming session, integrating literature reviews and clinical experiences to formulate 23 questions. Second, after completing the initial draft of the questionnaire, we conducted a pilot test involving four nursing graduate students and two MICI patients. According to their feedback, further modifications were made to refine the final version of the transitional care demand questionnaire. Third, we consulted six experts in relevant fields (including four researchers specializing in chronic disease management and two experienced clinical cardiovascular nurses) to evaluate the content validity of the questionnaire. The average age of the experts was 40.67±9.67 years, with four holding a master' s degree or above and four having associate senior professional titles or above. The experts assessed the content validity of each item using a 4-point rating scale (1–4 points, representing inappropriate, somewhat inappropriate, somewhat appropriate, appropriate, respectively) to determine whether the items appropriately represented the intended contents. The results indicated good content validity with Item-level Content Validity Index (I-CVI): 0.833-1.000, Scale-level Content Validity Index using the Universal Agreement method (S-CVI/UA): 0.957, and Scale-level Content Validity Index using the Average method (S-CVI/Ave): 0.993.

We designed the phrasing of the questionnaire questions and response options based on the Kano model [25]. For each demand, two opposing questions were asked. For example, "How would you feel about receiving reminders for your upcoming follow-up visits and examinations after discharge?" (functional question), followed by "How would you feel about not receiving reminders for your upcoming follow-up visits and examinations after discharge?" (dysfunctional question). Respondents selected the most appropriate answer from the following options: "I like it that way", "It must be that way", "I am neutral", "I can live with it that way", and "I dislike it that way". There were 25 (5*5) possible results, each corresponding to a specific Kano attribute (Table 2).

[IMAGE OMITTED: SEE PDF]

Based on sample size estimation methods commonly used in medical statistics, the sample size for a cross-sectional survey should be 5 to10 times the number of independent variables [26]. Our study included 23 independent variables, and we considered a maximum loss to follow-up rate of 10%. Therefore, the minimum required sample size was calculated as (23*5)/0.9=128. The quality control of the online survey was as followed. (1) The online questionnaire was set to require answers for both the positive and negative questions for the 23 needs (a total of 46 questions), so no answers were missed, (2) the online system recorded the time taken to complete the questionnaire. Questionnaires completed in less than 2 min were considered invalid and removed during the data cleaning process, (3) manual checks were performed, and questionnaires with obvious logical errors or contradictions (e.g., selecting "Strongly Agree" or "Strongly Disagree" for all 46 questions on the 23 needs) were deemed anomalous and removed during the data cleaning process.

Data collection for qualitative study

A semi-structured interview was conducted to collect qualitative data. The development of interview questions was as follows. First, we conducted a literature review on transitional care needs and organized a brainstorming session within the research team [24, 27,28,29,30]. Based on this, five key questions were formulated. Next, two rounds of pilot interviews were conducted, revealing that participants needed additional prompts to help them recall specific aspects of their transitional care experiences. To address this, we incorporated core components of transitional care, including wound, medication, diet, exercise, and mental health as prompts to facilitate more engaged and comprehensive interviews. The final five key questions were: (1) "How have you been recovering since returning home?" (2) "What precautions do you find important regarding wound, medication, diet, exercise, and mental health after discharge?" (3) "When managing your wound, medication, diet, exercise, or psychological well-being after discharge, what assistance from healthcare providers have you found necessary?" (4) "What other concerns do you have that healthcare providers could help you with?" (5) "What is your attitude toward the involvement of healthcare providers in your transitional care, and how do you feel about incorporating technology, such as smartphones, into this process?".

Patients for the qualitative study were purposefully selected and included after obtaining their consent for both the interview and recording. The interviews were conducted by one author (S.J.L.), a master's student in nursing with completed coursework in qualitative research. Given that the interviewees were from both the southern and northern areas in China, the interviews were conducted by phone. Given that the interviews were conducted online, we invited participants to review the transcribed texts and findings to avoid any potential misinterpretation of their responses. They were asked to provide feedback on whether the interpretations accurately reflected their perspectives, thereby enhancing the reliability of the qualitative results. Data saturation was achieved when no new themes emerged [31]. The interview took place in August 2024 and January 2025, with each interview lasting between 20 and 30 min.

Data analysis

The authors (J.Y., W.Q.L. and Q.T.L.) downloaded quantitative data from the online Wenjuanxing platform, and imported it to the IBM SPSS version 20.0. and Excel software. The authors (Y.W.L. and S.J.L.) analyzed the data. Descriptive statistics were used to summarize the socio-demographic information. Continuous variables that follow a normal distribution were presented as means±standard deviations (mean±SD), while those that do not follow a normal distribution were reported as the median (25th percentile, 75th percentile) [Median (P25, P75)]. Categorical variables were expressed as frequencies and percentages. The Kano model was utilized to analyze the relative importance of different demands from the perspective of customer satisfaction, using the Better-Worse coefficient [25]. A higher better coefficient refers to a higher Satisfaction Index (SI), calculated as $SI = (A+O)/(A+O+M+I)$. Conversely, a higher worse coefficient is linked to a higher Dissatisfaction Index (DSI), calculated as $DSI = (O+M)/(A+O+M+I)$. We Performed correlation analysis between one-dimensional needs and patients' demographic data (e.g., age and sex). For categorical demographic variables, chi-square test was used; for continuous variables, Spearman's rank correlation was applied. A two-tailed test was conducted, with $P<0.05$ indicating statistical significance. Qualitative data were analyzed using thematic analysis [32]. All recordings were initially transcribed verbatim into Word documents using NetEase Jianwai, a transcription tool developed by the Chinese company NetEase within 24 h after each interview. To prevent errors in the software' s transcription, the interviewer then listened to the recordings and revised the text based on the audio to ensure the accuracy of the final transcription. To ensure a thorough understanding of the data, each transcript was read three times by two researchers (Y.W.L. and S.J.L.). Initially, two researchers independently coded the first six transcripts, then compared and discussed their findings to reach a consensus and establish the initial codes. The interviewer continued coding the remaining transcripts and collaborated with the second researcher to reach a consensus when new codes emerged. Two authors induced the coded data into themes after the coding process was completed. The themes were subsequently reviewed and discussed by the entire research team to reach a consensus.

Results

Quantitative results

Characteristics of participants

From June 2024 to August 2024, we surveyed a total of 160 participants. However, 23 questionable answers were removed after data cleaning, resulting in 137 valid questionnaires being included in the data analysis. The effective response rate was 85.6%. The characteristics of the participants were summarized in Table 3. Among the included 137 participants, the average age was 58.54 years, with a majority being male (75.2%). High school education was the most common level of education (39.4%) and 92.7% of the participants were married. More than two-thirds (73.7%) of the participants had two or more children. The majority of participants reported a monthly income of less than 6,000 Renminbi. Most participants had good visual and hearing condition. The number of patients from northern and southern China was roughly equal. The types of surgeries included cardiac stent operation (77.4%) and radiofrequency ablation operation (12.4%), etc. The mean length of hospital stay after operation was 4 days, and 46.7% participants had a normal weight.

[IMAGE OMITTED: SEE PDF]

Demand analysis based on the Kano model

A total of 23 demands were included in the Kano model analysis, with each demand having its own better-worse coefficient. The detailed attributes of these demands were shown in Table 4. The satisfaction index ranged from 0.678 to 0.857, while the dissatisfaction index ranged from 0.203 to 0.289. To distinguish different attributes of these demands (including one-dimensional, attractive, indifferent, and must-be), we categorized them into four quadrants based on the mean values of the satisfaction and dissatisfaction indices (average SI: 0.750 and average DI: 0.237) across all demands. The classification was visually presented in the scatter plot shown in Fig. 1.

[IMAGE OMITTED: SEE PDF]

[IMAGE OMITTED: SEE PDF]

One-dimensional demands (high priority)

All demands related to health monitoring services, such as reminders about upcoming follow-up visits and examinations after discharge, were classified as one-dimensional. Additionally, demands related to medication guidance, symptom management, and personalized exercise plan were also categorized as one-dimensional. These demands showed consistently high satisfaction indices (SI: 0.758–0.857) and dissatisfaction indices (DI: 0.246–0.289).

Attractive demands (innovation opportunities)

Demand such as providing continuous health monitoring and guidance each time you exercise (demand 6), providing adjusted dietary plan based on your physical condition or dietary preferences (demand 9), and providing assistance in better searching for health-related information (demand 23) were classified as attractive. These elements demonstrated high satisfaction potential (SI: 0.764–0.768) with lower dissatisfaction risk (DI: 0.228–0.234).

Indifferent demands

Demand such as providing weight loss guidance for you, providing supervision and guidance on quitting smoking and limiting alcohol consumption, and providing evaluation and monitoring on your sleep quality were classified as indifferent. These services had relatively lower satisfaction indices (SI: 0.678–0.744) and dissatisfaction indices (DI: 0.203–0.228) compared to other demands, indicating that patients were generally neutral about their inclusion in transitional care programs. This finding is particularly noteworthy given that these aspects are traditionally emphasized in cardiac rehabilitation programs, indicating a potential mismatch between standard care practices and patient preferences during the transition period.

Must-be demands

No demands were categorized as "must-be".

Associations between demographic factors and one-dimensional demands

Detailed associations were shown in Table 5. Among the included patient characteristics, one-dimensional demands were mainly associated with age (D1, D2, D5), residence status (D1, D3, D13) and body mass index (BMI) (D1, D2, D3, D4) with $P<0.05$, and the differences were statistically significant. In addition, the number of children ($P=0.005$) and hearing condition ($P=0.007$) were also related to the demand of checkup reminder (D1). However, the three one-dimensional demands of D4, D12 and D16 did not show associations with demographic data ($P>0.05$), which, to some extent, reflected that these three demands were universal for patients. No associations were found between other demographic factors (i.e., sex, educational level, marital status, monthly household income, visual condition, city of medical treatment, type of operation, length of hospital stay after operation, and comorbidity) and one-dimensional demands.

[IMAGE OMITTED: SEE PDF]

Qualitative results

Characteristics of participants

A total of 13 MICI patients participated in the interview. We initially interviewed 10 participants. After identifying the topic, we continued with 3 more interviews to ensure that no new topics emerged, and subsequently terminated the qualitative data collection. Table 6 showed the characteristics of the 13 interviewed participants. The average age of the patients was 56.62 ± 14.04 years, with 8 of them being male. Almost half of the participants had a middle school education level, and 12 were married. Additionally, eleven patients had comorbidities, such as hypertension and diabetes.

[IMAGE OMITTED: SEE PDF]

Key themes

Through semi-structured interview, we have identified eight themes of demands to provide a holistic demand identification, shown in Fig. 2. Detailed interview content is presented in the supplementary file 1.

[IMAGE OMITTED: SEE PDF]

Theme 1: Physical recovery and lifestyle guidance demand

Some patients felt loss of energy after operation and hoped to regain their vitality to come back to normal life. Exercise guidance was an important part of lifestyle guidance, with participants expressing various demands, including overcoming barriers to exercise, seeking individualized exercise plans, and developing exercise intention and habits.

Sometimes it feels like I have less energy than before the operation. (P1)

The weather is too hot, so I haven't been exercising. I'm afraid to go out. It's too hot. I feel dizzy under the sun. (P4)

The doctor has said that exercise is needed, but he has not said the level of exercise. (P5)

These days, I'm mostly just sitting around at my shop, not really getting much exercise. I'm planning to start moving more, like walking around the park, but I haven't started yet because this bump hasn't gone away. I think I still need to focus on resting. (P6)

Theme 2: Psychological support demand

Participants experienced various psychological changes, such as fear of operation, anxiety about postoperative recurrence, and a sense of loneliness. Each participant faced unique psychological challenges and required tailored support during the period.

I'm in my fifties now, and I've never been hospitalized before. This time, I felt some chest tightness, so I went for a checkup and they did an angiogram. Then they told me I needed a stent. I've never been in the hospital before, so I was pretty scared—it was my first time, and I was really nervous. (P1)

I' m alone at home, and there' s nothing I can do about it. They went back, and I' m just here by myself. My grandson needs to go to school. (P2)

Theme 3: Comorbidity management demand

For MICI patients, many also had chronic diseases (e.g., hypertension, and diabetes). Managing these comorbidities while ensuring successful postoperative recovery was no easy task.

Blood sugar is a little high, and it' s not down even with insulin. Now it' s equivalent to about 9 mmol/L before meals. (P1)

I had hypertension for many years, and the blood pressure is really high, about 200 mmHg. (P2)

Theme 4: Medication-related demand

Medication was another critical aspect that patients pay attention to. From the perspective of many patients, successful operation and strict medication adherence were key to recovery. Therefore, they expressed various medication-related demands. Patients faced some medication adherence challenges such as forgetting the right combinations or timing of different medications. Patients also had some concerns about the potential side effects, leading them to search the Internet to get some information. Some patients also reported that doctors do not give clear information about the signal of discontinuing medication, leaving them confused about the appropriate timing to stop taking them.

Some medications need to be taken together, but I' m not always sure about the right combinations. Sometimes, I also don' t get the timing quite right. (P5)

I' m a bit confused right now about which medications I still need to take and which ones I can stop. (P9)

Theme 5: Symptom management demand

Participants experienced various symptoms that affected their daily lives, leading them to focus on these issues and may require symptom management. Pain was a frequently mentioned symptom, significantly impacting their quality of life.

My blood vessels are naturally very thin, so after drawing blood, I might get some lumps or bruises on my hand that still haven' t gone away. (P2)

The uncomfortable part is that the areas on both sides of my thighs hurt a lot when I lie down. I feel fine when I' m sitting, but as soon as I lie down, the pain kicks in. (P12)

Theme 6: Health monitoring and checkup reminders demand

Participants closely monitored their vital signs, such as heart rate, and often visited the hospital for lab tests to ensure there are no underlying issues.

After my operation, my heart rate is still around 80 to 90 beats per minute, and sometimes it even goes over 90. It' s noticeably high and quite unstable. (P8)

I would like to receive reminders about any lab tests I need to do and important things to watch out for after being discharged. (P9)

Theme 7: Financial-related demand

Participants expressed a need for transparency in medical costs, as they often did not really know where the medical expenses are going. The lack of transparency could lead to significant confusion and anxiety. Additionally, patients had their financial burdens that required support.

My thought is, as long as I recover, that' s all that matters. I' m not thinking about anything else, especially since money' s tight. (P4)

The financial pressure is definitely high; it' s so hard to make money these days. We' re basically just working folks. (P6)

Theme 8: Medical information demand

Most participants lacked medical information, and no one told them the basic knowledge about their diseases and treatments, leading to confusion. They also sought information on lifestyle modifications. No one provided professional advice for them, and communication between doctors and nurses was scarce. Consequently, they just searched on the Internet to find the information they needed to relieve their anxiety.

I don't really understand where exactly this operation was done. Is it around the area below my throat, in the heart? Where exactly is the stent placed? (P4)

The day I got discharged, my husband took a popsicle out of the freezer for me, and I wasn't sure if I could eat it. So, I looked it up online and found that it's better not to eat things like ice cream after getting a stent. After reading that, I decided not to eat it. (P6)

The qualitative findings strengthened the quantitative results while revealing additional detailed patient needs, particularly around comorbidity management, psychological support and financial transparency. This mixed-method approach revealed both the relative importance of different demands (through Kano analysis) and the deeper context and reasoning behind these needs (through interviews). The findings suggest opportunities for targeted interventions, particularly in health monitoring, medication guidance, symptom management, and information provision.

Discussion

Main findings

To our knowledge, this is the first study to investigate the demands of MICI patients during the transition from hospital to home using a parallel mixed-method approach. We revealed three key insights about MICI patients' transitional care demands. First, through Kano model analysis, we identified health monitoring, medication guidance, symptom management, and personalized exercise plan as one-dimensional demands that significantly impact patient satisfaction. Second, continuous exercise monitoring and dietary planning emerged as attractive features that could enhance care quality without risking dissatisfaction if absent. Third, our qualitative findings uncovered deeper contextual factors, particularly around comorbidity management, psychological support and financial transparency, that weren't captured in the quantitative analysis alone.

Interpretations of quantitative and qualitative results

To assess the relative importance of the included demands, the Kano model was employed. Three classifications were identified: one-dimensional, attractive, and indifferent.

Must-be category

No must-be demands were found in our survey. However, although no demand was categorized as "must-be", this does not necessarily imply a lack of fundamental need. Considering the proven health benefits of transitional care after discharge, its successful application in western countries, and the identified demands through qualitative studies, the absence of must-be needs may be due to the low expectations of transitional care among Chinese people [33, 34]. The concept of transitional care is not widely adopted in China, and MICI patients have become accustomed to being unguided and unaided after discharge. As the healthcare system in China continues to evolve, patients' expectations may still be developing.

One-dimensional category

One-dimensional demands, which are highly valued by patients, should be prioritized. According to our results, all health monitoring services were categorized as one-dimensional, indicating that patients are particularly concerned about their health status, and hope to be immediately informed of any changes. Therefore, from the patient's perspective, the identification and diagnosis of health abnormalities are paramount. Health monitoring demands were also mentioned and summarized through semi-structured interview. Some patients reported using the Huawei Band, a popular health monitoring device in China, to monitor their heart rate. The widespread use of these wearable devices highlights the importance of health abnormalities identification. With advancements in technology, patients now have greater opportunities to be aware of their health conditions in real time. However, a key gap between these existing wearable devices and their practical application in healthcare lies in their seamless integration with existing electronic health records (EHRs). This integration can be facilitated by using standards for the exchange, integration, sharing, and retrieval of electronic health information. For example, the Fast Healthcare Interoperability Resources (FHIR) standard has gained widespread attention as an effective solution in this field [35]. After successful integration, nurses can leverage AI-powered wearable devices or telehealth to monitor vital signs, identify abnormalities, and intervene promptly, even for patients staying at home. For instance, real-time data from a wearable can alert a nurse to potential arrhythmia, enabling timely follow-up or referral. Over time, with accumulated medical data, the AI

system could offer personalized health recommendations by learning from and analyzing large datasets. Apart from health monitoring, checkup reminders are also important for patients. Studies have shown that text messaging reminders help improve medical appointment compliance by addressing issues of forgetfulness [36].
Medication guidance services were also classified as one-dimensional, which was further validated by the qualitative results. Patients attach importance to medication. In summary, medication-related demands mainly included medication adherence management and medication information demands. Commonly mentioned concerns include medication timing, discontinuing schedules, dosages and drug combinations. Nurse-led interventions, such as patient education and medication management, are well-suited to address these demands.
Additionally, patients often feel confused about these drugs, and are worried about potential side effects, leading to anxiety about medication information. These demands can be addressed through artificial intelligence approaches [37, 38]. With the emergence and popularity of large language models, these technologies have the potential to answer patients' different questions including medication information and other medical information demands, such as diet information demands mentioned in the qualitative study, providing tailored suggestions. However, AI-generated information should be treated with caution, especially in the medical field. Fortunately, new methods such as retrieval-augmented generation and knowledge graph have been proposed and applied to help AI produce more professional and accurate texts [39, 40]. AI-enabled platforms, supervised by clinical nurses, may address patient concerns in real time.
Symptom management was another demand categorized as one-dimensional, primarily because severe symptoms, such as pain, significantly impact daily lives. This was also highlighted in the interviews, where patients expressed that pain affected their ability to use the toilet, climb stairs, and sleep. The importance of postoperative pain management has also been emphasized in previous studies, as undermanaged postoperative pain can lead to complications such as sleep disturbances, anxiety, and delayed mobility [41, 42]. Incorporating remote triage tools, including wearable technology and patient self-reporting apps, into the existing healthcare system may improve the management of symptoms. For instance, real-time data collected from wearable devices and apps can provide nurses with notifications containing up-to-date information on pain levels, enabling them to adjust analgesics or make other interventions, maintaining patient comfort and preventing future complications. However, the relatively low health information literacy among patients and the limited AI competency among nurses in China act as significant barriers to implementing remote transitional care [43, 44]. To overcome these challenges, it is essential to provide education that teaches patients how to use these devices effectively, as well as training for nurses to improve their ability in interpreting and responding to data from AI-driven tools. In addition, the collaboration and communication between nurses and AI experts should be strengthened and supported to successfully implementing user-friendly AI-driven transitional care.
In patients' opinion, providing a personalized exercise plan was a priority, which aligns with the qualitative findings. This can be explained by the phenomenon that over 40% of global population was physical inactivity [45]. The reasons for physical inactivity are varied and highly personalized. According to our qualitative results, patients expressed reasons such as hot weather, lack of specific exercise guidance, or pain as barriers to exercise. Therefore, personalized exercise plans are more appropriate than general ones. Nurses trained in cardiac rehabilitation can incorporate AI-assisted exercise tracking to tailor exercise programs for patients and motivate them to overcome barriers. Nurses can use AI-based tools to monitor exercise and provide immediate feedback on performance. Such interventions not only enhance physical recovery but also foster long-term healthy behaviors.
Attractive category
Three demands were classified as attractive. Health-related information and health monitoring demands have already been emphasized and explained in previous sections. One notable finding that deserves attention is dietary plans. In our survey, we provided two options. Compared with personalized dietary plan, patients tended to have adjusted ones because they already have established dietary habits and preferences. This was further validated in qualitative findings that patients prefer to continue their existing eating habits with only minor modifications. In the AI era, innovative technology can be used to generate dietary plans and analyze patient's food logs to suggest

adjustments, minimizing drastic lifestyle changes that may reduce adherence. Meanwhile, nurse-led dietary interventions, in collaboration with dietitians, can adapt meal plans to patients' cultural and personal preferences [46, 47].

Indifferent category

The remaining demands, mainly related to weight loss guidance, quitting smoking, limiting alcohol, sleep guidance, fundamental nursing, skill learning, and psychological and social support, were regarded as indifferent. All findings were consistent with the qualitative results, except for psychological and social support. In our semi-structured interview, patients expressed concerns such as anxiety about postoperative recurrence and feelings of loneliness. This discrepancy may be due to their lack of awareness regarding their anxiety. Additionally, previous evidence shows that postoperative psychological interventions are generally more effective than preoperative ones, significantly reducing acute pain and disability [48]. Nurses can incorporate structured mental health and lifestyle screenings, such as questionnaire surveys or facial image recognition, into routine follow-ups through AI-based tools, detecting latent issues like anxiety or depression. After diagnosing psychological problems of patients, AI tools, including chatbots or virtual counsellors hold substantial potential to generate personalized plans to intervene in patients' psychology and alleviate their psychological symptom [49].

The application of AI for patients with depression, loneliness or anxiety holds great promise due to several key advantages. First, compared to traditional psychological counselling, AI-driven psychological interventions are much more cost-effective, enabling mental health support more accessible to a larger population. Second, feelings of shame or stigma are significant barriers for many patients who fear seeking psychological treatment. The anonymity and privacy offered by AI enhance patients' willingness to seeking help [50]. Currently, with the rapid development of AI technology, many AI-driven psychological products, such as Woebot and Replika, have been widely used. Integrating the useful features of these products into transitional care interventions may be another area of future research [51, 52].

However, although these fully automated tools can provide patients with immediate support between visits, AI-driven mental health diagnosis faces limitations, such as potential bias in data, failure to account for the complexity and individuality of mental health conditions, and a lack of empathy in treatment [53]. Integrating these tools into existing EHRs and ensuring that nurses are involved in reviewing and interpreting the data are necessary to guarantee correct psychological screening and enhancing current healthcare processes.

Clinical implications

The integration and reflection of quantitative and qualitative results

Overall, based on our results and discussions, the quantitative approach using Kano model identified health monitoring, medication guidance, symptom management, and personalized exercise plan as high-priority demands, while continuous exercise monitoring and dietary planning were recognized as innovation opportunities. Qualitative studies revealed additional demands not captured in quantitative results, including comorbidity management, psychological support and financial transparency. The results highlight the complementary nature of the mixed-method approach. By addressing physical health demands and assisting patients in cultivating health lifestyle, nurses can offer more comprehensive, patient-centered care. Paying attention to psychological support and financial transparency could significantly improve patient satisfaction and outcomes, which are often overlooked in traditional healthcare models.

Targeted interventions

According to the results of associations between patient characteristics and priority needs (one-dimensional needs), we derived clinical implications for more targeted interventions. Age and residence status were factors that required our attention. Older patients and those living along were more likely to need checkup reminders, personalized exercise plans, health monitoring, and medication guidance. These needs arise from the combination of age-related health decline and the lack of social support, which increases their dependence on healthcare services. Digital health interventions, provide continuous monitoring and personalized care in the context of home care, thereby offering significant potential to improve health outcomes and enhance recovery for these populations [54]. Those who were overweight or obese had greater health demands than other populations, as they were more concerned about potential health issues. This is because a higher BMI is often associated with comorbidities, such as diabetes, hypertension, and cardiovascular diseases, which increase their concerns about their health status [55]. No significant correlation was found between comorbidities and priority needs, which may be due to the inclusion of post-PCI patients, who are more focused on post-intervention concerns rather than chronic conditions (e.g., diabetes and hypertension). Although our study did not reveal significant associations between other demographic factors (such as sex and education level) and priority needs, these factors should not be overlooked. Gender differences may influence patterns of health service utilization. For example, females may prioritize the health needs of their families over their own, which could lead to delayed or unmet healthcare demands [56]. The impact of education level on patients' demands should also be considered. Lower educational attainment is often associated with limited health knowledge, non-compliant health behaviors, and underutilization of healthcare services. These factors can make individuals less aware of their health needs, less likely to follow medical advice, and less inclined to seek proper medical care, leading to unmet health management needs. As a result, overall health status may be negatively affected [57]. Additionally, socioeconomic status is a critical factor influencing patient demands. Research has also shown that individuals with lower socioeconomic status may face greater health risks and experience inequities in accessing health services and resources [58]. Future research should explore how these factors affect health needs in different contexts, enabling the development of more targeted and effective strategies to better address patients' needs.

Challenges in implementing AI for transitional care

In the AI era, innovative technology can be used to support transitional care from hospital to home. This article provides a comprehensive demand analysis, offering a more thorough understanding of the demands of MICI patients. Some solutions addressing these demands were mentioned in the previous section. However, several challenges arise when integrating AI technology into transitional care.

Firstly, the acceptance of AI-driven interventions is questionable among people with knowledge gaps and financial constraints. According to a survey study investigating public perception of AI-driven interventions with 466 adult participants, 305 (65.5%) respondents expressed very low knowledge of AI-driven interventions, and only 24 (5.2%) reported a high level of trust in this type of intervention [50]. In addition, people with lower education level tend to have less knowledge, understanding, and trust in AI, which results in a relatively low acceptance of AI [59, 60]. To ensure these interventions reach a broader population, we recommend initiating health education programs targeting health information literacy to help patients, particularly those from lower educational backgrounds, embrace new technology. These programs should provide clear and understandable explanations of AI-driven interventions.

One notable advantage of AI-driven interventions is that they are likely to be widely accessible. These technology-based interventions have the potential to break geographical barriers to provide high-quality transitional care to populations in remote areas where medical resources are limited. However, if these services are too expensive, they may widen the digital divide, particularly between high-income and low-income populations. Qualitative interviews also highlighted the demand for financial support. For people with lower income, the financial burden is a significant barrier to accessing these intelligent services [61]. Therefore, the involvement of policymakers is essential to ensure that ordinary people have the opportunity to access such healthcare services through measures such as insurance.

Secondly, technical feasibility, particularly data privacy, security and standardization, is another aspect that needs attention when applying AI in transitional care. AI techniques typically requires a large amount of data, including sensitive patients' personal health monitoring data, medical history, and behavioral data, to generate accurate predictions about their health status. This high reliance on data raise concerns about data privacy and security especially in healthcare setting where patient confidentiality is essential [62]. One possible solution to the issue is the use of block-chain technology, with its decentralized data storage that distributes data across multiple nodes, including those operated by patients and healthcare institutions, unlike traditional centralized systems [63]. The nature of decentralization removes the necessity for a single organization to store all healthcare data, ensuring data security and privacy.

Furthermore, data exchange across different healthcare systems is critical for AI-driven solutions to work smoothly. As healthcare data are typically stored in different platforms such as EHRs and patients' wearable devices, with varying data formats. Therefore, data standardization is essential to ensures smooth healthcare data transmission across various platforms [64]. The application of data standards, such as FHIR and Systematized Nomenclature of Medicine –Clinical Terms (SNOMED CT), would be helpful in solving these problems.

Thirdly, with the rapid developments of AI, several concerns have emerged. One key ethical issue is bias in AI models. If the medical data used to train AI models primarily comes from high socioeconomic groups, rather than a broader, more diverse population, it could lead to unfair and unequal healthcare outcomes. Therefore, regulations should be carefully designed to address these risks and ensure that the benefits of AI are shared equitably among all individuals, rather than favoring specific groups. The Council and the European Parliament (EP) agreed on the Artificial Intelligence Regulation (AI Act, AIA) in February 2024 [65]. Regarding the application of AI in medical field, China's National Medical Products Administration (NMPA) has released many regulations in line with its AI development plan [66]. AI regulation should evolve alongside the development of AI, and joint collaborations among AI expert, and regulators are essential to ensure effective regulation.

Strengths, limitations and future research directions

The study demonstrated several strengths in contributing to AI-driven transitional care for MICI patients. Firstly, we addressed a significant and pressing research question regarding the transitional care demands of MICI patients in the context of AI, a topic not fully explored in China due to nursing staff shortages. Secondly, we employed a mixed-method approach to perform the demand analysis. The use of Kano model in the quantitative part allowed for the categorization of demands into different classifications, prioritizing them based on their importance. The introduction of qualitative study enabled mutual comparison and validation between quantitative and qualitative results, which enhanced the reliability of our findings. Finally, based on demand analysis results, actionable AI-based strategies and solutions were fully discussed, providing insights into potential future developments. However, the study also has some limitations. Firstly, our sample size was relatively small, especially in the qualitative part. While the mixed-method approach helped mitigate this limitation, a small sample size restricts the generalizability of the findings. Although data saturation was reached in the qualitative study, the limited sample size raised concerns about whether the experiences reflect those of the broader population and whether some demand themes may have gone undetected. Additionally, the small sample size in the quantitative analysis may have limited the detection of subtle trends in the demand analysis. Therefore, the findings should be interpreted with caution, and future studies with larger and more diverse samples are required to validate and strengthen our insights. Secondly, we analyzed each demand independently, but they are interrelated. For example, searching for medication information may lead to patients' anxiety, but if information-seeking problem is solved, their anxiety might be relieved or even eliminated. Independent analyses of demand may restrict a holistic understanding of these needs. This presents another potential direction for future research, suggesting the implementation of a more integrated approach that considers the interdependencies among demands. This limitation should be considered when designing interventions targeting the needs of post-discharge MICI patients.

Thirdly, we used a self-designed questionnaire due to the lack of a comprehensive demand scale. However, we cross-checked the survey findings with the qualitative results and consulted six experts to evaluate the content validity of the questionnaire, ensuring that no critical demand categories were missed. This also indicates an important future research direction: the development of a scale to assess the post-discharge needs of MICI patients, considering the significance of home care nursing for this population. Lastly, regarding participant recruitment, although we included patients from four hospitals located in both northern and southern China, all four hospitals are situated in second-tier cities. The selection bias limits the external validity of the demand analysis results for patients in first-tier cities or rural areas, where patients' expectations and needs for transitional care may differ from those of participants included in our study. Specifically, in first-tier cities, where there are better medical care resources, higher educational levels, and greater financial stability, people tend to have higher expectations of transitional care. This is primarily because most residents understand the importance of post-discharge rehabilitation through health education provided by qualified medical professionals. Additionally, they typically receive follow-up visits based on their previous healthcare experiences, which is a key component of transitional care. Furthermore, individuals in these cities have easier access to advanced medical technologies, such as telemedicine and mobile health applications, as well as specialized care delivered by high-quality community medical services. This greater exposure enables a better understanding of the intentions and purposes behind conducting this research on AI-driven transitional care. In contrast, in rural areas with limited medical resources, lower educational backgrounds, and financial instability, people are less likely to be well-informed about transitional care by professional medical staff. This is partly due to the limited availability of healthcare education in these regions. In rural settings, the focus is often on acute care in hospitals, where receiving medical treatment in a hospital is typically viewed as curing diseases. As a result, the concept of transitional care, including follow-up visits, is less understood. Moreover, limited exposure to advanced technologies makes the use of AI-driven solutions seem distant and less relevant. Besides, financial constraints, along with health literacy and access to healthcare technologies, also significantly shape people’ s awareness of transitional care. In rural areas, economic limitations often prevent people from seeking follow-up care and post-discharge rehabilitation, whereas individuals in first-tire cities are more likely to have the financial access to engage in rehabilitation. Therefore, the heterogeneity of transitional care expectations and needs across different regions limits the applicability of the results of this study. We suggest that future studies explore the demand for transitional care among patients in these regions.

Conclusions

By uncovering MICI patients’ most pressing transitional care demands, this study provides valuable directions for designing AI-supported, nurse-led interventions that are both feasible and patient-centered. Prioritizing one-dimensional demands—including health monitoring, medication adherence, symptom management, and personalized exercise—has the potential to improve patient satisfaction and reduce hospital readmissions. In parallel, implementing attractive features like continuous exercise monitoring and personalized dietary plans can further enhance patient engagement without generating dissatisfaction if not provided. In addition, comorbidity management, psychological support and financial transparency are areas that warrant further attention. Nurses, as frontline caregivers and care coordinators, are in a key position to integrate these technological solutions into daily practice. With supportive policies, adequate training, and redesigned workflows, nurse-led AI interventions may help address staffing challenges and bridge transitional care gaps, potentially improving the recovery outcomes of MICI patients in China and beyond. However, due to the limitations of our study, these insights require further validation and exploration.

Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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DETAILS

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Streamlining Sensor Technology: Focusing on Data Fusion and Emotion Evaluation in the e-VITA Project

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ABSTRACT (ENGLISH)

This paper explores the use of sensor-based multimodal data fusion and emotion detection technologies in e-VITA, a three-year EU–Japan collaborative project that developed an AI-powered virtual coaching system to support independent living for older adults. The system integrates these technologies to enable individualized profiling and personalized recommendations across multiple domains, including nutrition, physical exercise, sleep, cognition, spirituality, and social health. Following a review of related work, we detail the implementation and evaluation of data fusion and emotion detection in e-VITA. The paper concludes with a summary of the key research findings and directions for future work.

FULL TEXT

1. Introduction

Over the past century, life expectancy has increased dramatically, leading to a rapid growth in the proportion of older adults in the global population. This demographic shift has been accompanied by a growing desire among seniors to maintain their independence and continue living in their own homes, creating an urgent need for innovative solutions to support active and healthy aging [1,2].

There is growing interest in the use of non-invasive interventions, such as those based on behavior change, as a means of disease prevention and health promotion. One example is mobile app-based health management services. Nevertheless, there is no comprehensive system that can address multiple domains at an individual level, especially among older people. A further challenge is the lack of professional and scientific information on the impact of app design and behavior change and well-being programs. This is a key issue that needs to be addressed when adopting digital technologies in the future.

This paper describes research into the use of sensor technologies and emotion detection in e-VITA, a three-year collaborative research and development project that was jointly funded by the European Union's H2020 Programme (Grant Agreement no. 101016453) and the Japanese Ministry of Internal Affairs and Communication (MIC, Grant no. JPJ000595) [3].

The main aim of the e-VITA project was to promote active and healthy aging among older adults in Europe and Japan, supporting independent living and reducing the risk of social exclusion. To achieve this, a virtual coaching system was developed to provide individualized profiling and personalized recommendations across multiple domains including nutrition, physical exercise, sleep, cognition, and spirituality. The system identified risks in the user's daily living environment by collecting data from external sources and non-intrusive sensors, offering support through natural conversational interactions with social robots.

In this paper, we focus on the application and evaluation of motion tracking and emotion recognition to enhance digital coaching and promote independent living for older adults. Other aspects of the virtual coaching system, including the Dialogue Manager responsible for natural conversational support, are discussed in [4,5].

The paper is structured as follows. Section 2 provides an overview of state-of-the art research on sensor-based multimodal data fusion and emotion detection technologies. Section 3 describes the implementation and integration of these technologies within the e-VITA project. Section 4 examines how sensor data and the Emotion Detection system facilitated proactive dialogues related to various aspects of daily living. Finally, Section 5 concludes with a summary of the key findings, discusses their implications, and offers suggestions for future research in AI-assisted healthy aging.

2. Related Work

Given the significant increase in life expectancy over the past century, it has become clear that traditional methods for the care of older adults have become unsustainable. This has led to an exploration of how new developments in Artificial Intelligence and related technologies can complement and enhance human-based approaches. In this section, we review related work in data fusion and emotion detection as applied in the e-VITA project.

2.1. Data Fusion

In general, a data fusion process can be described as a multidimensional approach aimed at enhancing the reliability of decision-making or event identification based on information from multiple sensors. In particular, it has been used in Human Activity Recognition (HAR), which is also its main purpose in e-VITA [6].

The data fusion process can be implemented at different levels, depending on the level of information used in the fusion process, as illustrated in Figure 1.

The Data or Observation Signal Level involves information from various environmental sensors. Observations are typically organized as vectors, which can represent either preprocessed signals (direct-level fusion) or analyzed signals (feature-level fusion). Furthermore, raw digitized signals can be used as, e.g., in a series of binary impulses from a passive infrared (PIR) detector. The vectors are then processed using identification or classification methods such as Kalman filtering, Neural Networks, or Support Vector Machines, and the methods are applied globally to the dataset to determine the probability of normal or abnormal events occurring.

The Decision System Output Level involves the outputs of different decision systems operating in parallel on complementary or redundant signals, such as classifiers or expert systems. Results are usually expressed as recognition scores (likelihood or a posteriori probabilities). At this level, score-fusion techniques are applied. These techniques were originally developed for image and speech processing, for example, in the fusion of phonetic signals and viseme-based pattern recognition, where visemes represent visual speech elements such as lip movements [7,8].

The fusion process can interpret signal or recognition score data in several ways, including competitive, complementary, or redundant approaches, depending on the fusion architecture and the correlation properties of the different sources or modalities involved [9]. Typically, the data or decision outputs being fused are homogeneous, especially in competitive data fusion scenarios.

Figure 1

Different levels of data fusion. Source: [10].

[Figure omitted. See PDF]

However, multimodal data may not be homogeneous at the same fusion level. For instance, data might come from diverse sources, such as pattern-matching approaches (e.g., HMM, GMM) and rule-based processing, or involve different structures (e.g., continuous versus binary signals). Therefore, it is beneficial to consider fusion approaches that can integrate different data types without necessarily considering their structure or level of abstraction.

To address heterogeneity in signal and data processing, various approaches have been developed, such as Fuzzy Logic combined with rule-based systems, Bayesian networks, and Evidential Networks based on Belief Theory [9,11,12]. For example, Bayesian score fusion, which involves multiplying all class posterior probabilities from parallel statistical pattern recognition processes, was applied to bi-modal audio-visual recognition by [7,8].

The experiments highlighted the need for heterogeneous data fusion due to the diverse nature of the data sources, including the following: actimetry data (movement signals), sound signals, and vital parameters (heart rate). To address this, heterogeneous unsupervised data fusion approaches such as Fuzzy Logic, introduced by Zadeh in 1965 [13], and Evidential Networks based on the Dempster–Shafer theory by Shafer in 1976 [14], have been employed. These methods not only handle data heterogeneity but also mitigate issues related to the scarcity of training data for supervised classification, particularly for rare events like falls or distress, and to a lesser extent, daily activities [15].

In a recent research project on ADL (CoCaps FUI-project), the authors in [16] developed a localization system using PIR sensors and the transferable belief model based on the Dempster–Shafer theory. This system provides accurate localization within the user's home environment and correlates it with the user's ADL (see Figure 2).

Over the past decade, deep machine learning approaches have revolutionized pattern recognition and fusion techniques, offering significantly improved performance compared to traditional methods. These advancements primarily involve specialized neural network architectures, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory Networks (LSTMs). Recently, Deep Neural Networks have been applied to actimetry signal acquisition, particularly in wearable tracking systems for fall prevention and Activities of Daily Living (ADL) monitoring, as demonstrated in the works of [15,17,18,19]. Additionally, Ref. in a comprehensive state-of-the-art review LSTM approaches are compared with traditional Kalman and Extended Kalman Filtering (EKF) methods, highlighting the limitations of the latter due to their reliance on noise assumptions [18].

In the context of the e-VITA project, these advanced approaches have been explored and applied to data fusion problems involving multiple data inputs. For example, localization signals from a PIR sensor network and actimetry signals from wearable devices (including 3D accelerometery and inertial sensors) have been integrated for interaction with Knowledge Graphs and Dialogue Manager systems. Moreover, a definition of data fusion was introduced within the e-VITA context in which two paradigms were proposed based on combined algorithmic and architectural principles ref. [4]. This approach involves multiple algorithmic principles interfacing with a kernel that manages various data sources. Consequently, the data fusion platform (see below Section 3.2) is designed to implement this architectural principle, effectively embodying the conceptual framework of data fusion.

2.2. Emotion Detection

The detection of emotion in conversation is a crucial aspect of human–computer interaction and affective computing. Accurately identifying emotions during conversations can enhance the quality of interactions, improve user experiences, and provide valuable insights into human behavior and mental states.

Computers and robots therefore need to be taught how to identify, understand, and express emotions to interact authentically with users [20]. A coach capable of detecting and reacting to the user’s emotional state will increase the user’s general acceptance as well as the success of the coach’s interventions [21,22]. Recent studies examine the integration of emotion detection in virtual assistants and chatbots to enhance user experiences, employing various modalities such as natural language approaches, video, and speech, to recognize basic emotions like anger, joy, and sadness [23,24]. The mental health chatbot SERMO was designed to help users regulate their emotions through cognitive behavioral therapy (CBT) techniques [23]. The chatbot functions as a mobile application that integrates a chatbot prompting users to report their daily events and emotions. The chatbot automatically detects the user’s basic emotions based on a natural language and lexicon-based approach and suggests personalized activities or mindfulness exercises accordingly. The application also features an emotion diary, a list of pleasant activities, mindfulness exercises, and information about emotions and CBT. The usability of SERMO was evaluated, with positive feedback regarding its efficiency, perspicuity, and attractiveness.

Applications like the personal assistant “Edith” leverage deep learning techniques to detect emotions and support users experiencing social anxiety or depression [24]. This assistant adjusts its responses based on the detected emotional state, providing more empathetic and supportive interactions. Such dynamic interaction not only enhances user experience but also addresses emotional needs, rendering the assistant more effective and personable. This research underscored challenges in achieving high accuracy in emotion recognition due to subtle differences in facial expressions and potential dataset biases. Additionally, maintaining user privacy and data security is identified as a critical challenge. The specific challenges of audio and video emotion recognition in older adults were addressed in a study that investigated how virtual agents can accurately detect and respond to emotional expressions in this demographic [25]. The study highlighted the variability in facial expressions and the necessity for tailored interaction strategies. It also pointed out the difficulty of recognizing emotions in older adults due to limited relevant datasets, calling for more comprehensive evaluations to ensure system reliability.

In an earlier study on adaptive dialogue interventions, an embodied conversational agent was developed for mindfulness training and coaching through natural language dialogues [26]. The "Virtual Mindfulness Coach" could initiate or change topics, focusing on "affect-adaptive interaction", where the coach's responses were tailored based on the student's emotional state. A pilot evaluation comparing the effectiveness of this virtual coach-based training with a self-administered training program using written and audio materials showed that the virtual coach-based training was more effective.

3. Sensor and Emotion Detection Technologies Used in the e-VITA Project

A key component of the e-VITA system is its ability to enhance user interaction through a virtual coaching framework. It incorporates real-time data fusion from multiple sources—such as smart home sensors and wearable devices—to generate personalized insights and proactive notifications. Additionally, the system employs advanced emotion detection models to assess user emotional states based on speech analysis, enabling more empathetic and adaptive interactions.

This section explores the core functionalities of the e-VITA system, detailing its data fusion platform, proactive notification system, and emotion detection capabilities. Through these innovations, e-VITA aims to provide a comprehensive and intelligent support system for users, particularly in promoting well-being and safety.

3.1. The Digital Enabler Platform

The e-VITA system is based on the Digital Enabler platform [27]. The platform is designed to handle data from heterogeneous devices, including smart home sensors such as temperature, humidity, and intrusion sensors, and wearable devices such as smart watches, smart bands, and smart rings. It also enables interaction with coaching devices such as social robots and holograms. Additionally, the platform provides capabilities for data storage, context management and overall communication with external systems. Special attention is paid to data privacy and security, as well as authorization. Figure 3 shows a high-level view of the e-VITA platform.

The e-VITA platform enables the integration between the devices and the primary components of the e-VITA virtual coach—the Dialogue Manager, the Multimodal Data Fusion module, and the Emotion Detection module. The user is registered as the user of the system and a particular interface device through the dashboard, through which the user can also provide personal properties and features which affect the interaction. We will not go into the details of the platform as this is beyond the scope of the current paper. For a detailed description, see [4].

The platform operates as a messaging system—the system maintains message queues and messages are sent to the appropriate components while the information is processed within the individual components like the Dialogue Manager (DM) and the Emotion Detection System (EDS), according to their own specifications. More specifically, the user interacts with the system by typing in the text input on the interface device or speaking into microphone of the selected social robot (in the latter case, the spoken utterance is transformed into text using the Google Automatic Speech Recognizer). The text input is passed further to the Digital Enabler where it is augmented, if applicable, with labels representing additional information fused from sensors and the emotion detection system. The response is generated by the Dialogue Manager as a reaction to the user input, and it is sent back to the Digital Enabler, which processes the response and sends it to the selected interface device (in case of the robot, the robot's Text-to-Speech system is used to output the system response as speech). In addition to the interactions initiated by users, system-initiated dialogues can be triggered through the notification management system, for example, to prompt the user about an upcoming appointment or to remind about taking exercise, see Section 3.2. The Dialogue Manager is described in further detail in [5,28].

3.2. Data Fusion Platform

The main objective of the Data Fusion Platform (DFP) is to provide higher quality information according to the different multimodal data sources, and as mentioned, in the e-VITA project, the specific objective is to provide human activity recognition (HAR). Our data sources are as follows: inertial information (accelerometer, gyroscope, and magnetometer) from smartphone; location (latitude, longitude, altitude, and speed) from smartphone; motion, or intrusion detection with DeltaDore (EU)/EnOcean (JP) sensors; indoor climate with Netatmo Smart Indoor Air Quality Monitor, measuring temperature, humidity, CO_2 and noise level; the EnOcean ETB-RHT, measuring temperature and humidity; and health information (such as bpm, sleep, and steps) with the Huawei smart band.

In order to build initial models from smartphone inertial or motion/intrusion sensors, we used the following two public datasets:

- Ambient sensors: "Human Activity Recognition from Continuous Ambient Sensor Data" from the University of California, Irvine (UCI);
- Smartphone: "KU-HAR: An Open Dataset for Human Activity Recognition" from Medeley data.

Based on the data collected from the different sensors, the DFP calculates for each user a set of real-time labels and stores them in the Digital Enabler (DE), as follows:

- Gait analysis: walk, run, lie, sit, stand;
- Human activity analysis: cooking, resting activity, enter home, leave home, …;
- Games: number of steps based on the mobile application;
- Time spent in each location of the user's home;
- WBGT value calculated based on temperature and humidity.

These labels are used to trigger proactive dialogues based on the situation of the user.

3.2.1. Heat Stroke Warnings

A key safety consideration addressed by environmental monitoring is the risk of heat stroke. Heat stroke, characterized by a sudden increase in body temperature due to exposure to excessive heat or a combination of heat and humidity, poses a significant threat, particularly to older people, as it overwhelms the body's natural heat-regulation mechanisms. The technical approach adopted to mitigate this risk involves using the Wet-Bulb Globe Temperature (WBGT) as a crucial indicator for assessing the degree of heat stress. WBGT serves as the basis for developing preventive guidelines. More specifically, for indoor environments, the WBGT index is computed using the following formula:

$$WBGT=0.567 \cdot T+0.393 \cdot H+3.94$$

where T is the temperature (°C), and H is the relative humidity (%). This formula allows the DFP to tailor suggestions based on real-time sensor data, offering timely alerts for potential heat stroke risks [29].

3.2.2. Triggering Proactive Conversations

To initiate proactive dialogues based on the predicted user situations, the e-VITA system employs an Event Processing/Rule-based approach. This is implemented as a notification system which is integrated into the communication scheme among the different components of the e-VITA system. The architecture is presented in Figure 4, and the components in the notification system include the following:

- Event Processing (EP)/Rule-based component: Identifies specific data patterns using sensor data or events based on rules to trigger notifications or provide textual advice to the user;
- RASA Dialogue Manager: Responsible for activating dialogues based on specific intents;
- Notification Manager (NM): A specific component of the DE, more specifically, a part of the e-VITA Manager component, managing the notification flow and message queues;
- Coaching Device (CD): The device used by the user to engage in dialogue with e-VITA after a specific event occurs.

The general flow of the notification system is as follows:

1. The EP identifies a specific event related to a data pattern (e.g., high temperature) or time schedule;
2. The EP evaluates the data and identifies if any specific rule is met;
3. If the conditions are satisfied, the EP sends a notification request ("sendNotification(deviceID, message, INTENT)") to the Notification Manager (NM);
4. The NM places the message in the message queue and send back a conformation about the creation of the notification;
5. The CD periodically queries the NM to retrieve relevant notifications using the "get-Notification(deviceID)" method;
6. The NM receives the request, checks the queue, and responds with the corresponding "message", "deviceID", and "INTENT";
7. The CD sends the "INTENT" to RASA via the e-VITA Manager ("sendData(INTENT)"). The CD does not display any message to the user at this stage;
8. The message is sent to RASA as the usual flow with the "deviceID" of CD;
9. RASA activates the intent;
10. RASA responds with a message, continuing the dialogue flow;
11. The message is delivered to the user via the CD.

The e-VITA system employs Perseo [30] as its brain for processing events. Perseo listens to changes, follows rules, and takes actions. Conceptually, it serves as a smart organizer that understands events in a simple language and reacts accordingly by triggering actions and dialogues. Perseo rules follow a simple JSON structure made up of the following three mandatory key-value fields: *name*, *text*, and *action*. The structure of these rules is sketched in the following JSON code:

The *name* field refers to the name of the rule, and it is used as rule identifier. It must start with a letter, and it can contain digits (0–9), underscores (_), and dashes (-). Their maximum length is set to 50 characters.

The *action* field states the action to be performed by Perseo when the rule triggers. We can also use an array of action objects if needed. Each of those actions will be executed when the rule is fired.

The *text* field contains the valid EPL statement to be sent to the Esper-based core rule engine. The value of this field must follow the EPL syntax.

A sample rule in e-VITA has the following structure:

The name is an identifier for the rule, enabling it to be selected and configured according to the user’ s preferences.

In e-VITA rules, all actions are HTML POST requests to the NM with the identifier of the CD (deviceId,deviceToken) for which the notification is intended. The *message* in the POST query contain the *INTENT* (in our case, External_user_steps_motivate) that the CD should send to RASA to start the correspondent dialogue.

The EPL clauses in e-VITA can be time-based, sensor event-based, or both. The following text field is extracted from the above e-VITA rule:
select,from pattern[every(timer:at(30,12,,,,0,'CET')→(ev=iotEvent(cast(cast(steps?,String),float)<4000andtype=’ ’ Dev
ice’ ’)))wheretimer:withinmax(30 min,1)]

This EPL clause monitors the value of the steps made by the user by 12:30 and will trigger a dialogue to motivate the elder to take more exercise if it is below 4000. The threshold and the time can be personalized according to the user’ s preference.

The DFP in the e-VITA project offers better flexibility than traditional data fusion methods, as described in Section 2.1. Unlike conventional approaches that focus on homogeneous data, the DFP integrates heterogeneous multimodal sources, including inertial sensors, environmental monitors, and health-tracking devices. By leveraging real-time labels, it enhances HAR and enables proactive, context-aware interactions.

This flexible, heterogeneous fusion approach enables a more comprehensive understanding of user behavior, overcoming data diversity and real-time variability challenges. The DFP evolves beyond conventional fusion paradigms, offering a robust, real-time decision-making system that improves personalized support in home healthcare and well-being applications.

3.3. Emotion Detection

Automatic emotion detection facilitates the development of emotionally aware and empathetic technology. As part of its affective computing capabilities, the e-VITA platform incorporates an Emotion Detection System (EDS) to detect emotions from the user during the interaction with the coaching system based on speech.

Typically, audio-based emotion recognition predominantly focuses on speech in terms of paralinguistic features [31]. The following four broad types of speech data variables can be analyzed according to [32]: continuous acoustic variables (pitch/F0 height and range, duration, intensity, and spectral makeup), pitch contours (pitch variation in terms of geometric patterns), tone types (intonational phrases or tone groups), and voice quality (auditory descriptions such as tense, harsh, and breathy). In previous research, different types and shapes of various parts of a tone were found to be relatable to different emotions [32].

A use case was developed specifically for this speech interaction, facilitating natural and flexible engagement. In this scenario, the coaching system greets the user upon entry, asks the user about their day, and utilizes the Speech Emotion Recognition (SER) model implemented in the EDS to assess the user’s emotional state based on their verbal response. For this reason, a dialogue function entitled "External_how_was_your_day" was designed specifically for speech-based interaction, see Section 4.2.

The EDS was extended in the second phase of the project by integrating video-based emotion recognition (VER) models to enable the analysis of facial expressions in video data. In the field of video-based emotion recognition, analyses of facial expressions are most common. Here, emotion is often expressed by subtle changes in one or a small set of discrete facial features. For example, anger might be displayed by a tightening of the lips, or sadness by lowering the corners of the mouth [33]. In general, facial expressions are based on changes in various muscular action units, coded in the Facial Action Coding System (FACS) developed by [34]. They defined 44 action units, of which 30 are anatomically related to the contractions of specific facial muscles as follows: 12 are related to the upper face and 18 to the lower face. The action units can be analyzed individually as well as in combination [35].

The VER model is meant to be seen as a complementary tool for providing a more comprehensive assessment of the user’s emotional state. While VER adds valuable capability, its deployment is best suited for scenarios where users can be positioned directly in front of the system.

3.3.1. Emotion Detection Model for Speech Signals

The EDS is a deep neural network model for speech emotion classification, constructed from a two-dimensional time distributed convolutional neural network (2D-CNN) and a Long Short-Term Memory (LSTM) network. The model processes log-mel spectrograms of audio signals, using four local feature learning blocks (LFLBs) to extract temporal and spectral features, followed by a LSTM layer to model temporal dependencies. This architecture allows the system to learn both local and global features from the input data.

3.3.2. Emotion Detection Models for Facial Expressions

For VER, we developed and tested the following two frameworks: the Conventional Framework and Shallow Convolutional Neural Networks.

Conventional Framework

This framework uses the Facial Action Coding System (FACS) [36] in conjunction with a Support Vector Machine (SVM) [37]. FACS are mapped to action units (AUs) by using the open-face behavior analysis toolkit [38]. The extracted AUs are treated as features which are further used to train the SVM.

Shallow Convolutional Neural Network

This approach uses Convolutional Neural Networks (CNNs) [39] which are state-of-the-art deep learning models for image recognition tasks [40]. CNNs learn and automatically extract the generalized features from the given images using learned kernels; hence, manual curation for feature extraction is not required. In the e-VITA project, we used CNNs for meaningful feature space learning, and a dense layer for the mapping of feature space to decision space. The end-to-end Shallow CNN has four convolutional and pooling layers for feature extraction and two fully connected (dense) layers for mapping the features from latent space to decision space.

Preprocessing of the input image is done in two stages, as follows: In the first stage, extraction and face cropping are performed with the Python open source MediaPipe library [41]. In the second stage, the cropped faces are transformed from RGB to grey scale, and the images are resized to $48 \times 48 \times 1$.

The Shallow CNN architecture consists of four convolutional and max-pooling layers (see Figure 5). First the cropped and resized faces ($48 \times 48 \times 1$) are fed to the first convolutional layer, which has 32 kernels (3×3), followed by a batch normalization layer [42]. In the second convolutional layer, the resultant features are then further convolved with 32 kernels, followed by another batch normalization layer and the down-sampling of the features with a max pooling (2×2) layer. To further minimize the impact of overfitting, drop-out regularization (0.5) [43] is employed. In the third convolutional layer, features from the second layer are convolved using 64 kernels (3×3) followed by batch normalization. The fourth and final convolutional layer contains 64 kernels (3×3), batch normalization, max pooling (2×2), and dropout (0.5).

Convolved features from the fourth layer are fed into the first fully connected (dense) layer with 64 neurons with batch normalization and dropout (0.5). The second dense layer is the classification layer (softmax), which contains seven neurons, representing the emotions of interest. For all the convolutional and the first dense layers, non-linearity is introduced with rectified activation linear unit (Relu) [44].

3.4. Datasets

3.4.1. Training and Validation Datasets for VER Models

The Training Dataset for the VER model uses the publicly available Kaggle Facial Expression Recognition (FER-2013) dataset [45] for training and validation. FER-2013 contains 48 $\times$48-pixel grayscale images of cropped faces. The training set of the FER-2013 dataset consists of 28,709 examples, whereas test set of FER-2013 consists of 3589 images of the seven following emotions: Angry, Disgust, Fear, Happy, Sad, Surprised, and Neutral.

The Validation Dataset of the model consists of 3589 test images of the FER-2013 dataset. The validation accuracy of the employed Shallow CNNs model on the FER-2013 test dataset is 61%, the fine-tuned Mobile net V3 is 50%, and the conventional framework is 43%. The fine-tuned Mobile net V3 achieved up to 88% training accuracy and 50% validation accuracy, which is a clear indication of overfitting. Therefore, we did not include the pre-trained model for further analysis.

3.4.2. Evaluation Datasets for VER Models

The Trained VER models were evaluated on the two different Datasets of senior people: the LivingLab Datasets, and the Corpus of Interaction between Seniors and an Empathic Virtual Coach in Spanish, French and Norwegian (CISEVCSFN) [46].

The LivingLab Dataset is a video dataset of senior people created in the LivingLab studies of the University of Siegen. The first testing of the VER-model used the e-VITA age-specific subsample of this data. Data Collection was done during a living lab session conducted at the University of Siegen, where a video data corpus comprising eight participants was generated. During the session, the participants engaged in a thirty-minute interaction with an android robot. The initial phase of interaction was carefully crafted as a Wizard-of-Oz setup [47], wherein the android' s utterances were under the control and authorship of the researchers. The participants were recorded with an external camera on a tripod standing next to the Android Robot. All the videos were post-processed and re-encoded to .mp4 format with around 30 frames per second and maintaining the original aspect ratio.

The videos were labeled manually by one expert annotator. For the video emotion annotations, the whole video was considered, i.e., video segments that correspond to the user speaking, and video segments that correspond to the user listening to the virtual coach. The videos were annotated with temporal start-end marks for each emotion using ELAN software (ELAN Version 6.2). Only surprise, anger, happiness, and neutral have been annotated, as other emotions did not occur within the interaction between the seniors and the Android Robot.

The CISEVCSFN dataset consists of the following emotion classes: Angry, Happy, Sad, Pensive, Surprise, and Others. It was labeled by two annotators, who sliced the full videos of each participant into small chunks and assigned one of the above-mentioned labels to each chunk. It was possible for both the annotators to agree and assign the same label to one chunk, or both the annotators could disagree and assign different labels to the chunk, or one of the annotators could not distinguish the change of emotion and miss the chunk and could not assign the label to the given chunk. For our analysis, we only considered the video chunks where both the annotators agreed and assigned the same label. The distribution of the clean data is given in Figure 6. Concretely, both annotators assigned 824 snippets (Pensive: 531; Happy: 274; Others: 11; Surprise: 7; Angry:1; Sad: 0) with the same emotion label.

3.5. Evaluation Procedure

We used the AU in combination with the SVM-based model (conventional method) and the Shallow CNN on the LivingLab data corpus. During annotation, a time interval (with starting and ending time) of a video was labeled with one of the above defined seven basic emotions. Both the models were trained on static images, and to generate one prediction during the annotated time interval, frames were extracted after every 33 msec and a simple criterion was introduced to assign a label to the given video by calculating the mode of predicted outputs of all the frames of a video. Mathematically, this operation is represented in the equation below.
ypred(video)=modeypredframe

Next, the mode operation was applied to all the predictions of the extracted frames to get one final prediction. We evaluated the trained model on each recording session individually. The evaluation performance of both models on five selected recording sessions is shown in Table 1. Shallow CNN outperforms its counterpart (AU+SVM) on four out of five recording sessions. Overall, the Shallow CNN achieves 48.95% mean accuracy and AU+SVM achieves 21.92% accuracy.

In addition, we evaluated the trained Shallow CNN on CISEVCSFN, which contains a different set of example emotions. Originally, the Shallow CNN is an image classification model. Here, however, we have videos of small duration to classify. Therefore, the criteria defined above were used to extract the single label from the given video. Otherwise, slight adjustments in the name conventions were made, where we renamed “Neutral” as the “Pensive” class, and “Disgust” and “Fear” were combined and renamed “Others”.

3.6. Emotion Evaluation Results

3.6.1. VER Evaluation

Additionally, to report the results in a more transparent way, we used confusion matrices (see Figure 7 and Figure 8) on all the examples of all the recording sessions. Most examples of the evaluation dataset belong to the class “Happy”. The Shallow CNN correctly classified 22 examples, while AUs + SVM only correctly classified 9 examples out of a total of 26 examples. The class with the second highest number of examples is “Neutral ”, where the Shallow CNN correctly classified 3 and AU + SVM correctly classified 2 out of the 14 examples. The results shown in Table 2 and Figure 9 suggest that Shallow CNN is a better option than its counterpart, with an evaluation accuracy of 55.1% versus an evaluation accuracy of 22.4% demonstrated by the AUs + SVM model. However, it also suggests that the Shallow CNN is biased towards the “Happy” class.

In conclusion, the Shallow CNN model shows promising results since it outperforms the AU+ SVM model. However, the current version of Shallow CNN has certain limitations. Firstly, it exhibits a bias towards the “Happy” class, leading to the misclassification of neutral faces as happy faces. Secondly, its evaluation was conducted on a small subset of the available evaluation dataset. Thirdly, the evaluation dataset was labeled by only one expert annotator. To address these limitations and pave the way for future improvements, two potential approaches are recommended. Firstly, fine-tuning the Shallow CNN on both the University of Siegen training dataset and other datasets can enhance its performance. Secondly, annotating the data using the expertise of at least two experts would ensure more reliable and robust evaluations.

3.6.2. CISEVCSFN Evaluation Results

The evaluation performance of the Shallow CNN on the CISEVCSFN is shown in the confusion matrix (Figure 9). Here, the confusion matrix has the following classes: Angry, Sad, Happy, Others, Pensive, and Surprise, Pensive and other emotions were not defined in the training dataset, so we renamed them as "Neutral" and merged the "Disgust" and "Fear" classes and called them "Others".

The overall classification accuracy of the model is 64.9%. In addition to classification accuracy, we reported the precision (78%), recall (65%), and f-1 scores (71%) as additional evaluation metrics (see Table 2). These results demonstrate the high generalization quality of the Shallow CNN on the data of the people in the older-aged group.

4. Sensor Models in the Coaching Dialogues

4.1. Data-Driven Dialogues for Proactive Interactions

As stated earlier, the e-VITA virtual coach delivers accurate information on various aspects of daily living, offering proactive advice based on environmental sensor data. These proactive dialogues covered several domains such as daily activity, nutrition, safety, gaming, and motivation.

All proactive dialogues start with an intent that contains the External_ prefix. Daily activity and nutrition are dialogues started by the robot to ask about the user's daily routines and nutrition habits. The responses of the users are stored in the DE to personalize future interactions with the system involving these routines. Some time-based proactive dialogues are set up at different times of the day to ask about the user's feelings and to break up the loneliness of the user by starting dialogues about different topics. The initiation of the dialogues is conditioned by the presence of the user in the same room as the robot. The robot always starts by greeting and asking for permission to talk in the case of a proactive dialogue.

The diagram in Figure 10 outlines a decision tree within the e-VITA virtual coaching system, strategically designed for heat stroke prevention dialogues using the WBGT index. This user-friendly decision tree provides specific virtual coach actions and advice for various WBGT ranges, enhancing user awareness and safety.

The decision tree systematically guides users through different scenarios based on the WBGT index, ensuring appropriate actions are taken to prevent heat-related risks. It incorporates a repetitive alarm as a reminder mechanism, reinforcing the importance of user engagement. The advice provided escalates in accordance with the severity of the temperature conditions, with a particular focus on the heightened vulnerability of older individuals to heat stroke.

The decision tree customizes its responses according to three distinct WBGT labels, i.e., warning (25 °C $\leqslant$WBGT <28 °C), severe warning (28 °C $\leqslant$WBGT <31 °C), and danger (WBGT $\geqslant$31 °C), ensuring that users receive information relevant to the specific severity of the environmental conditions. The inclusion of the question "Did you hear the warning?" followed by the appropriate actions ensures user engagement. The repetition of the alarm in the case of a negative response is implemented in situations where users might miss or not hear the initial warning. The advice provided for each WBGT range is proactive, offering preventive measures, such as taking breaks, staying hydrated, and adjusting activities. As the WBGT index increases, the advice becomes more reactive and urgent, with specific recommendations for dealing with higher temperatures, including the use of air conditioning and, in extreme cases, the suggestion to call an ambulance.

4.2. Adaptive Dialogues Connected to the EDS

As previously discussed, a proactive dialogue framework was designed that adapts to the emotional state of the user based on the outcomes of the Emotion Detection system (EDS). The course of the dialogue is guided by the labels provided by the EDS's SER Model. The dialogue approach in "External_How_Was_Your_Day?" outlines a series of speech-based interactions between the user and the coaching system, facilitated by the analysis of the acoustic properties of the user's speech and decisions. An outline of the decision tree within the e-VITA virtual coaching system course of the dialogue is presented in Figure 11.

The interaction begins with the system greeting the user (e.g., "Hello -username-, how was your day?") to initiate a friendly and inviting conversation. This initial step elicits speech data for the subsequent acoustic speech analysis.

After the user shares details about their day, the coaching system analyses the response, focusing on acoustic cues to identify the user's basic emotions. If emotions like happiness, surprise, or neutral are detected, the user is presented with the options of engaging in conversation with a friend, practicing self-reflection, or listening to music. Self-reflection has been shown to increase awareness of positive experiences [48], while listening to music is associated with improvements in overall well-being [49].

If emotions such as anger, fear, or sadness are detected, the system offers targeted assistance. It first asks about the user's concerns (e.g., "Do you worry about those things?") to assess their openness to the proposed interventions. The user can then choose between Gratitude Journaling or Mindfulness Exercises if they like. Each intervention is designed to address or enhance emotional well-being. An exemplary screenshot of such a dialogue in the e-VITA dashboard can be seen in Figure 12.

In the case of choosing the Gratitude Journal, users are prompted to identify up to five things they are grateful for from the past day. Research indicates that gratitude journaling positively impacts well-being by enhancing emotional and social well-being [50], improving relationships, and promoting prosocial behavior [51]. Upon completing this exercise, the user has the option to set a reminder, including a timer, with the assistance of the coaching system to ensure the daily repetition of this beneficial practice.

In the case of choosing the mindfulness exercise, the user is subsequently presented with the option to engage in either a Body Scan Meditation or an Environmental Meditation. The Body Scan Meditation involves sequentially focusing on different parts of the body to increase body awareness and promote relaxation, helping individuals become more attuned to physical sensations and develop a sense of calm [52]. Environmental Meditation focuses on the surroundings during meditation, cultivating a sense of tranquillity and connectedness with the environment.

Mindfulness in general, as documented in existing research, enhances the capacity to respond to the present moment rather than react impulsively. Studies have shown that this practice reduces suffering and promotes well-being by fostering non-judgmental engagement with all experiences, whether positive, negative, or neutral [53].

If the user reports feeling unwell but declines to engage in an intervention, the coaching system recommends seeking a conversation with a trusted individual, such as a family member or friend. In the absence of available personal contacts, the system advises contacting a help hotline. This interaction enables users to share feelings, receive support, and gain new perspectives, thereby enhancing emotional support and overall well-being.

While only SER is employed in this specific dialog, the development of VER opens possibilities for future applications where combining SER and VER could deliver a more comprehensive emotional assessment. Scenarios where users are more stationary, or where smart home environments include cameras that capture facial expressions from a distance, could harness both verbal and facial cues to create a richer emotional profile and enhance personalization.

5. Conclusions and Future Work

In this paper, we explored the role of sensor technology in the e-VITA project, focusing on two important components of the e-VITA virtual coach: the data fusion and emotion recognition models. The data fusion model integrates heterogeneous data about the user’s activities and environment, while emotion recognition plays a crucial role in understanding the user’s mental state and tailoring the coach’s responses accordingly.

The Data Fusion Platform (DFP) collects data from a variety of smartphone and motion tracker sensors and calculates real time labels for each of the user’s activities. It also measures temperature, humidity, and CO2 and noise levels using an indoor climate monitoring system.

Our experiments show the need for heterogeneous data fusion due to the diverse nature of the data sources. We employed a flexible architecture framework involving machine learning-based HAR [6] to handle data heterogeneity issues. Issues with data fusion were explored especially in the area of user localization using a PIR sensor network and actimetry signals from wearable devices.

The DPF operation is illustrated through the following two key examples:

1. Environmental monitoring for heat stroke warnings;
2. A proactive notification system that alerts users to important events.

To initiate proactive dialogues based on predicted user situations, the e-VITA system employs an Event Processing/Rule-based approach. This is implemented as a notification system which is integrated into the communication scheme among the different components of the e-VITA system. The signals were integrated for interaction with Knowledge Graphs and the Dialogue Manager, using combined algorithmic and architectural principles.

The data fusion model for activity prediction assumes that there is one motion sensor in each room. However, in practice, this was a limitation for test scenarios, since some users did not allow the installation of several sensors in their home, so the tested scenarios were limited since the users were not equipped with a sufficient number of motion sensors.

The Emotion Detection System (EDS) includes voice-based emotion detection as well as visual emotion detection using state-of-the-art Convolutional Neural Network technology. The modules were implemented and evaluated separately, and the paper discusses these implementations and presents the results of the evaluations.

The speech emotion detection uses a deep neural network model for emotion classification, constructed from a two-dimensional time distributed convolutional neural network (2D-CNN) and a Long Short-Term Memory (LSTM) network. For visual emotion recognition, we developed and tested two frameworks as follows: The Conventional Framework and Shallow Convolutional Neural Networks.

A use case was developed specifically to evaluate the speech-based interaction, in which the coaching system asked the user about their day. We used the Speech Emotion Recognition model, implemented in the EDS, to assess the user's emotional state based on their verbal responses.

In this article we have discussed the application of the data fusion and emotion recognition models in a coaching dialogue framework based on the specifications of the e-VITA project. Considering future development, some limitations of the work can also be mentioned. For instance, the data fusion model for activity prediction assumes that there is one motion sensor in each room. In practice, however, this was a limitation for test scenarios, since some users did not allow the installation of several sensors in their homes. Thus, the tested scenarios were limited since the users were not equipped with a sufficient number of motion sensors.

Regarding the CNN-based emotion detection model, this was trained on static images rather than videos, so it does not account for temporal dynamics or subtle changes in facial expressions over time. This could impact its performance in real-world scenarios where emotions evolve dynamically. Additionally, the model was trained and validated on seven emotions from the FER 2013 dataset, but it was evaluated on a subset of emotions, such as "Happy" and "Neutral", which could limit its implications.

In future work, it will be important to integrate the two example use cases—environmental modeling and proactive notification system—more thoroughly with the dialogue capabilities of the e-VITA virtual coach. This includes modeling the use of environmental and user-related labels by the Dialogue Manager and the better modeling of the connections between human emotions and verbal communication. Moreover, it is important to pay attention to the limitations discussed above so as to be able to assess the implications of the models on the overall interaction.

The e-VITA virtual coach has been so far evaluated in a multinational proof-of-concept study across Europe and Japan, with results indicating the potential of AI assistants to promote active and healthy aging.

Another important area for future work is ethics and user privacy, while monitoring user activities is crucial for providing proactive assistance, it may also raise privacy concerns. A good balance can be achieved through transparency in the use of the data and by securing access to the data in such a way that it supports the user’s trust in the system. In the e-VITA virtual coach, the Digital Enabler ensured the safe and secure storage of the user’s private information, and these considerations should also be extended to dialogue modeling, which needs to take care of personalized information presentation as well as the use of this information in interactive situations where spoken dialogues may unintentionally reveal private information to other participants in the situation.

Overall, the insights gained from the e-VITA project regarding the use of sensor and emotion-based information to coach older adults towards an active and healthy lifestyle can be considered invaluable, as they provide a solid basis for future research and development in healthcare applications.

Author Contributions

Conceptualization, K.J. and M.M.; Introduction, M.M.; Related Work (Section 2.1), M.H., J.B. and C.L.; (Section 2.2), S.D.R. and M.S.-U.-R.; Technologies used in the e-VITA platform (Section 3.1), M.M.; (Section 3.2), M.H., J.B., C.L. and F.S.; (Section 3.3), S.D.R. and M.S.-U.-R.; Conclusions K.J.; Review and Editing, M.H., K.J. and M.M.; Original Draft Preparation, M.M.; Project Administration, R.W. and T.O. All authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement

The e-VITA project was conducted in accordance with the Declaration of Helsinki, and it was approved by the Institutional Review Board (or Ethics Committee) of the e-VITA project Ethical Board (Antrag Nr. 22-002 an die Ethikkommission von Deutsche Gesellschaft für Pflegewissenschaft approved on 28 February 2022, Protocole CER-U Paris Cité Nr. 2022-33 approved on April 2022).

Informed Consent Statement

Written informed consent has been obtained from the patient(s) to publish this paper.

Data Availability Statement

Data are contained within the article.

Acknowledgments

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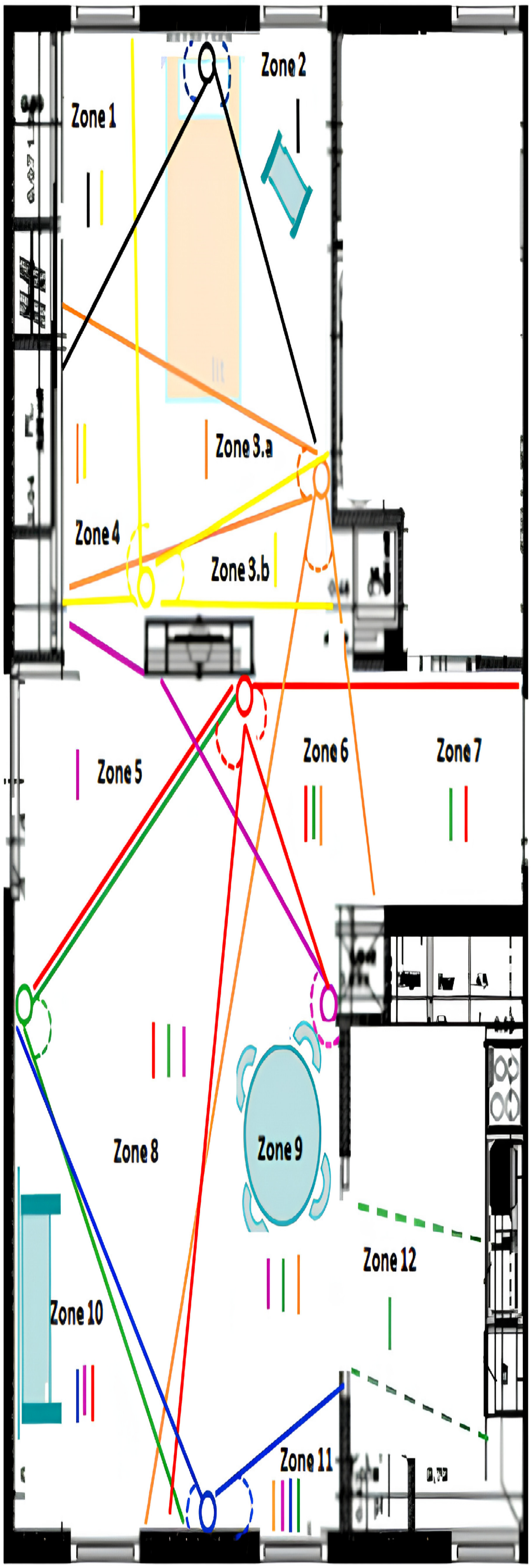
Conflicts of Interest

Authors Sonja Dana Roelen and Muhammad Saif-Ur-Rehman were employed by the company Institut für Experimentelle Psychophysiologie GmbH. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Footnotes

Figures and Tables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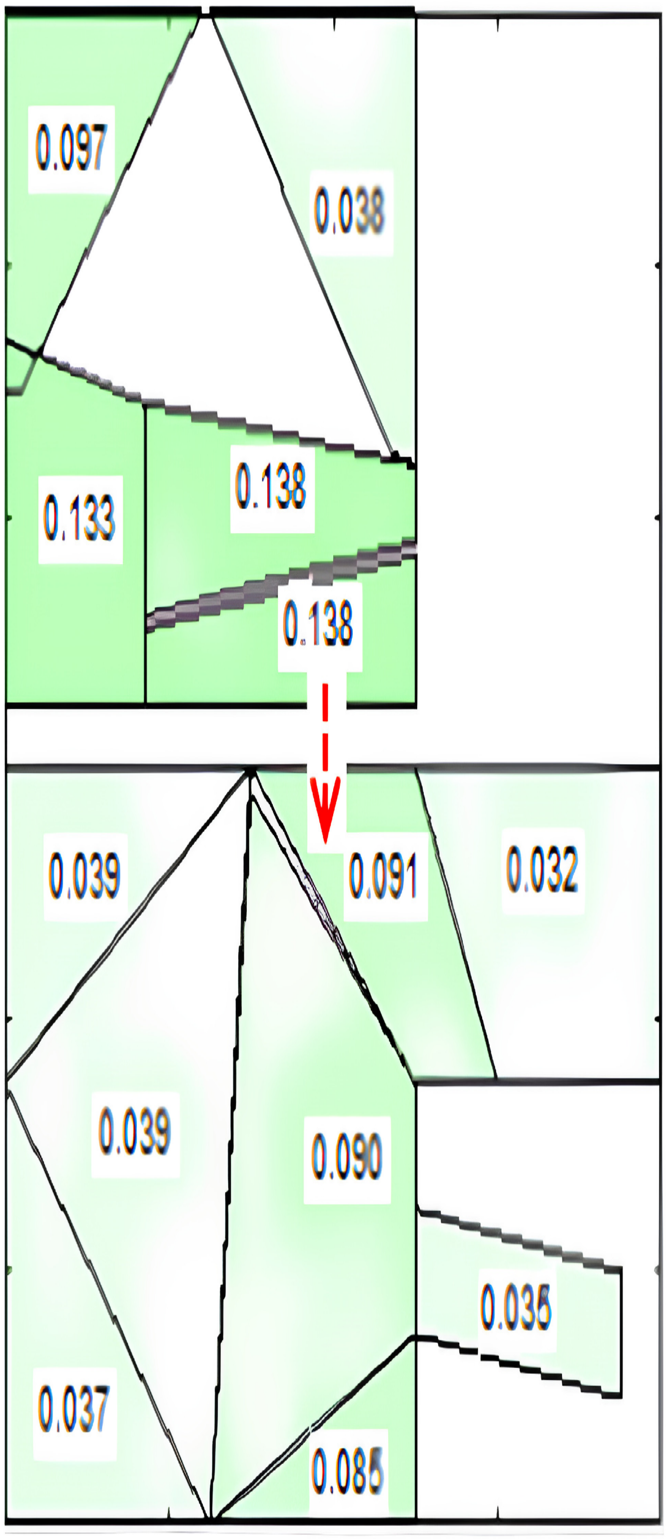
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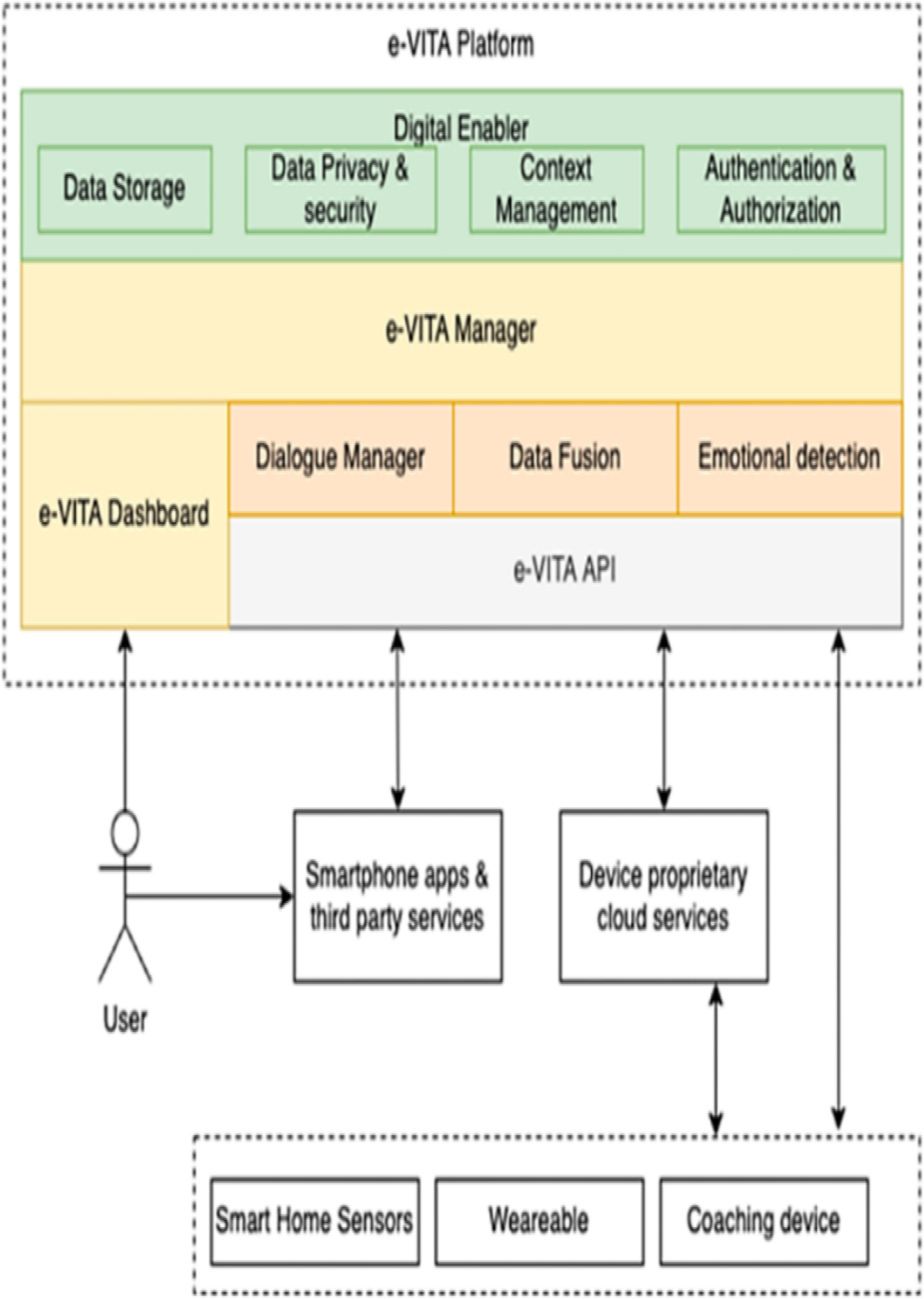

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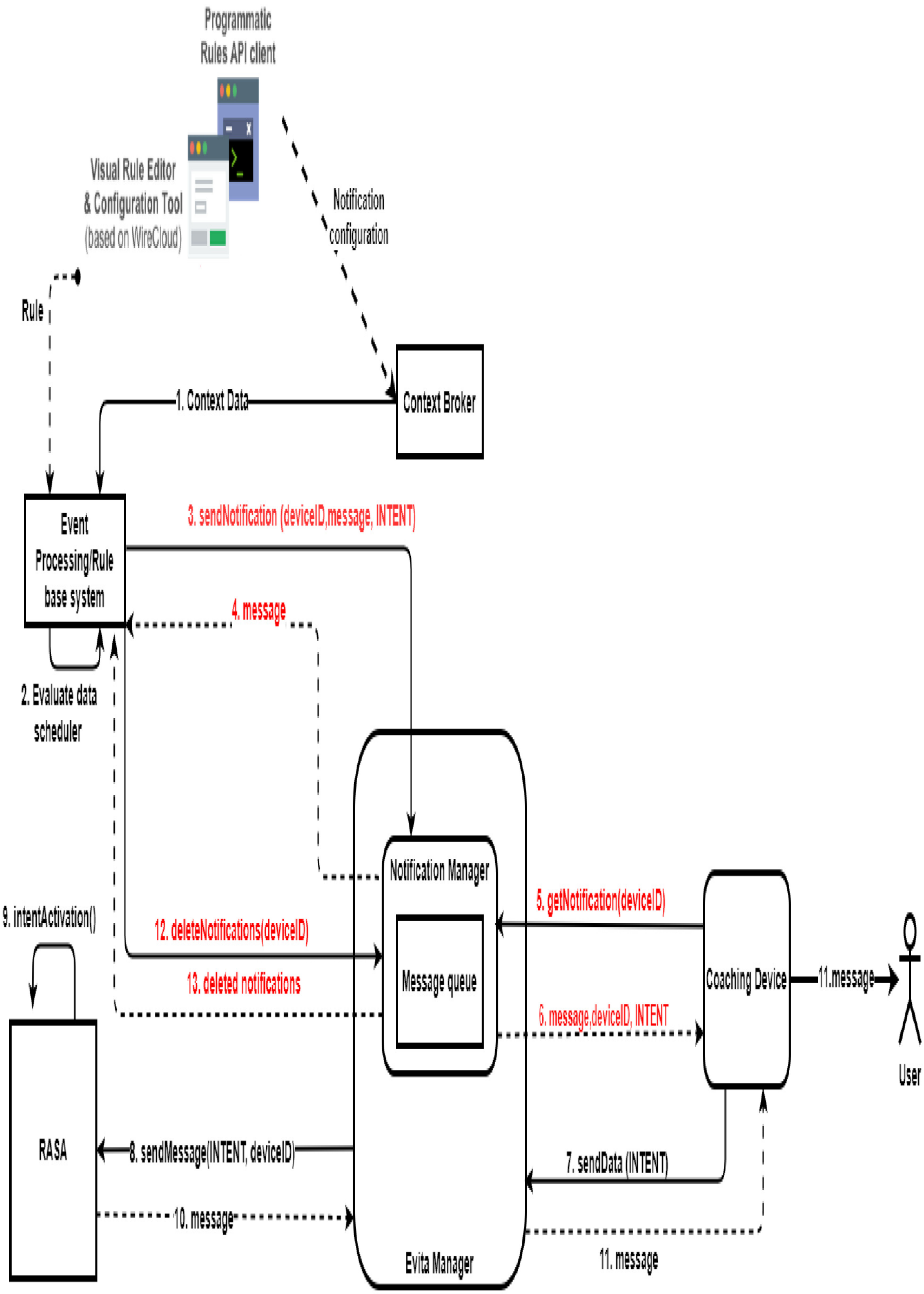

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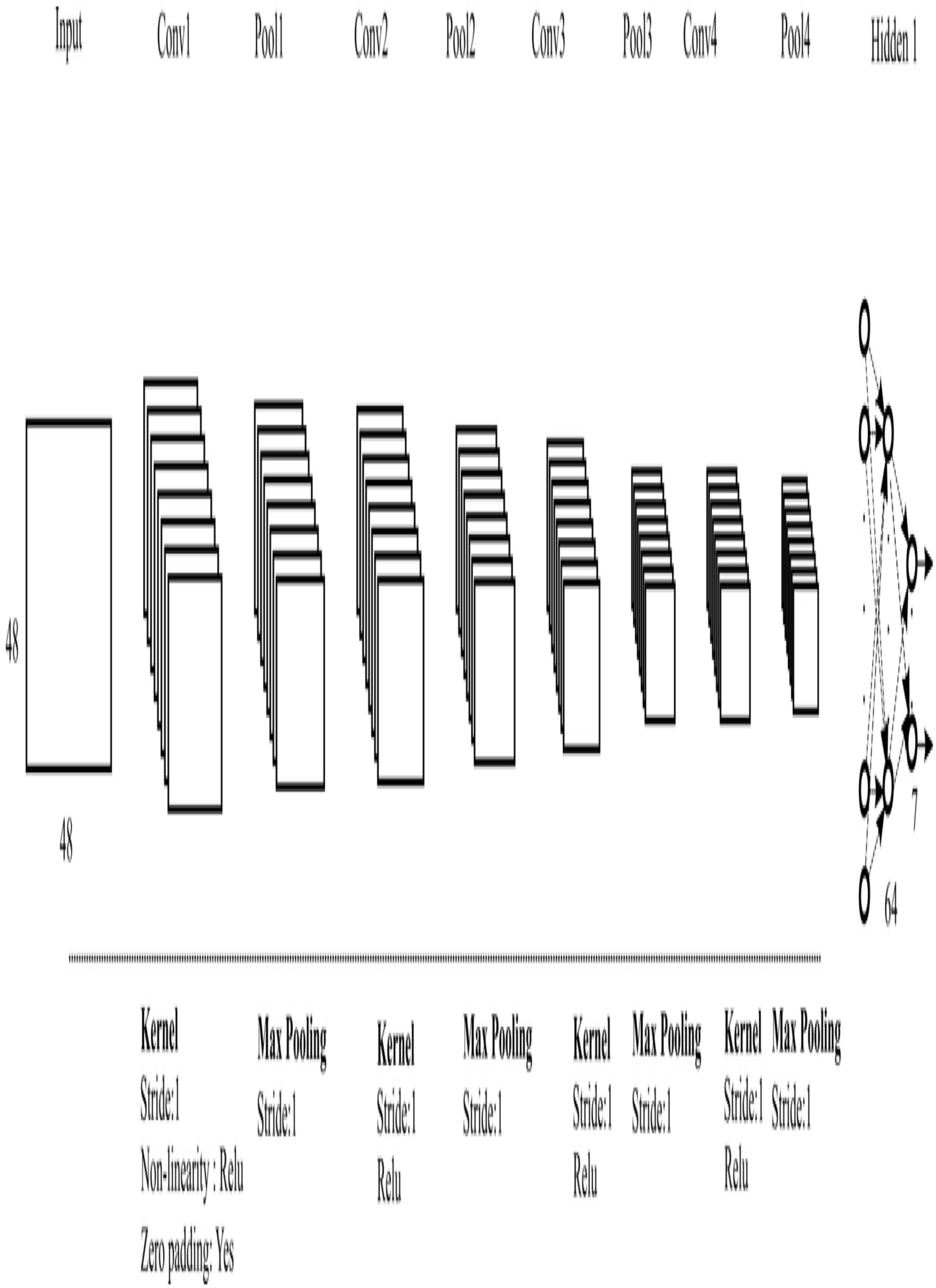

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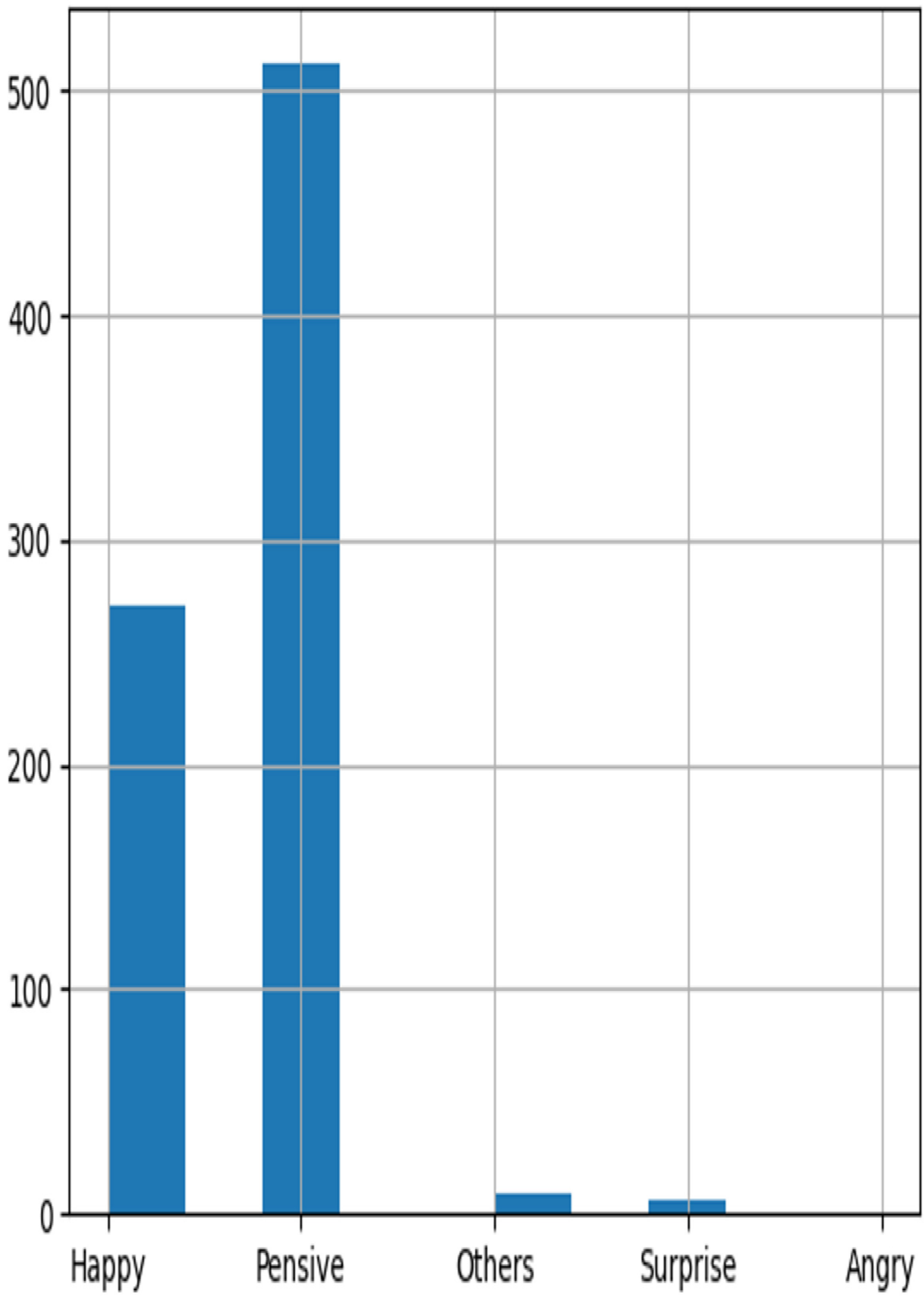

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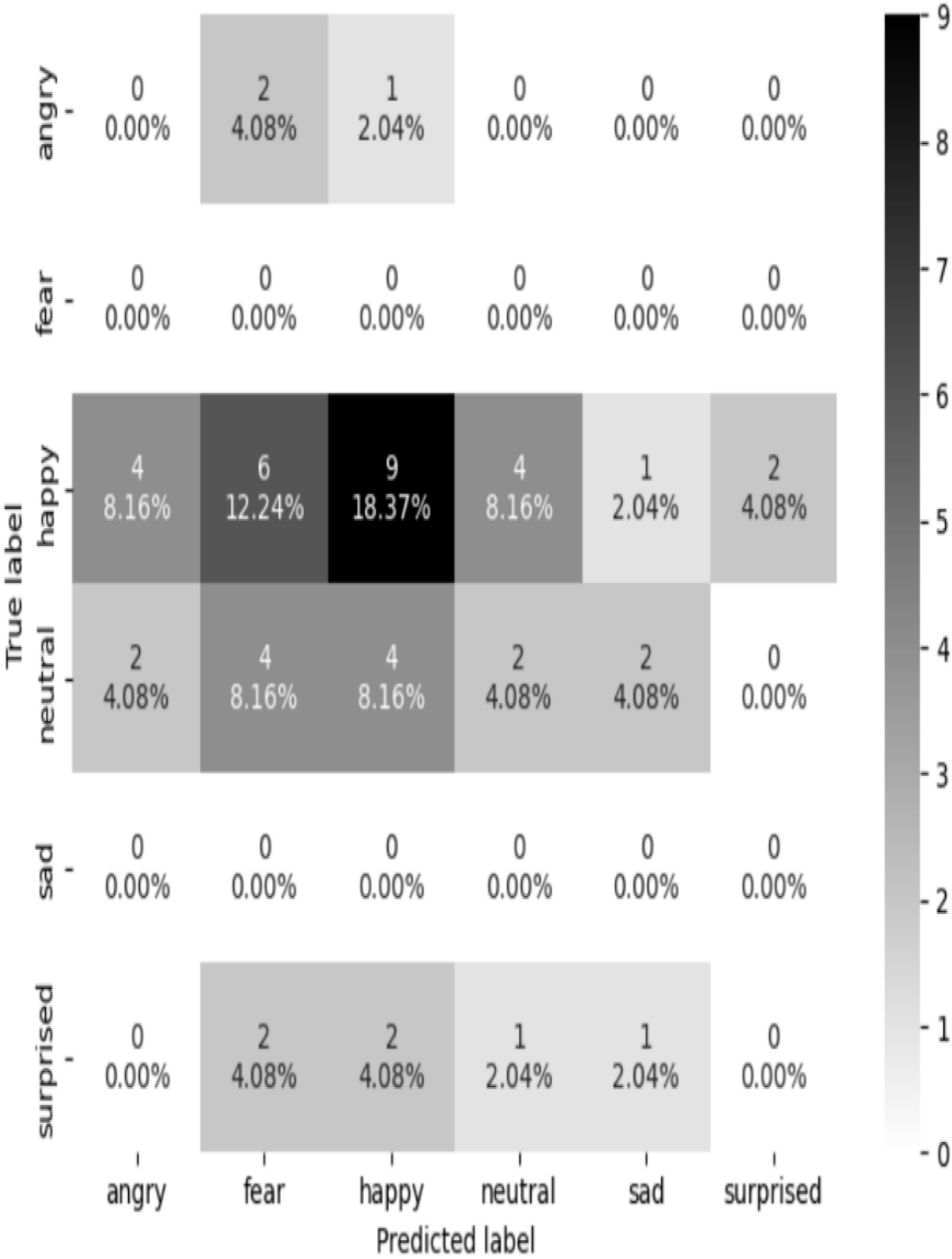

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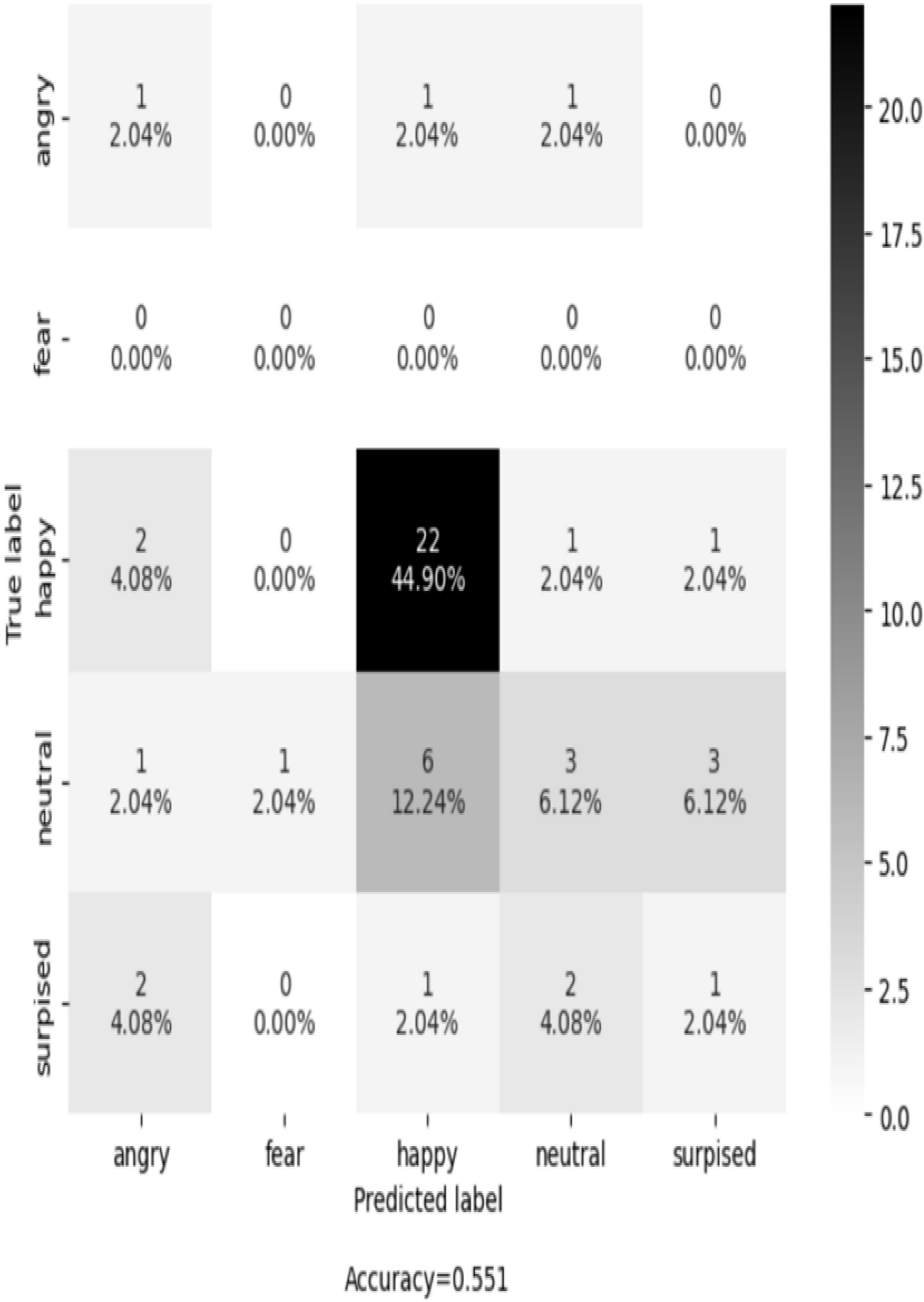

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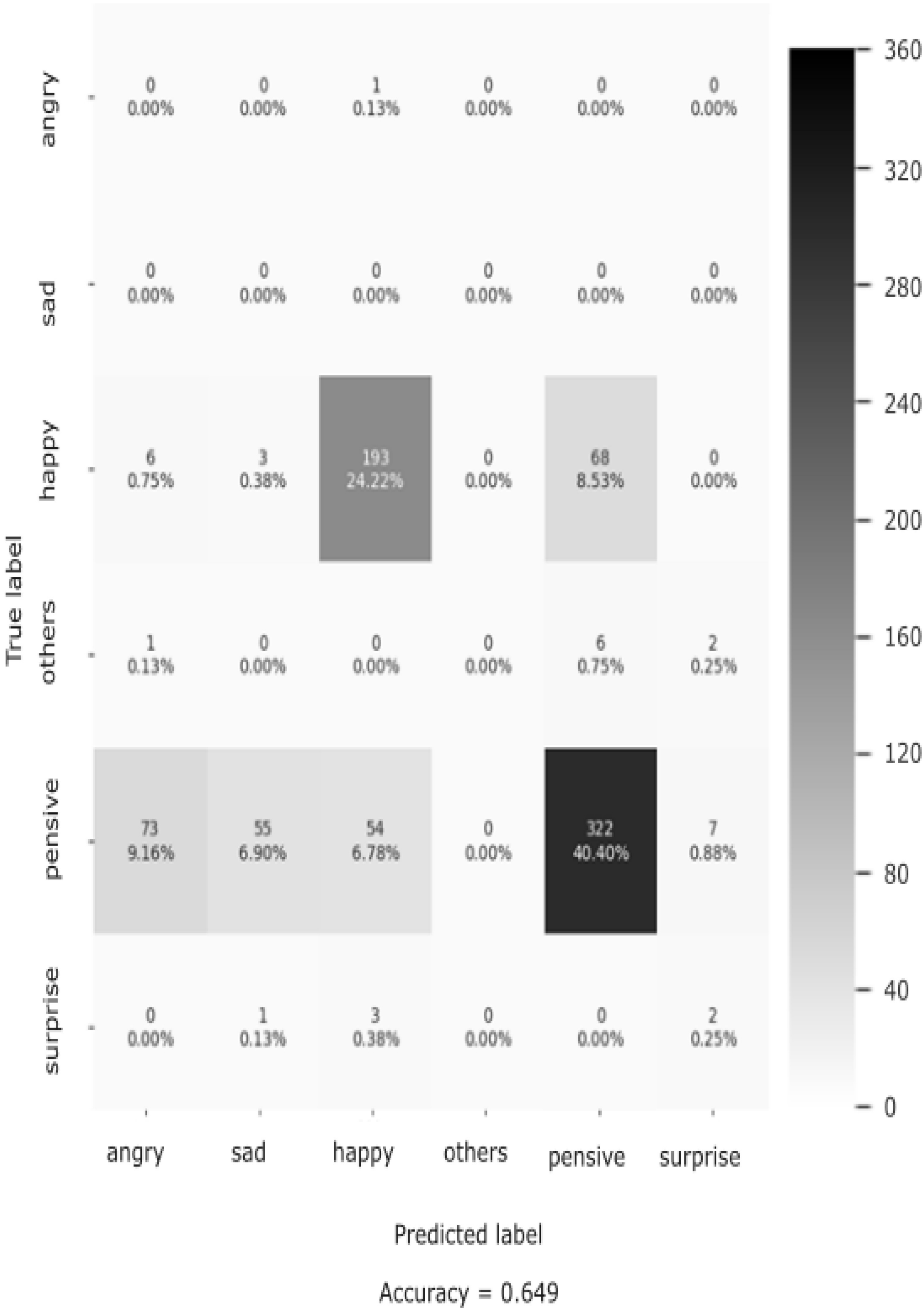

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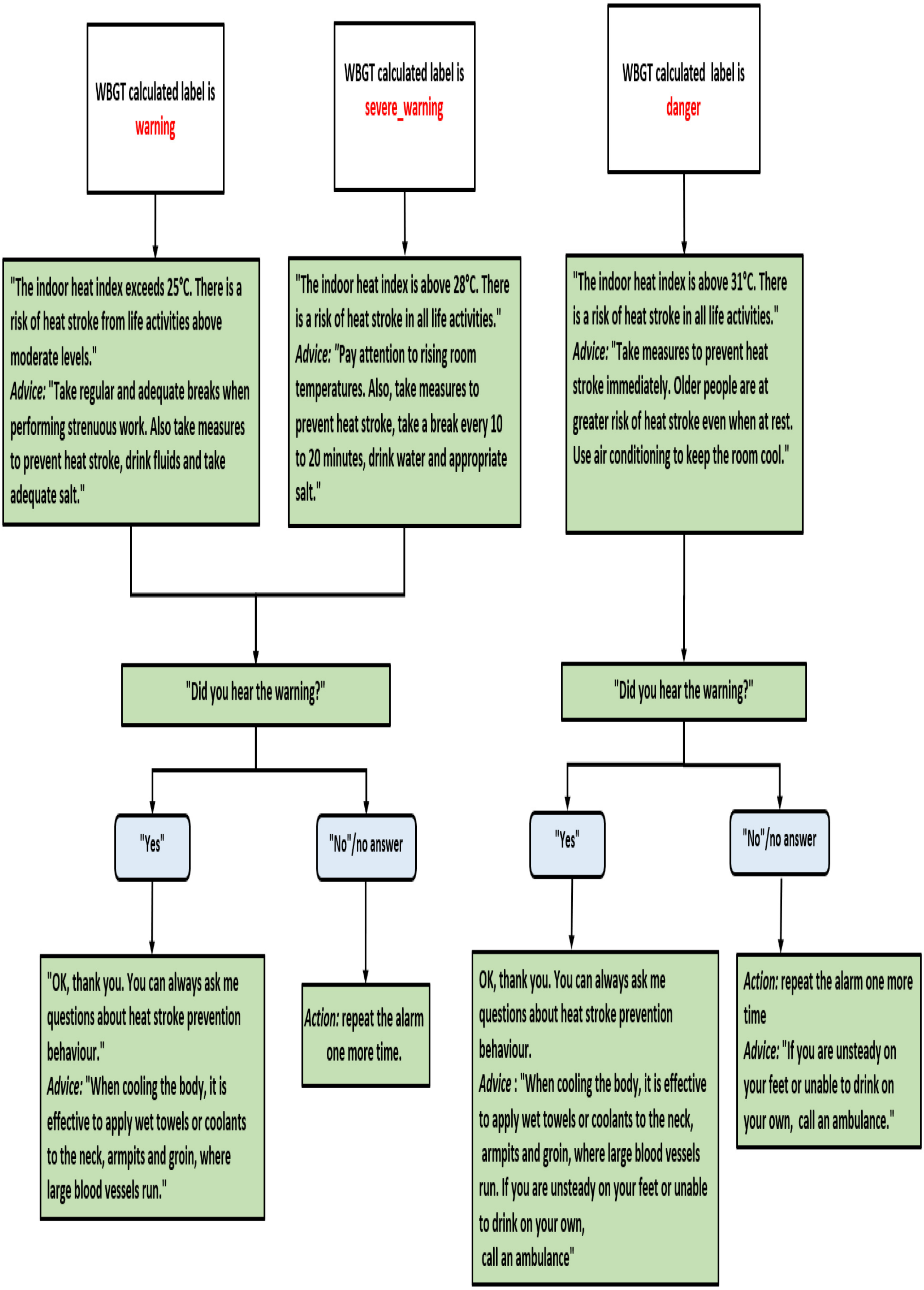

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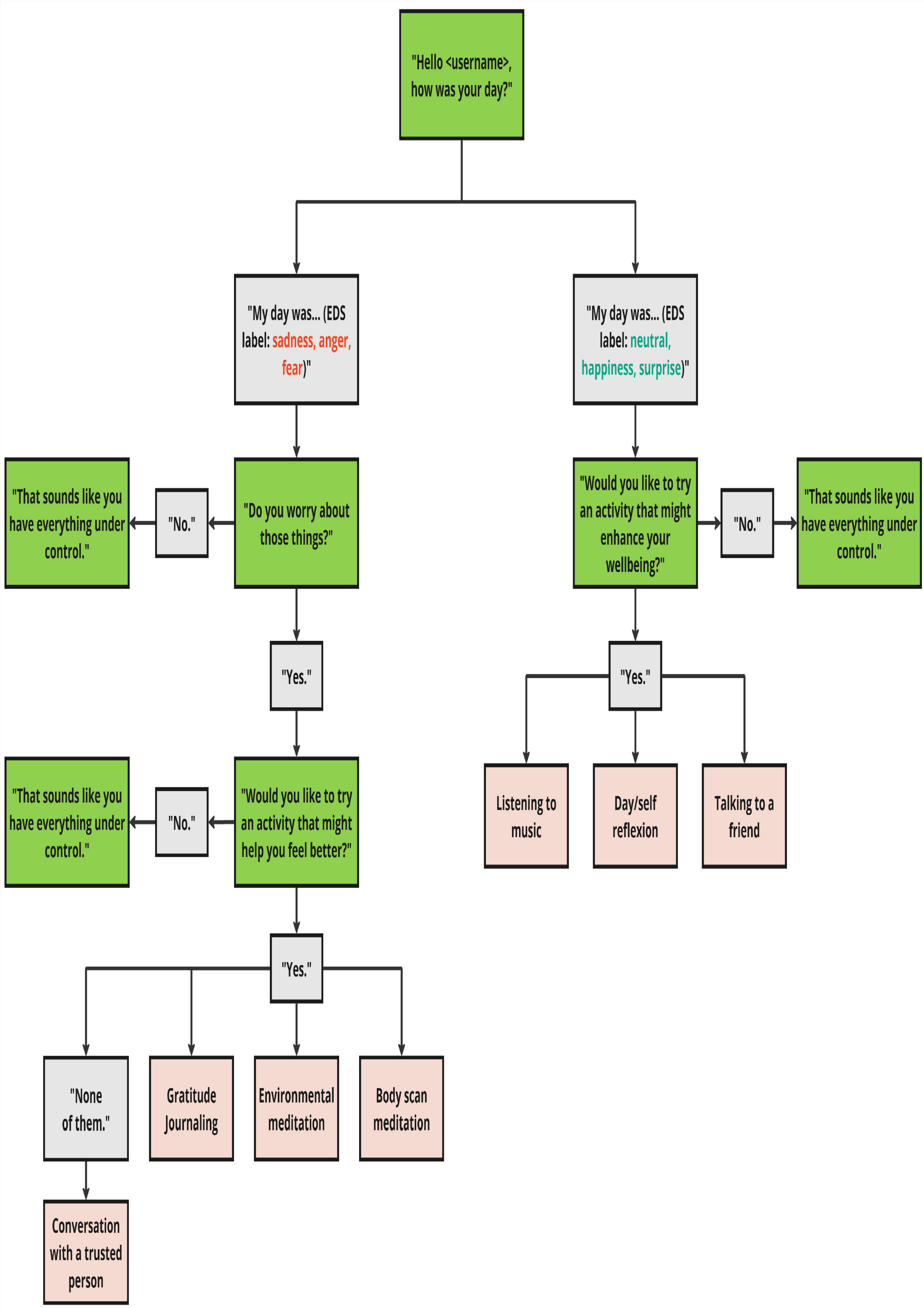

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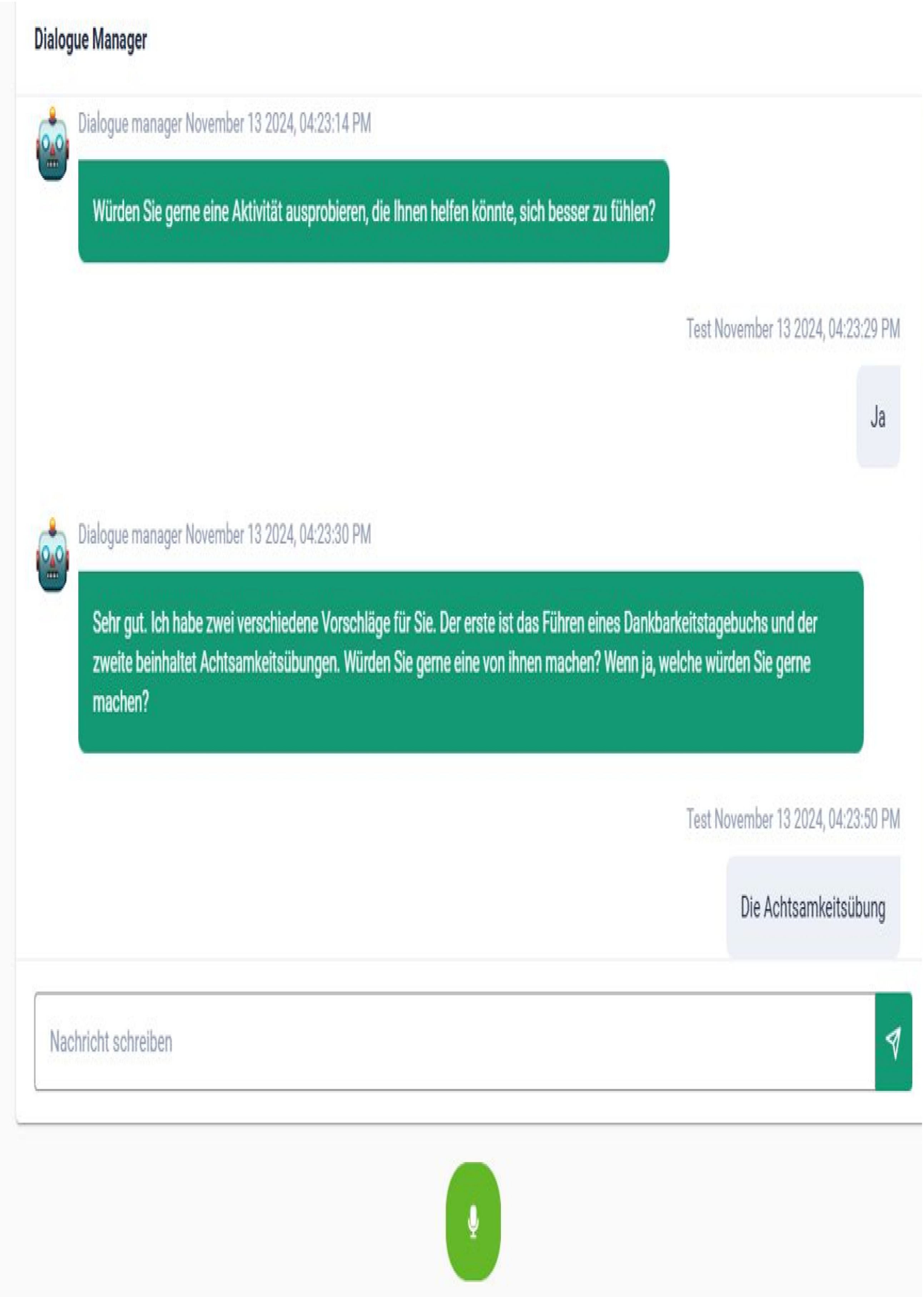

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Table 1
Evaluation performance of AU + SVM and the Shallow CNN on each annotated recording session individually. TN refers to the participant number. The mean accuracy of AU+SVM is 22% and the mean accuracy of the Shallow CNN is 49%.

Session Name	AU + SVM	Shallow CNN
TN1 Wizard	31.25 %	62.5%
TN2 Evita	11.11%	44.4%
TN2 Wizard	14.28%	42.85%
TN3 Evita	20.00%	20.00%
TN5 Evita	33.00%	75.00%
Mean ±std	21.92% ±8.81	48.95% ±18.75

Table 2
Performance evaluation of Shallow CNN on CISEVCSFN.

Weighted Average	Precision	Recall	F1-Score
	0.78	0.65	0.71

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DETAILS

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Technology and Emotions: AI-Driven Software Prototyping for the Analysis of Emotional States and Early Detection of Risky Behaviors in University Students

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ABSTRACT (ENGLISH)

Technology-assisted emotion analysis opens new possibilities for the early identification of risk behaviors that may impact the well-being of university students, contributing to the creation of healthier, safer, and more proactive educational environments. This pilot study aimed to design and develop a technological prototype capable of analyzing students' emotional states and anticipating potential risk situations. A mixed-methods approach was adopted, employing qualitative methods in the ideation, design, and prototyping phases and quantitative methods for laboratory validation to assess the system's accuracy. Additionally, mapping and meta-analysis techniques were applied and integrated into the chatbot's responses. As a result, an educational technological innovation was developed, featuring a chatbot structured with a rule-based dialogue tree, complemented by an ontology for knowledge organization and a pre-trained artificial intelligence (AI) model, enhancing the accuracy and contextualization of user interactions. This solution has the potential to benefit the educational community and is also relevant to legislative stakeholders interested in education and student well-being, institutional leaders, academic and well-being coordinators, school counselors, teachers, and students.

FULL TEXT

1. Introduction

The integration of technology into the educational field is a trend that opens new possibilities and broadens the horizons of knowledge. In this context, the development of technological tools based on artificial intelligence (AI) has significantly transformed various educational scenarios, standing out for their ability to analyze, interpret, and respond in a timely manner to the needs and expectations of students. A clear example of this reality is the application of technologies for emotion identification, facilitating a better understanding of the emotional behaviors that influence retention, social development, and academic performance.

In the current context of higher education, students face increasingly complex emotional challenges, such as stress, anxiety (Trunce Morales et al., 2020), and other states that can lead to adverse consequences, including academic dropout, school coexistence issues, risk behaviors, and significant impacts on their mental health (Jiménez Hurtado et al., 2023). Although universities have implemented psychological support and well-being services to address these needs, these efforts are often reactive and limited in scope, making it difficult to identify students' emotional needs early and implement preventive strategies. Following this reality, it is emphasized that, globally, 168 million adolescents and young people face mental health issues, with 44.7 percent of the population in Colombia experiencing similar challenges (UNICEF Colombia, 2024). Additionally, 230 cases of suicide have been reported within this demographic, highlighting the urgent need to implement mechanisms for the early identification of warning signs, continuous monitoring of student well-being, and the application of personalized interventions. On the other hand, the literature shows significant advancements in the use of emerging technologies, such as artificial intelligence, for emotion analysis. However, these technologies have not yet been integrated into university contexts to facilitate the prevention of risk behaviors. This highlights a significant gap in the research and development of technological solutions that combine personalization and adaptability to address the emotional needs of this population.

Based on the above, this study makes a significant contribution from the perspective of educational technology to address the central issue of the lack of technological tools that enable the identification and self-regulation of university students' emotional states. The goal is to facilitate the early detection of risk behaviors and promote emotional well-being. Complementing this, the research question is formulated to determine how emerging technologies can contribute to the self-regulation of university students' emotional states to facilitate the early identification of risk behaviors.

Technology is a key resource for addressing human needs, including the identification and self-regulation of emotions. Its ability to recognize and analyze data with precision and speed enables the prevention of mental health risks, providing effective solutions based on timely and detailed information.This statement is supported by the study conducted by Alslaity and Orji (2022), who treat the development of systems for the detection of emotions through machine learning techniques and infer that these techniques allow for the analysis of large volumes of data to extract emotional information, facilitating more natural and fluid interactions between humans and computers. From the same perspective, Tawsif et al. (2022), in their research on human–computer interaction, propose the use of physiological signals for emotion recognition. This approach not only significantly improves the ability of systems to accurately interpret human emotions but also opens new possibilities for designing more personalized and adaptive interactions that respond to the specific needs and behaviors of users. Additionally, Bilquise et al. (2022) highlighted the incursion of emotionally intelligent chatbots as one of the most innovative applications of advanced techniques of AI and natural language processing. They stand out, as the training of these chatbots not only gives them the ability to detect and analyze the emotions of the users in real time but can also generate emotionally appropriate responses, adapting to the affective state of the interlocutor and providing more empathetic and personalized interactions by marking before and after the evolution of conversational technologies.

Although the recent literature acknowledges the importance of technologies for emotion analysis in educational contexts, a gap is identified, primarily related to the fact that most of these tools do not integrate validated psychological scales or contextualized normative frameworks on school coexistence. Furthermore, few studies have developed solutions that combine emotional analysis with robust and personalized strategies for emotional self-regulation in university settings. This study seeks to address this gap by developing and validating an educational technology that responds to these needs.

This article presents the process of designing, prototyping, and developing an educational technology conceived as an emotional support tool for university students, promoting a more positive academic experience. The proposed innovation stands out for integrating advanced chatbot programming technology with a pretrained AI model. It uses the Positive and Negative Affect Schedule (PANAS) scale, which has been internationally validated to measure two dimensions of emotional states and the premises of the Colombian National School Coexistence System to recognize possible risk behaviors. In response, the chatbot was trained and validated in the laboratory to offer students recommendations for managing their emotions on the basis of bibliographies from different scientific fields, becoming a technological tool that responds to key challenges related to the emotional well-being of university students in an increasingly demanding context.

This technology contributes to the field of knowledge by integrating an interdisciplinary approach that combines technological advancements, psychological theories, and specific normative frameworks on school coexistence. It provides new perspectives for educational research and the design of solutions aimed at emotional management and student well-being while establishing a solid foundation for future applications in higher education. The article integrates the contextualization of innovation and a theoretical framework that emphasizes the incursion of technology in education, the automatic detection of emotions through technology and recommendation systems, and risk behaviors in students. It exposes the method of design, prototyping, development, and validation of the innovation. The results obtained from the processes developed are presented, and these results are discussed from a theoretical basis. Finally, the article concludes with the main aspects of the study, highlighting the benefits and limitations of innovation and presenting recommendations for the development of future innovations.

2. Foundations from the Literature

2.1. Research on Educational Technology

The technological revolution in education driven by the advances of the 5.0 era has caused an unprecedented transformation in the landscape of teaching and learning, opening doors to horizons and possibilities that were never thought of. Bozkurt (2020) highlighted that research on educational technology has evolved significantly since 1993, moving from approaches based on multimedia and instructional design to the use of big data and intelligent technologies. This evolution reflects a growing interdisciplinarity and greater participation of developed countries in research. Yildiz et al. (2020) inferred that educational technology is the operationalization of scientific knowledge produced in the sciences of education and its application in practice. They identify in their study that current trends in research on educational technologies focus on the practical application of scientific knowledge, emphasizing the importance of adapting educational technologies to the specific needs of students and teachers. Another perspective is presented in the study by Gusho et al. (2023), who indicate that research on educational technology has focused on improving the learning environment, developing effective pedagogical approaches, optimizing assessment, and providing support to students with special needs. They emphasize that the possibilities of educational technologies have been expanded to facilitate access to educational resources, design personalized teaching methods, and improve feedback and evaluation for all students. In this context, research on educational technologies and their development in the 5.0 era should be continued and deepened to identify both existing gaps and new possibilities. This will allow educators and students to adapt effectively to technological innovations, allowing them to use most of these tools to enrich their educational process and better prepare for future challenges.

In line with this evolution, students, as primary actors, have found it necessary to adapt and advance along with educational technologies. They have had to learn to use them effectively to take full advantage of their benefits and to be able to access these tools from anywhere, thus facilitating their training process. Castro (2019) emphasized that digital tools in learning not only facilitate access to education for a greater number of students but also personalize learning activities, improving academic performance and student satisfaction. These tools allow them to learn at their own pace more efficiently, contributing to a more inclusive educational experience tailored to individual needs. Authors such as Manzano Pérez et al. (2023) noted that technological innovation in education not only strengthens the quality of teaching but also promotes self-learning, develops critical skills, and fosters a more interactive and engaged learning environment. In line with this perspective, Bedenlier et al. (2020) stated that educational technology significantly supports student participation in higher education. They highlight the importance and effectiveness of tools such as blogs and mobile learning to promote student engagement, facilitating more dynamic and enriching interactions in the educational process. Together, these technologies not only enhance the active participation of students but also contribute to creating a more inclusive and accessible learning environment. They facilitate the implementation of innovative and effective pedagogical strategies for teachers and provide researchers with valuable opportunities to explore new methodologies and optimize the use of digital tools in education.

2.2. Automatic Detection of Emotions Supported by Technology and Recommendation Systems

Detection and emotion analysis has become a valuable strategy for preventing and detecting possible behaviors that may lead to risky situations, especially in educational settings. This approach allows educational institutions to identify early signs of stress and emotional distress, intervening before situations evolve and turn into crises. Rodríguez-Riesco et al. (2022) reported that the use of technologies for emotional analysis can reveal patterns of anxiety and depression that are not easily detectable through traditional observation and evaluation methods. Similarly, Ringeval et al. (2013) emphasized that the integration of AI systems in emotional evaluation has been shown to be effective in identifying subtle changes in the emotional state of individuals, providing an early warning for intervention. It is important to highlight that the ability of these systems to process large volumes of emotional data in real time enables continuous and accurate monitoring, facilitating timely and appropriate intervention in risk situations (McDuff et al., 2015). These details account for the potential of technology and how it has been integrated into emotional analysis, allowing a deeper, faster, and more accurate understanding of human emotions.

The design and development of technological tools for the automated detection and analysis of emotions are currently a central concern in educational research. In this context, multimodal approaches, which integrate the analysis of emotions through text, sound, images, video, and physiological signals, offer a more advanced spectrum of possibilities. Taken to the educational field, these multimodal methods allow not only for a deeper understanding of the emotional state of the student but also for the faster and more precise recognition of said emotions, anticipating the identification of possible risky behaviors (Marechal et al., 2019). The identification and management of emotions through text analysis with machine learning represents a significant challenge in the implementation of technological and scientific advances aimed at improving the interaction between students and machines. Chatbots, also known as chatterbots, are products of AI that are capable of integrating with any messaging application. These programs can hold conversations with humans via voice commands, text, or both and are considered among the most promising applications of natural language processing (Machová et al., 2023). The literature classifies and describes chatbots in different categories. One of the most common forms of classification is according to the communication channel, which can be text, voice, or images. From the perspective of the knowledge domain, that is, the scope and specialization of the information that they handle, generic or open/cross-domain chatbots, which operate in more than one area of knowledge, and domain-specific chatbots or closed chatbots, which are limited to answering only questions related to a particular knowledge area, are distinguished. The objectives or purposes they seek to fulfill can be divided into informative and conversational chat and tasks (Adamopoulou &Moussiades, 2020). The ability of conversational chatbot systems to maintain a natural conversation with the user, simulating the interaction of a real person, is determined by the design of the conversational workflow, the use of advanced techniques of natural language processing (NLP), and the implementation of a well-structured ontology. The ontology provides a formal representation of knowledge in a specific domain, which allows the chatbot to better understand the relationships between concepts and generate more precise and coherent responses. The response generation module is based on this ontological structure to produce responses via one or more of the three main response approaches, which are the following: rule-based models, which follow predefined patterns and take advantage of the ontology to ensure that the rules are aligned with the knowledge of the domain; recovery-based models, which select the most appropriate response from a knowledge database that is organized and structured by ontology; generation-based models, which create original responses in real time through neural networks and deep learning and use ontology to ensure that the answers are contextually correct and semantically relevant (Colace et al., 2018)

In the educational field, the incorporation of technologies, especially chatbots, powered by machine learning is presented as an innovative alternative both for academic activity and to support the emotional well-being of students. In higher education, chatbots are used in various support roles, both as service assistants and in teaching roles. Its implementation not only aims to improve the academic aspect but also aims to promote accessibility to support services, promote cultural inclusion, and detect the mood of students, thus representing a significant advance in the integration of educational technology (Pérez et al., 2020). An example of the above is the study by Senapati and Phapale (2023), which evaluated the implementation and testing of an emotional support chatbot, yielding promising results for education. Among the total number of students who used it, 85 percent favorably valued it, and those who used it regularly reported lower levels of stress and anxiety, along with an increase in positive emotions such as confidence and happiness. Consequently, 82 percent said that they understood and 70 percent experienced an improvement in their emotional well-being. Another relevant example in the educational field that highlights the integration of emotional support chatbots is EduChat (Dan et al., 2023), a large-scale chatbot system based on language models designed to offer personalized and intelligent education. Among its multiple capabilities, EduChat stands out for offering emotional support to students, owing to its training in a variety of rules and datasets. This chatbot works as an empathetic and compassionate advisor on the basis of a psychological research framework that incorporates approaches such as Rational Emotive Behavioral Therapy and other methodologies focused on the psychology of emotions. The implementation of these conversational tools, with their ability to generate precise, coherent, and contextualized responses, has the potential to positively influence educational processes, facilitating more personalized, empathetic, and accessible learning and the early identification and management of the emotions of students.

2.3. Emotions and Risky Behaviors in Students

Emotional regulation in university students is a continuous and essential process for overall well-being and the prevention of risky behaviors, as the inadequate management of emotions can lead to impulsive and potentially dangerous behaviors. The relationship between emotions and risky behaviors in university students is a topic of growing interest in research. According to Hatkevich et al. (2019), difficulties in emotional regulation during adolescence are strongly associated with the development of severe psychiatric disorders, substance abuse, and suicidal behaviors. They argue that the inability to adequately manage negative emotions can lead to risky behaviors as mechanisms to cope with emotional distress. Similarly, Cerniglia et al. (2023) emphasize the importance of emotional regulation as a central factor in preventing dangerous behaviors during adolescence. These authors examined the interrelations between risky behaviors and difficulties in emotional regulation, finding that the lack of access to emotional regulation strategies is linked to self-harm and risk-taking behaviors. A study conducted by Trógolo et al. (2022) supports this idea by demonstrating that adolescents who experience intense negative emotions and have difficulties regulating them tend to adopt impulsive behaviors as a way to mitigate emotional distress. The authors note that although these behaviors may provide temporary relief, but, in the long term, they worsen mental health problems, perpetuating a negative cycle that affects both the psychological and physical well-being of young people. Together, the studies highlight how the inability to adequately regulate emotions can lead to potentially dangerous behaviors as escape mechanisms. When young people lack effective tools to manage their emotions, they are more likely, in an attempt to relieve emotional distress, to resort to impulsive decisions that can be classified as risky behaviors, affecting both their physical and mental well-being.

Risky behaviors are behaviors that increase the likelihood of negative consequences for individuals and society; these behaviors can include substance use, unprotected sexual behaviors, violence, suicide attempts, and eating disorders. Adolescents are especially vulnerable to these behaviors because of the rapid changes they experience in their physical, cognitive, and social development. These behaviors have the potential to cause physical, emotional, or social harm, affecting both the individual and the community in general (Leather, 2009).

According to Sanci et al. (2018), risky behaviors are characterized by a high potential for physical, social, or emotional problems. During adolescence, individuals are more likely to engage in these behaviors due to various factors, including hormonal changes, social pressures, and the search for identity. Studies have shown that these behaviors are not the result of a single factor but rather of a complex interaction of elements, such as peer influence, a lack of family support, and adverse personal experiences, which make adolescents more prone to take risks.

From an evolutionary perspective, risky behavior in adolescents can also be interpreted as a strategy to obtain potential benefits related to survival and reproduction. This approach suggests that some risky behaviors are not simply impulsive but can be strategically planned. This view challenges traditional frameworks that attribute adolescent risky behavior primarily to a lack of impulse control (Maslowsky et al., 2019). For example, engaging in activities that challenge boundaries can be a means of gaining respect and acceptance within a social group, which is vital during adolescence.

The environment in which adolescents operate also plays a relevant role in the manifestation of risky behaviors. Environmental influences, such as access to substances, exposure to violence, and cultural norms, can encourage or deter the development of these behaviors. Prevention and education programs can be effective in addressing not only individual behavior but also the environmental conditions that contribute to risky behaviors.

University students face a number of challenges that can contribute to the adoption of risky behaviors. These factors include the transition to a new social environment, lack of parental supervision, academic pressure, and the desire to belong to social groups. Experimentation and sensation seeking are common characteristics at this stage of life and can lead to behaviors that put physical and mental well-being at risk (Leather, 2009). Furthermore, El-Ansari et al. (2009) noted that the presence of multiple risky behaviors in college students is associated with an increased risk of poor academic performance, morbidity, and premature mortality. Studies have shown that behaviors such as smoking, excessive alcohol consumption, and physical inactivity are prevalent in this population. These habits not only affect the immediate health of students but can also have long-term consequences, such as chronic diseases and difficulties in professional life. The pressure to excel academically and social expectations often exacerbate these problems, leading students to seek relief in unhealthy behaviors.

To address these challenges, it is necessary to implement preventive strategies that do not focus solely on a single risk factor but that address multiple possibilities. Universities can play a critical role in providing support programs that promote healthy lifestyles, as well as counseling and mentoring services to help students manage stress and anxiety. It is also important to foster an inclusive and supportive environment where students feel safe to seek help without fear of being judged; promoting recreational and sports activities offers them healthy alternatives that help them channel their energy in a positive way.

3. Materials and Methods

This study follows a mixed-methods research approach and has been conceived as a pilot study, predominantly integrating qualitative methods in the ideation, design, and prototyping phases to understand key needs and perceptions for the development of a prototype. The method applied in this phase is primarily related to the Design-Based Research methodology, which combines empirical educational research with theoretical design in learning environments. This approach aims to create and evaluate educational interventions in real-world contexts, adjusting the design based on observations and feedback received (Baumgartner et al., 2003). In the laboratory validation phase, quantitative methods were employed to assess the system’s accuracy in a controlled laboratory environment. Additionally, mapping techniques and meta-analysis were applied to identify and extract the main self-regulation recommendations generated by the system.

The objective of this study was to design and develop a technological prototype aimed at analyzing the emotional states of university students to offer support and facilitate the early detection of possible risk behaviors. For this purpose, software programming technology and a pretrained AI application capable of analyzing and processing emotional data in real time were used. The research question that guided this study was as follows: How can emerging technologies contribute to the management of the emotional states of university students, facilitating the early identification of risk behaviors? Next, the stages followed in the ideation, design, prototyping, development, and laboratory validation of the innovation are detailed at a methodological and practical level.

3.1. Ideation, Design, and Prototyping Methods

The method used for ideation, design, and prototyping is based on participatory and collaborative approaches characteristic of qualitative methodology, with a particular emphasis on User-Centered Design (UCD). This design approach was implemented in two stages as follows:

1. Cocreation: In this initial stage, 50 university students from different semesters of the academic program of risk management, safety, and health at work, belonging to a Colombian public higher education institution, were integrated as active agents of the design process. Those who gave their consent to participate in a collaborative group activity conducted in a single session were distributed across 7 randomized work groups; the students identified priority areas of intervention linked to their needs for support and student accompaniment, providing key perspectives to guide the development of the prototype and promoting a user-centered approach aligned with their particular contexts. The cocreation session made it possible to collect various perceptions, identify relevant problems, and validate in a contextualized way the proposals for the improvement of the support and accompaniment processes. Table 1 presents a summary of these perceptions as well as the improvement proposals made by the participating students.

2. Prototyping: Using simple stationary materials, each group of students developed prototypes, physical models, or mockups aimed at proposing viable solutions to address the identified priority areas of intervention. These prototypes were subjected to a validation process among the students themselves, allowing direct feedback to be obtained and thus enriching the initial proposals.

In the collaborative workshop, which applied the User-Centered Design method (see Figure 1), the idea with the greatest impact was selected through an interactive vote. The students, using their mobile devices, evaluated and chose the proposal they considered the most appropriate, on the basis of criteria such as feasibility, potential impact, and coherence with the priority areas of intervention. As a result, the students selected the idea of a "humanoid robot" capable of monitoring students' emotions and sending automatic alerts to offer emotional support in real time.

In general terms, as Miranda et al. (2020) noted, the collaborative process promoted and facilitated the generation and socialization of ideas among students, fostering a creative, participatory, and conscious approach to meeting the needs and requirements of university students.

3.2. Educational Technology Development Method

Upon concluding and documenting the results of the collaborative workshop, and on the basis of the prototype selected by the students, the group of researchers channeled and refined the concept, transforming it into an educational technology based on programming software supported by AI. The innovation technical development process was structured according to the phases shown in Figure 2.

3.3. Initial Validation Method in the Laboratory

Once the educational technology (chatbot robot) was developed, a validation process was carried out to determine the level of accuracy in identifying emotions, according to the affective states of the PANAS scale, validated for a sample of university students in Colombia (Moreta-Herrera et al., 2021). The validation of the chatbot was conducted using pre-designed test cases based on the risk typologies analyzed by the robot (Kaner et al., 1999) before and after the integration of the AI "RoBERTuito" using cases. The validation followed the following phases:

1. Use case design: Use cases were documented for each risk category (Types I, II, and III), simulating critical and relevant scenarios for the university context.

2. Assignment of emotional dags: A specific emotion tag was assigned to each predefined case on the basis of the emotion identified in the content.

3. Preintegration accuracy validation: Chatbot accuracy was evaluated prior to AI integration.

4. Postintegration accuracy validation: Chatbot accuracy was evaluated after AI integration to analyze possible performance improvements.

5. Registration and optimization: The results of the validation were documented, identifying areas of improvement in the detection of emotions and responses generated by the chatbot.

To enhance the validity of the research design, the precision validation record file Validation Document (https://docs.google.com/spreadsheets/d/1oSJt4gmjbxREIT0hgz4AceCV4Klcw8wN/edit?usp=sharing&ouid=105191236480538870852&rtpof=true&sd=true, accessed on 27 February 2025) presents the cases or scenarios evaluated for each risk level.

4. Results

In the presentation of the results of this study, several aspects are addressed to understand how the initial concept was transformed into a technological reality. The innovation is detailed from its conception to its technical development and laboratory validation, highlighting the operational functionality of the chatbot, as well as the technologies and tools used in its development. Additionally, the training program planned for the deployment stage is described, aimed at both end users and administrators of the technological tool, including report generation and monitoring.

4.1. Description of the Innovation: From Concept to Technological Reality

Taking as a reference the perceptions identified during the co-creation and prototyping process collected in the collaborative workshop, the researchers developed an emotional analysis and management robot called DOCO, an acronym in Spanish for "Docente Consejero" (Advising Teacher). This robot has the ability to capture and analyze information about university students' emotions in real time, identify and measure them, and offer personalized recommendations and support resources for their management. Similarly, it can identify potential risk situations for both the student and the institution.

Students can access the DOCO robot mobile application from their personal devices or use it on interactive screens strategically located in high-traffic areas of the university campus. Based on the acceptance of the personal data processing policy, students provide information such as age and academic level, among others. Next, the student self-reports his state of mind via the emotions defined in the Positive and Negative Affect Schedule (PANAS) evaluation scale, which was proposed by psychologists David Watson, Lee Anna Clark, and Auke Tellegen (Watson et al., 1988). This scale, widely used in the fields of psychology and education, makes it possible to reliably measure 20 emotions in two main dimensions: positive affect and negative affect. The PANAS scale integrated into the DOCO robot corresponds to the PANAS scale validated in a sample of university students from Colombia and Ecuador (Moreta-Herrera et al., 2021) (Table 2). This scale, which is based on the reliability and factorial invariance of the PANAS scale in both countries, ensures that the evaluation of students' emotions is accurate and culturally relevant. The information provided by students is processed by the robot to offer support and emotional support tailored to their specific emotional needs in an immediate and personalized way.

The management recommendations provided by the robot are supported by principles from educational, psychological, neuroeducational, medical, and other fields, ensuring a solid, reliable, and objective operational foundation. These recommendations have been compiled from the results of a systematic literature review on emotional self-regulation within the mentioned fields of knowledge, using indexed databases (Scopus, PubMed, Web of Science, and PsycINFO) and the peer-reviewed academic literature. The review included studies exploring theoretical approaches, practical interventions, and innovative technologies applied in educational and clinical contexts, enabling the identification of evidence-based emotional regulation strategies. Furthermore, these recommendations have been carefully reviewed to ensure their applicability to diverse educational contexts, including those with high emotional vulnerability.

The search was conducted using the following search string: ("emotional regulation" OR "emotion management" OR "self-regulation") AND ("educational settings" OR "schools" OR "higher education") AND ("psychological interventions" OR "neuroscience" OR "mental health" OR "student support") in indexed databases such as Scopus, PubMed, Web of Science, and PsycINFO. The number of included documents, after applying inclusion and exclusion criteria, is summarized in Table 3. This table outlines the stages of the selection process, from the initial identification of records to their final inclusion in the qualitative synthesis and meta-analysis.

DOCO collects data on the emotions of students through the interactions and analyses of patterns. This information is processed in real time to identify signs and behaviors that can be framed as possible risk behaviors, in accordance with the provisions of the National Coexistence System Colombian School (República de Colombia, 2013). The emotions and other data recorded by the students help the robot DOCO understand their emotional state, and the analysis of this information is correlated with the robot, owing to the integration of a model of pretrained artificial intelligence called "RoBERTuito", which makes it possible to relate the emotions detected with the possible situations that, according to the regulations, may affect school coexistence and the exercise of human, sexual, and reproductive rights. These situations are classified into three types:

- Type I situations include improperly managed conflicts and sporadic situations that negatively affect the school climate but do not damage the body or health.
- Type II situations refer to situations of aggression, bullying, and cyberbullying in school that do not meet the characteristics of a crime and that present any of the following characteristics: *They manifest repeatedly or systematically. *They cause damage to the body or health without generating disability for any of those involved.

- Type III situations include situations of aggression in school that constitute alleged crimes against freedom, integrity, and sexual training, in accordance with the provisions of the current criminal law in Colombia.

Given that one of the proposed objectives of the technology development is to provide a proactive support system that also enables student support staff to intervene before emotional issues escalate into crises that could affect the student or the educational community, the robot has been programmed to generate alerts directed to administrators and student counselors. This allows for a swift and appropriate response to students' emotional needs.

Figure 3 graphically displays the start window, including the robot's conversation interface. Its intuitive, user-friendly, and accessible design stands out, facilitating navigation and quick access to the main functions, ensuring an optimized and efficient user experience for students.

Similarly, to provide greater clarity regarding the robot's interactions with the student, Figure 4 shows an example of the dialogue generated by the robot in the scenario of registering positive emotions. In this case, two variations are included: when the student wishes to receive recommendations to maintain these emotions, and when they choose not to request them. This resource aims to illustrate how the system identifies, interprets, and adapts its responses based on the student's needs and preferences, promoting both self-regulation and proactive emotional support. Additionally, the example highlights the robot's ability to respect the student's autonomy while fostering a personalized and effective interactive experience.

4.2. Conceptualization and Technical Development

This chatbot is structured as a dialog tree, a common technique in rule-based chatbots that guides interactions through predefined flows, where each node represents a predefined interaction or question. User responses trigger the transition to a different node within the tree. This ensures that conversations follow a defined and controlled logic.

- Tree structure: The dialog tree is organized hierarchically, with nodes representing possible user inputs and system responses. Decisions within the tree are based on defined rules (transition rules), through which logical conditions that determine the next node on the basis of the identified emotion have been implemented.

  The dialog flows are designed to go from general questions to more specific questions on the basis of the user's responses, thus allowing a detailed exploration of the user's emotional state.

- Design and development of the rule-based chatbot: The application was developed in its user interface (front-end) via Blazor, an open-source framework from Microsoft, which guarantees a fluid and adaptable user experience. The mobile version, compatible with both Android and iOS, was created using .NET MAUI, a tool that allows the development of applications for multiple platforms, integrating the C and XAML programming languages for interface design. On the back end, the .NET Core 8 API was used, with the data being stored in an SQL server database, which ensured efficient and secure information processing.

- Integration of the AI Model into the Chatbot: A pre-trained AI model has been integrated into the rule-based chatbot (dialogue tree), which uses mapping rules to identify language patterns associated with the emotions from the PANAS model and the consequent risky behaviors as outlined in Colombian Regulatory Decree 1965 (República de Colombia, 2013). This AI model, named "RoBERTuito," acts as a complement to the system, analyzing user responses to detect specific patterns corresponding to positive or negative emotional states.

  The AI integration is based on the fact that RoBERTuito is a model implemented in the cloud and accessible via a RESTful API. This means that the chatbot sends the text entered by the user to RoBERTuito's API and receives a response containing the emotion classification and a confidence level.

RoBERTuito has been used as a pretrained AI model with mapping rules to identify language patterns associated with the specific emotions of the PANAS model. The fine-tuning process is carried out with a labeled dataset that contains affirmations. These affirmations are classified according to their emotional polarity: positive, negative, or neutral. The key aspects of the model training process are as follows:

- Labeled dataset: A dataset of texts in Spanish in which the sentences are already manually classified into categories of emotions was selected. The source for the construction of the data sheet came from social networks (namely X and Facebook), product reviews, or news articles.
- Fine-tuning the model: RoBERTuito adjusted itself via these emotion labels, optimizing its weights so that it learned to predict the emotional polarity of a text on the basis of the context. During this process, the model parameters were updated to maximize the accuracy of the emotion classification.
- CLS classification tokens: The model used a special CLS token at the beginning of each text sequence, which was used to condense the representation of all the text. In the analysis of emotions, this token was essential for the model to emit its final prediction (positive, negative, or neutral) on the basis of the contextualized representation of the text.

4.3. Laboratory Precision Validation Results

The validation was carried out in the laboratory by the design team, following the previously defined validation method. The adaptability of the DOCO robot to respond appropriately according to the emotion identified and the type of associated risk was verified before and after the integration of the AI, according to a reference metric set at 90 percent coincidence.

Evaluated Scenarios:

- Type I: Minor conflicts and sporadic situations: 20 cases
- Type II: School assault or bullying without crime characteristics: 20 cases
- Type III: Situations constituting serious crimes: 20 cases

To validate the greater precision of the chatbot after the integration of the AI "RoBERTuito", the results showed that in cases I and II, the precision increased with the integration of the AI, whereas in case III, both systems maintained the same level of precision (95 percent). Below is a graphical visualization that demonstrates the differences in performance for each category of case Figure 5.

The consolidated results by case and risk level are recorded in a spreadsheet, which is available for consultation at the following link: Validation Document (https://docs.google.com/spreadsheets/d/1oSJt4gmjbxREIT0hgz4AceCV4Klcw8wN/edit?usp=sharing&ouid=105191236480538870852&rtpof=true&sd=true, accessed on 27 February 2025).

4.4. User Training

The training process planned for the robot deployment stage is structured in two stages, according to the experience-based training method experiential learning (Chen et al., 2022; Datta, 2023) proposed by David Kolb. This method is based on an experiential learning cycle that includes four stages: concrete experience, observational reflection, abstract conceptualization, and active experimentation.

In the first formative stage, permanent training is developed that includes explanatory material and individual accompaniment sessions, allowing students to reflect on the importance of mental health care and to become aware of this issue. Throughout this phase, users have their first interaction with the robot, allowing them to experiment and explore its functionalities. This direct interaction constitutes the necessary experience for users to become familiar with the pilot implementation program. During this process, users are encouraged to reflect on their experiences to gain a deeper understanding of how the robot can contribute to the generation of emotional well-being.

The second stage will focus on final training, where users receive more detailed and practical instruction on the full use of the robot, both in its mobile version and the fixed version on the university campus. In this phase, experiences and feedback are collected and analyzed to make final adjustments, ensuring it effectively meets the students' needs. This final training ensures that users are fully prepared to integrate the robot into their routines, maximizing its positive impact on the university community.

4.5. Administration of the Technological Tool

The administration of the technological tool is a shared responsibility that involves various actors within the institution. This collaborative effort focuses on the area of student well-being and the academic vice-rectory, which coordinate the area of student guidance and accompaniment. On the other hand, student counselors and psychologists are important actors in this process, as they can use the platform to proactively monitor and support the emotional well-being of students, ensuring that each receives the necessary support for their well-being emotional development. The management of this software not only increases the capacity of the institution to respond effectively to the emotional needs of its students but also, as highlighted by Aithal and Aithal (2023), strengthens collaboration between the different areas of the university. With the effective coordination between the area of student welfare, the academic vice-chancellor, and the counseling services, the educational institution can offer more cohesive and proactive support, which responds not only to the individual needs of the students but also to the emerging demands of the academic environment.

The main reports generated by the software in relation to the expectation of use are detailed in Table 4. This table provides a comprehensive view of each type of report, including its purpose and the information it offers. These reports range from monitoring emotional states and the effectiveness of interventions to evaluating participation in emotional support programs and the impact on academic performance. The ability to generate these reports allows educational institutions not only to monitor the emotional well-being of students on an ongoing basis but also to make informed decisions to promote a healthier academic environment.

4.6. Ethical and Legal Considerations in the Implementation of the Technology

The design of this technology aims to balance students' ability to self-regulate their emotions with the institutional support necessary to prevent emotional risk situations that could impact their well-being or that of the educational community. This approach aligns with the Mental Health Guidelines for the Higher Education System issued by the Colombian Ministry of National Education in 2023, which emphasize the importance of fostering educational environments that integrate prevention, timely intervention, and respect for fundamental rights. The technological tool enables students to reflect on and become aware of their emotional state, fostering self-regulation and self-care. The alerts generated are exclusively directed to trained professional staff, such as student counselors or administrators, who act in accordance with established protocols to provide the appropriate support.

In this pilot study, the feasibility and preliminary impacts of the innovation are analyzed before large-scale implementation. This process acknowledges and addresses the ethical and legal concerns associated with the collection and use of emotional data, ensuring compliance with privacy regulations and the protection of participants. In this context, the system adheres to the principles of Law 1581 of 2012 on Personal Data Protection, guaranteeing that students or their legal representatives provide informed consent for the processing of sensitive information. During the ideation phase, conducted through a participatory workshop with students, all participants signed an informed consent form specifying the purpose, the use of the collected information, and the confidentiality measures adopted. In the validation phase, since it was conducted in a controlled laboratory environment without direct student participation or the collection of personal data, approval from the institutional ethics committee was not required. However, in future phases of the study, when the system is evaluated with end users, prior ethical review and approval will be sought to ensure compliance with applicable regulations and the protection of participants.

Likewise, the provisions of Colombian Law 2383 of 2024 are observed, promoting the creation of safe and healthy educational spaces while prioritizing privacy, confidentiality, and human dignity at all stages of data management. In this way, the proposed technology is positioned as a preventive support tool, designed to complement mental health strategies and enhance institutional capacity to proactively address students' emotional needs.

5. Discussion

The discussion scheme focuses on how research in educational technology, the automatic detection of emotions supported by technology and recommendation systems, and risk behaviors in students are interrelated and how a chatbot (robot) designed to identify and manage emotions can have a significant effect on the prevention of risky behaviors.

The development of a chatbot robot to assist in the identification and management of emotions in students finds a solid theoretical foundation in the evolution of research in educational technology. As highlighted by Bozkurt (2020) and Yildiz et al. (2020), educational technology has progressed toward a more practical and interdisciplinary approach, where the application of intelligent technologies such as AI has become instrumental in enhancing learning. This advancement has facilitated not only the personalization of educational activities but also the ability to address the emotional and psychological needs of students through advanced tools trained for emotional analysis.

From the perspective of educational technology, the incorporation of chatbots in learning environments also aligns with current trends toward more inclusive and accessible teaching. As suggested by Manzano Pérez et al. (2023) and Bedenlier et al. (2020), these systems not only improve the quality of education and self-learning but also foster a more interactive and engaging learning environment. The ability of chatbots to generate natural and adaptive responses, which is based on a structured conversational model, allows them to play a key role in promoting the emotional well-being of students, an important component in reducing the risk of negative behaviors and facilitating personal development and academics.

A fundamental aspect of the chatbot robot design is that it arises from the identification of the real needs of the students, who are the main actors in the educational process. By putting their concerns and emotions at the center, we ensure that the chatbot not only detects emotional patterns but also responds directly to the specific challenges students face in their academic and personal environments. This approach is aligned with the vision of Gusho et al. (2023), who highlighted the importance of adapting educational technologies to address the individual and specific needs of users.

In this context, the automatic detection of emotions with technologies based on AI, as described in the studies by Rodríguez-Riesco et al. (2022) and Ringeval et al. (2013), has become an important strategy for the prevention and management of risky behaviors. The DOCO robot uses the Positive and Negative Affect Schedule (PANAS) methodology (Watson et al., 1988) to evaluate the affective states of the students; this is a tool that was specifically validated in the university population of the project development area (Moreta-Herrera et al., 2021). This methodology not only provides an accurate measurement of positive and negative emotions but also establishes a solid scientific basis for analyzing emotional states and their possible implications for student behavior.

Risky behaviors in students, such as substance use, depression, and violence, are strongly influenced by emotional and contextual factors. Sanci et al. (2018) and Maslowsky et al. (2019) reported that these behaviors are not the result of a single factor but rather of complex interactions among social, emotional, and environmental influences. The use of a chatbot that can identify and correlate these signals with normative aspects of the educational environment to provide personalized interventions not only supports a proactive approach in emotional education but also aligns prevention strategies with the specific needs of the individual, addressing both the causes and the manifestations of these risky behaviors. As a complement, the robot offers personalized recommendations and support resources drawn from the Rational Emotive Behavioral Therapy (Dan et al., 2023) and scientific literature in the educational, psychological, neuroeducational, and medical fields. This interdisciplinary approach ensures that interventions are not only based on emotional detection and evaluation but also supported by strategies and scientific knowledge that facilitate a more effective response tailored to the individual needs of students.

Importantly, the university environment presents unique challenges that can exacerbate risky behaviors in students. The transition to a new social environment, academic pressure, and the desire to belong to social groups are factors that, according to Leather (2009) and El-Ansari et al. (2009), increase the susceptibility to adopting dangerous behaviors. In this sense, chatbot DOCO can offer emotional guidance and specific resources to students, making it a valuable tool not only for managing stress and anxiety but also for promoting healthier lifestyles and reducing the incidence of risky behaviors.

The robot DOCO is distinguished by its ability to optimize its performance and reach multiple advantages. Integrated development with .NET MAUI allows the application to run smoothly on Android, iOS, and desktop platforms. Additionally, using Blazor to create dynamic user interfaces ensures a smooth and engaging user experience. The precision validation carried out allowed us to evaluate the reliability of the chatbot in the identification of emotions and their corresponding classification according to the type of risk. By simulating cases, the design team observed how the chatbot responded to different predesigned scenarios, adjusting their responses to specific emotions and risk levels, which confirmed their efficacy in the management of critical situations in the laboratory.

The results of the validation carried out showed an improvement in the accuracy of the chatbot after the integration of the AI (RoBERTuito), although some aspects that must be refined before being tested with the end user are identified. This validation not only allows us to demonstrate the positive impact of AI on the performance of the chatbot, but also provides important information to continue optimizing the system to offer more precise and sensitive monitoring that allows us to detect risk behaviors early and support the emotional well-being of students.

The chatbot DOCO system presents various challenges that consolidate it as a tool in constant update and evolution. One of the broadest future possibilities is the integration of multimodal systems, which combine the analysis of different signals, such as text, voice, facial expressions, and physiology, to offer a comprehensive and deep vision of the emotional state of the student, as inferred by McDuff et al. (2015). These multimodal systems allow for a more precise and contextualized evaluation by offering the possibility of analyzing and understanding emotions in real time from multiple data sources. Likewise, the integration of other scales of affective states validated for the context of higher education, as well as a broader spectrum of recommendations for emotional management on a scientific basis, represents a valuable opportunity to increase the precision and depth of the system in the detection of emotions, allowing a more complete accompaniment adapted to the needs of the students. Another aspect is related to the continuous incursion of new AI, which could offer opportunities to complement and strengthen, expanding its adaptation and response capacities.

Similarly, the robot faces certain limitations and challenges that must be considered for its effective implementation. First, there is a need for the constant updating and retraining of the model to maintain its effectiveness. This includes not only incorporating new data that reflect changes in students' communication patterns and emotional expressions but also adapting to diverse cultural and linguistic contexts, especially in heterogeneous populations. The system also faces technical challenges related to its ability to interpret complex emotions, such as mixed or ambiguous states, and to distinguish between explicitly expressed emotions and those that are implicit or nonverbalized. Additionally, the proper management of students' emotional data privacy and confidentiality becomes a significant challenge. Even with the implementation of protection and anonymization measures, there is always a risk of data security vulnerabilities, requiring substantial efforts to address this aspect effectively. Finally, the implementation of the robot requires ongoing technical and pedagogical support, including the training of educational staff to interpret and act on the alerts generated by the system.

6. Conclusions

To respond effectively to the needs and requirements of university students and offer comprehensive support that fosters their emotional and academic well-being, it is necessary to fully understand their perceptions, experiences, and expectations. In response to these factors, the design and implementation of support strategies that integrate collaborative learning and technological innovation allow better adaptation to the specific demands of student life.

The incorporation of technological tools such as educational chatbots powered by AI allows us to offer continuous and accessible support to the emotions of students. These systems can monitor emotional states in real time, identify possible risk situations and provide resources and guidance immediately, significantly improving the perception of accompaniment and support. These tools are essentially based on a multidisciplinary approach that integrates scientific knowledge from psychology, education, and technology, ensuring that the recommendations have a solid foundation, are empathetic, relevant, and focused on the comprehensive well-being of the student.

This study suggests that conversational chatbots such as DOCO, structured as a rule-based dialog tree that guides interactions through predefined flows and the integration of pre-trained AI models, have the potential to be beneficial for the identification and management of emotions, as well as for the prevention of risky behaviors in students. Through the integration of the Positive and Negative Affect Schedule (PANAS) and the correlation of emotional states with the risky behaviors defined in the Colombian National School Coexistence System, the DOCO chatbot has demonstrated its potential to anticipate and respond to critical emotional situations effectively and proactively.

The design and development of applications and technological tools is a driving factor for innovation in educational institutions. Rule-based chatbots, which operate by following predefined patterns and use ontology to ensure that their responses align with domain knowledge, can significantly enhance institutions' ability to monitor and support student well-being, thus fostering an educational environment that values and promotes the integration of innovative technological solutions. Likewise, the incorporation of AI and advanced data analysis systems in the educational field expands the ability of institutions to adapt and evolve in an increasingly dynamic and complex environment.

This study demonstrates the potential of the DOCO chatbot as a technological tool for emotional support in the university environment. Through initial validation in the laboratory, it was found that the integration of AI (RoBERTuito) improves the precision and adaptability of robots in the identification of emotions and possible risk situations. The initial results highlight the importance of incorporating advanced technologies in the design of psycho-emotional support solutions, allowing timely and effective interventions in educational contexts.

One of the main benefits of the chatbot is its ability to provide targeted support for students' emotional needs. Another important benefit is its accessibility, allowing access through interactive screens located in high-traffic areas on the university campus or via mobile devices. This encourages its use and makes it easier for students to seek support when they need it. The technology also offers an anonymous and safe environment where students can share their feelings without fear of being judged, which is especially important during a stage of life when many may feel social pressure or anxiety.

In general, it is recommended that educational institutions integrate this type of technology as part of a comprehensive student well-being program, ensuring the availability of trained human resources to interpret the alerts generated and respond in a timely manner. Similarly, legislators and regulators, as key stakeholders in the process, should establish regulatory frameworks that support the responsible use of AI-based technologies in education, prioritizing the protection of sensitive data and promoting innovation aligned with human and educational rights. For their part, technology developers must provide regular system updates, incorporating relevant data that reflect changes in students' communication patterns and emotional states. They should also continuously work on improving the security and accuracy of the model, with special attention paid to its applicability in culturally diverse contexts.

Future research should focus on the development and promotion of innovative technologies in the educational field while ensuring their responsible use. This involves not only advancing the design of tools that address the needs of the educational context but also establishing ethical and regulatory frameworks that guarantee privacy protection, equity in access, and sustainability in their implementation. Likewise, addressing concerns about dependency on technology and proposing policies and practices that strengthen the protection of student confidentiality are vital aspects of this field. This approach will not only ensure a safe and ethical educational environment but also deepen the understanding of emotional learning, contributing to the design of more equitable, inclusive, and effective educational systems.

Author Contributions

Conceptualization, methodology, investigation, data analysis, writing—original draft, and project administration were all equally contributed by A.C.A.-N., M.-J.R.-C., J.P.H.-R. and J.W.C.-S. All authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

Data are contained within the article.

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Conflicts of Interest

The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

DOCO	Counselor Teacher
AI	Artificial Intelligence

Footnotes

Figures and Tables

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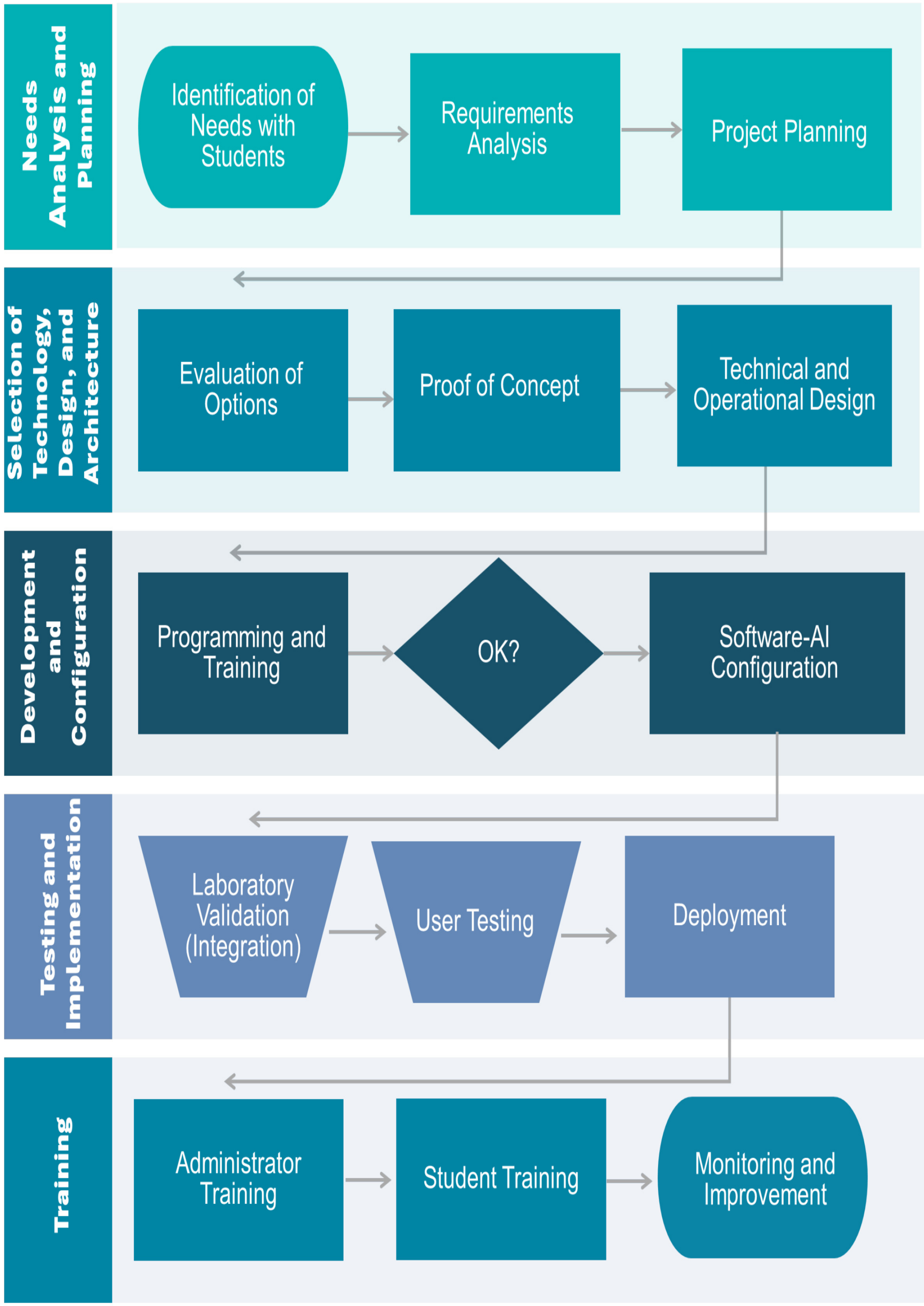
Needs Analysis and Planning
Identification of Needs with Students
Requirements Analysis
Project Planning
Selection of Technology, Design, and Architecture
Evaluation of Options
Proof of Concept
Technical and Operational Design
Development and Configuration
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OK?
Software-AI Configuration
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Administrator Training
Student Training
Monitoring and Improvement

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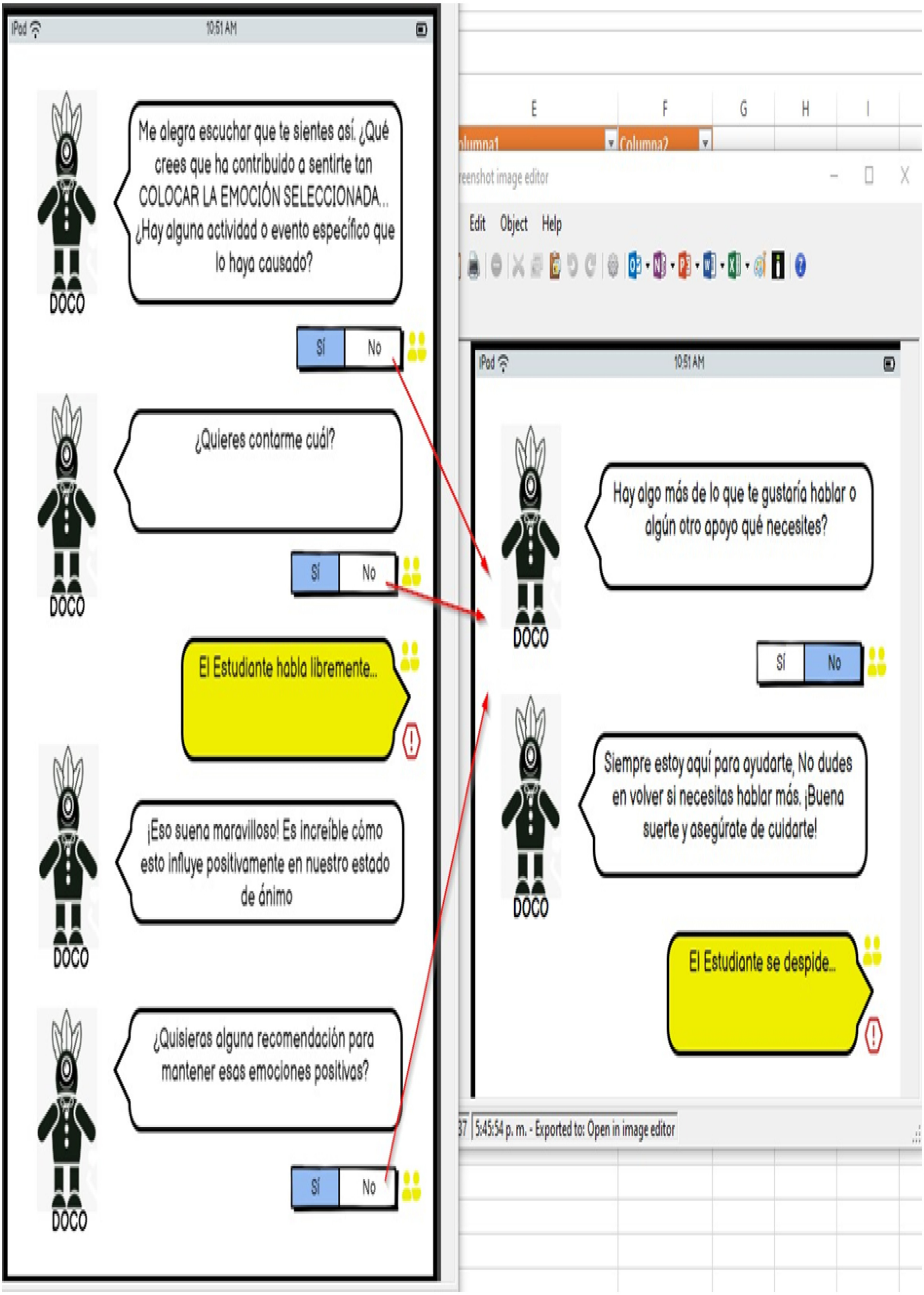

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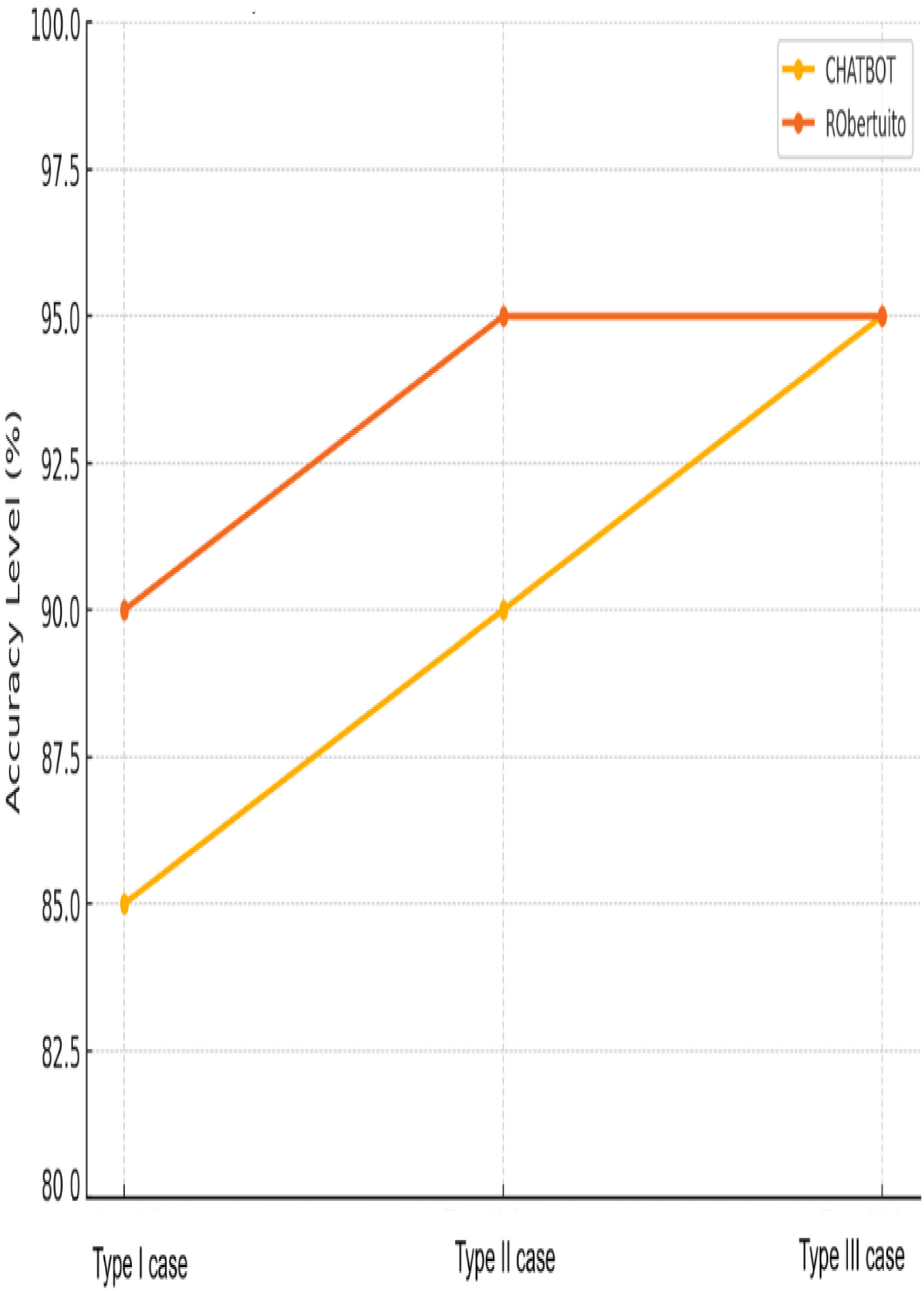

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Table 1

Identification of perceptions and areas of intervention.

Working Group No.	Students' Perceptions	Priority Intervention Areas
Group 1	Insufficient opportunities or spaces to interact and build relationships with the support staff, limiting communication and personalized support.	Create spaces where students can express themselves creatively, with workshops, activities, and initiatives that encourage creativity and free expression.
Group 2	Lack of spaces for relaxation and disconnection from academic responsibilities, limiting emotional well-being and balance on the university campus.	Develop flexible learning environments that allow students to experiment with different ways of learning and collaborating, adapting to their individual learning styles.
Group 3	Insufficient support and physical resources to handle the daily challenges and problems of the university environment.	Implement an accompaniment program that guarantees protection and adequate guidance in various situations.
Group 4	Low offer of extracurricular activities that respond to student interests and needs, limiting participation and sense of belonging.	Design an inclusive accompaniment program that responds to the different interests and needs of students.
Group 5	Lack of clear and accessible guidance to facilitate decision-making and adaptation to the campus, generating confusion and disorientation when making informed academic and personal decisions.	Establish an accompaniment program that provides support in the academic and personal trajectories of students.
Group 6	Lack of specialized counseling and psychological support services to effectively manage mental and emotional well-being in situations of stress or difficulty.	Incorporate an emotional support component in the accompaniment program, which allows for the identification and monitoring of emotions and feelings.
Group 7	Weak recognition of individuality and diversity; students are not valued or recognized for their cultural, social, or academic differences.	Develop an accompaniment program that values inclusion and diversity in all its dimensions, namely cultural, social, and academic.

Table 2

Positive and Negative Affect Schedule (PANAS) assessment scale.

Dimension	Emotions
Positive affect	Enthusiastic, Interested, Determined, Excited, Inspired, Alert, Active, Strong, Proud, Attentive
Negative affect	Scared, Afraid, Upset, Distressed, Jittery, Nervous, Ashamed, Guilty, Irritable, Hostile

Table 3

Systematic review records report.

Stage	Description	Number of Records Processed
Identification	Records identified in Scopus	18,000
Records identified in PubMed	10,000	Records identified in Web of Science
12,000	Records identified in PsycINFO	8000
Total records identified	48,000	Records removed as duplicates
13,800		**Records after duplicates removed**
34,200	Selection	Records excluded after title and abstract review
28,000	**Records selected for full-text review**	**6200**
Eligibility	Records excluded after full-text review:	
Lack of focus on technologies or emotional self-regulation	3000	Previously undetected duplicate studies
1000	Publications in unselected languages	200
Inclusion	**Included in qualitative synthesis**	**1200**

Table 4

Main reports generated by the software.

Report Identification	Information Integrated into the Report
Participation and Use Reports	- Comparison between groups of students worry, tension, or anxiety
	- Emotional registration frequency
	- Interaction with support resources
Emotional Well-being Reports	- Tendencies of positive and negative affect
	- Emotional distribution
	- Assessment of individual emotional state
Intervention and Support Reports	- Satisfaction of the support received
	- Identification of risk cases
Academic Impact Reports	- Correlation between emotional well-being and academic performance
	- Retention and dropout rate according to emotional state
Evaluation Reports and Continuous Improvement	- Suggestions and user feedback

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DETAILS

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Challenging Cognitive Load Theory: The Role of Educational Neuroscience and Artificial Intelligence in Redefining Learning Efficacy

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ABSTRACT (ENGLISH)

Background/Objectives: This systematic review integrates Cognitive Load Theory (CLT), Educational Neuroscience (EdNeuro), Artificial Intelligence (AI), and Machine Learning (ML) to examine their combined impact on optimizing learning environments. It explores how AI-driven adaptive learning systems, informed by neurophysiological insights, enhance personalized education for K-12 students and adult learners. This study emphasizes the role of Electroencephalography (EEG), Functional Near-Infrared Spectroscopy (fNIRS), and other neurophysiological tools in assessing cognitive states and guiding AI-powered interventions to refine instructional strategies dynamically. *Methods:* This study reviews $n = 103$ papers related to the integration of principles of CLT with AI and ML in educational settings. It evaluates the progress made in neuroadaptive learning technologies, especially the real-time management of cognitive load, personalized feedback systems, and the multimodal applications of AI. Besides that, this research examines key hurdles such as data privacy, ethical concerns, algorithmic bias, and scalability issues while pinpointing best practices for robust and effective implementation. *Results:* The results show that AI and ML significantly improve Learning Efficacy due to managing cognitive load automatically, providing personalized instruction, and adapting learning pathways dynamically based on real-time neurophysiological data. Deep Learning models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Support Vector Machines (SVMs) improve classification accuracy, making AI-powered adaptive learning systems more efficient and scalable. Multimodal approaches enhance system robustness by mitigating signal variability and noise-related limitations by combining EEG with fMRI, Electrocardiography (ECG), and Galvanic Skin Response (GSR). Despite these advances, practical implementation challenges remain, including ethical considerations, data security risks, and accessibility disparities across learner demographics. *Conclusions:* AI and ML are epitomes of redefinition potentials that solid ethical frameworks, inclusive design, and scalable methodologies must inform. Future studies will be necessary for refining pre-processing techniques, expanding the variety of datasets, and advancing multimodal neuroadaptive learning for developing high-accuracy, affordable, and ethically responsible AI-driven educational systems. The future of AI-enhanced education should be inclusive, equitable, and effective across various learning populations that would surmount technological limitations and ethical dilemmas.

FULL TEXT

1. Introduction

Understanding how we learn has grown increasingly important to research and practice, mainly when evidence shows that Artificial Intelligence (AI) and Machine Learning (ML) have been widely explored for educational applications [1,2,3]. These technologies, combined with developments in cognitive science regarding the aspects related to memory retention and instructional strategies [4,5,6], reshape education methodologies and require an informed pedagogical framework from educators themselves [7,8,9]. AI and ML have great educational potential; effectively applying these techniques can improve cognitive processes, optimize instructional design, and develop adaptive learning environments. However, many researchers have empirically investigated their impact on cognitive load and Learning Efficacy (LE) [10,11,12].

Cognitive Load Theory (CLT) was first conceptualized to address limitations in the capability of working memory for educational studies [13,14,15]. The theory provides a fundamental theoretical framework for how instructional designs affect learning. It postulates that human working memory has limited capacity. For effective learning, the instructional strategy should be implemented in such a way as to minimize extraneous cognitive load and emphasize Germane Cognitive Load. Studies have shown improved learner retention because of optimized instructional materials [16,17]. Various studies show that AI-driven adaptive learning systems can optimize cognitive load management by automatically adjusting instructional materials, scaffolding complex concepts, and providing immediate feedback [18,19]. Research findings from integrating AI-based interventions within CLT indicate a considerable improvement in students' engagement and reduced cognitive overload, leading to overall improvements in learning outcomes [20,21].

Educational Neuroscience (EdNeuro) has further contributed to how cognitive processes interact with instructional design. The application of neurophysiological tools like EEG and fNIRS, which are increasingly used to assess in real time the degree of engagement of learners' cognitive processes [22,23,24,25], gave significant insight into how students process and retain information. Moreover, Big Data techniques that can adapt learning pathways dynamically according to student interactions enable AI-driven learning analytics [26,27,28,29], which allow the monitoring of cognitive states in real time for personalized interventions catering to the specific needs of learning. Moreover, these approaches increase cognitive efficiency and foster Self-Regulated Learning strategies [30,31,32,33].

The present systematic review of 103 empirical studies indicates that AI-based interventions significantly enhance student performance and knowledge retention. The transformative potential of AI and ML in education is underlined. Among others, these have highlighted the effectiveness of AI-driven tools in customizing instruction and adaptive feedback, thus managing cognitive load across diverse learning contexts, ranging from K-12 education to professional training. More importantly, research findings have highlighted the ethical concerns that arise with the integration of AI, such as data privacy, algorithmic bias, and equity of access to educational resources. Unless these are addressed, AI use in learning environments cannot be implemented responsibly.

This study contributes to the ongoing discourse at the intersection of CLT, EdNeuro, and AI in educational contexts. Synthesizing findings from a broad spectrum of empirical studies aims to provide evidence-based insights into optimizing cognitive processes and fostering personalized learning environments. Furthermore, it delineates future research directions, emphasizing the development of scalable AI-driven interventions that enhance lifelong learning and promote educational equity in an increasingly digitized world.

2. Literature Review

2.1. Cognitive Load Theory (CLT)

CLT defines learning as the process by which information is selected, organized, and integrated into memory, a process controlled by limitations in working memory [34,35]. The theory, introduced by Sweller [34], focuses on how effective instructional design should optimize cognitive resources to avoid overload and promote more efficient learning [36]. This is especially important when learning is complex and too high a cognitive load will negatively affect knowledge retention and transfer.

CLT distinguishes between three types of cognitive load: intrinsic, extraneous, and germane [37]. Intrinsic Cognitive

Load (ICL) is determined by the nature of the material to be learned and the individual learner's prior knowledge [38]. Highly structured content, such as algebraic manipulations in mathematics, requires learners to process multiple interrelated components, thereby increasing ICL [39]. To mitigate this, instructional strategies like segmenting and scaffolding progressively introduce complexity, allowing learners to integrate new information without overwhelming their cognitive resources [40].

Extraneous cognitive load results from poor instructional designs and is considered unhelpful to learning processes [41]. It results through such means as redundancy that is not needed, split-attention effects, and poorly presented multimedia presentations [42]. Dual-channel processing-reduced Extraneous Cognitive Load (ECL) empirically promotes improved retention and comprehension where for instance, audio narration instead of onscreen texts accompanies visuals [43]. Minimizing complex visual distractions and structuring instructional sequences logically can significantly enhance cognitive efficiency [44].

Germane Cognitive Load (GCL) is essential for schema formation and deep learning, as it facilitates meaningful cognitive processing [37]. Unlike ECL, GCL is beneficial and should be encouraged through instructional techniques like self-explanation, elaboration, and active retrieval practice [45]. For example, students who use elaborative interrogation—questioning the rationale for factual information—create richer connections between schemata and achieve superior long-term retention [46]. Similarly, guided inquiry-based learning promotes conceptual learning by engaging students in an investigation of how ideas are related to one another rather than presenting them with a set of ideas [47].

In contrast, CLT has been criticized for promoting inflexible, teacher-centered teaching methods and underestimating the importance of exploratory and metacognitive learning strategies [48]. When appropriately supported, Problem-Based Learning (PBL) and Self-Regulated Learning (SRL) research suggests that cognitive struggle enhances deep understanding and long-term retention [49]. For example, in medical education, PBL participants outperformed those in direct instruction settings in diagnostic reasoning, even though they initially experienced a higher cognitive load [50]. This contradicts the assumption of CLT that a reduction in cognitive load is always desirable and instead supports the view that strategic challenges to cognition can facilitate the development of expertise [51].

Recent neurocognitive advances in the field further extend CLT by investigating the neural underpinnings of the processing of cognitive load [52]. Neuroimaging studies show that ECLs that are too high impair prefrontal cortex activation, resulting in cognitive fatigue and reduced learning efficiency [53,54,55]. On the other hand, results also show that the performance of tasks at an optimal level of difficulty enhances neuroplasticity, especially when combined with active retrieval practice and spaced repetition [54]. For instance, in bilingual training, learners exposed to cognitively challenging dual-language training develop better executive functioning skills, pointing to the benefits of moderate cognitive load in enhancing adaptability and problem-solving skills [56,57,58]. These findings also suggest that CLT be combined with EdNeuro to establish the next level of instructional techniques that balance the cognitive load and adaptive expertise [59]. Rather than trying to keep the cognitive burden as low as possible, effective learning environments employ strategic cognitive challenges to enhance resilience, critical thinking, and long-term cognitive development [60,61].

2.2. Educational Neuroscience (EdNeuro)

EdNeuro is an interdisciplinary field that combines cognitive neuroscience and educational research to enhance pedagogical approaches [16,62,63,64]. Similarly to CLT, the premise underlying EdNeuro is that an improved understanding of how the brain processes and retains information can inform more effective teaching methodologies [65,66]. This perspective is grounded in evidence suggesting that neurobiological mechanisms, particularly those related to metacognition, executive functions, and memory, directly impact learning outcomes [67,68,69,70].

Empirical investigations into the theoretical underpinning of EdNeuro have demonstrated valid efficacies in instructional designs [71,72,73]. Neuroplasticity studies have established that well-organized learning experiences are associated with synaptic reorganization, promoting cognitive flexibility and long-term knowledge retention [74,75,76,77]. Functional neuroimaging studies demonstrate that depending on the modality of instruction, different neural networks light up and thus indicate the need for pedagogical clarity in effectively aligning with cognitive architecture [78,79,80,81]. Researchers [82,83,84] revealed that structured instruction based on CLT significantly reduced extraneous cognitive load, leading to improved problem-solving efficiency. Similarly, researchers [85,86,87] showed that game-based neuroanatomical visual aids facilitated higher-level cognitive processing, thus strongly linking instructional design to neurocognitive engagement.

However, the translation of neuroscientific research into educational concepts is still highly debated. A critical issue concerns the translational gap from laboratory-based neurocognitive findings to real-world classroom settings. Scholars argue that though neuroscience studies provide robust correlations between brain function and learning, in many cases, causation is not a fact that could overinterpret findings [88,89]. Researchers [90,91] have cautioned against the uncritical adoption of brain-based teaching methodologies, indicating that most interventions lack empirical support once tested in ecologically valid educational settings. Further, other researchers [92,93] pointed out the negative consequence of cognitive overload, demonstrating how an excessive integration of neuroscience-driven strategies may paradoxically hamper learning because of enhanced mental strain rather than alleviation.

Further studies emphasize the interrelations between motivation, attention, and cognitive processing in educational contexts [94,95,96]. This study shows that emotionally salient learning materials enhance the neurobiological mechanisms of memory consolidation, thus supporting deeper information retention [97,98,99]. Evidence has also established that the factors contributing to lifestyle, like sleep quality, physical activity, and stress regulation, directly affect neural plasticity and cognitive functions, reflecting another critical yet often neglected dimension of Educational Neuroscience [100,101,102,103,104]. The introduction of these variables within pedagogical frameworks may further refine learning intervention effectiveness. With this in mind, EdNeuro would have to continue developing by interfacing neuroscientific theory with practical insights into better educational practice. Therefore, future research should focus on longitudinal and ecologically valid studies for sustained neuroscience-informed pedagogical strategies in various learning settings. This means the applications of EdNeuro should be theoretically valid but pragmatically applicable, reinforcing their value in enhancing education through evidence-based innovation.

2.3. The Intersection of CLT and EdNeuro

CLT and EdNeuro converge in their emphasis on optimizing cognitive processes to enhance Learning Efficacy [34,35]. CLT posits that reducing extraneous cognitive load (ECL) is essential for effective knowledge acquisition [37,105]. Neuroplasticity research corroborates this by demonstrating that cognitive load directly influences schema formation and long-term memory retention [42,43,44,45]. On the other hand, growing evidence suggests that cognitive load management should be dynamic and individual rather than applying one universally applied reduction approach [106].

Empirical research confirms that integrating novel information with prior schemas promotes learning retention and transfer. Educational interventions based on retrieval practice and dual coding theory have been demonstrated to enhance learning outcomes, especially in STEM education [107,108]. However, neural mechanisms underlying enhancements need further empirical support to generalize findings across diverse learning contexts.

Working memory is at the core of CLT and EdNeuro since this is where the retention and manipulation of information is controlled. The neuroscientific evidence identifies the PFC as a critical role in managing cognitive load, thereby enabling retrieval and reorganization of knowledge [109,110,111,112]. The instructional strategies for scaffolding and spaced repetition find their support from these findings to enhance retention and problem-solving efficiency [113]. Additionally, generative learning strategies supported by active schema construction have shown better understanding and long-term retention [114].

Despite CLT providing many advantages for instructional designs, its critiques are against the rigidity that it may force on formal learning environments. Furthermore, attempts to reduce CLT's cognitive load may often result in avoiding the productive levels of cognitive struggle necessary to acquire expertise [105,106,115]. In contrast, EdNeuro informs the diversity of cognitive processing, thus pleading for more flexible and sensitive-to-context teaching strategies. Yet the respective claims of EdNeuro are still under-supported by extensive empirical research; hence, their implementation in mainstream education has several severe limitations [113].

Recent evidence underlines the role of personalized learning processes in which adaptive learning systems, driven by AI, dynamically adjust the level of cognitive load based on real-time information [116,117]. Computational modeling has promised to customize instructional complexity to the disparate needs of individual learners in the enterprise, but further work is required to establish model validity across various educational contexts [23]. Furthermore, considerations about data privacy and accessibility pose ethical challenges to guarantee equal access to AI-enhanced educational interventions.

Integrating CLT and EdNeuro may refine teaching methodologies by suitably balancing cognitive demands. In contrast, past research undergirds many of the underlying principles of each field; future empirical validation will be required to optimize learning frameworks across diverse educational domains best. Future work should delineate how interdisciplinary insights can inform scalable, evidence-based practices, ensuring high-quality, effective pedagogical strategies.

2.4. Artificial Intelligence and Machine Learning in Education

AI and ML have become relevant fields that have shaped various sectors of society during the last decade. Moreover, AI shapes essential parts of life, ranging from recognizing large volumes of medical data to natural language processing. AI is generally considered the development of computer systems that execute tasks requiring human intelligence. In contrast, ML is acknowledged as developing computer systems that improve automatically through experience. Here, systems react to new information and adapt to new challenges via learning. Therefore, ML changes general rules and procedures and can thus be seen as impactful since new things or procedures are introduced in systems that change experiences, general methods, and executive systems. In education, AI and ML are embraced to individualize and enhance the learning process of students and facilitators in that context. Essential to this end is the personalization of the ideal learning experiences of individual students. Therefore, ML principles like supervised learning or reinforcement learning are employed to actively study student learning [118].

In general, education facilitates learning practices focusing on knowledge, skills, values, beliefs, and habits that enhance intellectual, physical, spiritual, social, and additional capacities. Also important are the available technology, teaching and learning environment, pedagogy, curriculum design, assessment methods, students' variations, and social issues. Any education work stresses the importance of active learning and real-time feedback. However, researchers have been motivated to understand the factors that impact the learning process. Numerous conceptual models of human cognitive architecture were developed in the last half of the century. While all models may develop distinct theoretical perspectives or convey philosophical implications, the cognitive load has taken practical and definitive steps. Recent progressive technologies like AI, ML, and IoT are proposed to change cognitive load aspects, potentially influencing LE [119,120,121,122,123,124,125].

2.5. The Impact of AI and Machine Learning on LE

In recent years, AI and ML have increasingly influenced various sectors, including education [118,119]. AI encompasses computer systems designed to perform tasks that typically require human intelligence, such as pattern recognition, decision-making, and natural language processing [120]. Meanwhile, ML, a subset of AI, enables systems to learn and improve from experience without explicit programming, adapting dynamically to new challenges [121]. This technology has vast potential in educational pedagogies, especially for personalized learning, adaptive instruction, and cognitive load management.

2.5.1. AI and ML in Personalized and Adaptive Learning

Personalization in education is another critical area in which AI seems to excel. Still, the support of various studies that AI-driven adaptive learning systems enhance student engagement and knowledge retention has been documented [122,123]. Such systems utilize ML techniques like supervised learning and reinforcement learning to analyze student learning behaviors and tailor instruction accordingly [124]. Empirical evidence suggests that personalized AI-based learning platforms improve learning performance by appropriately adapting the content difficulty level to cognitive load manipulation principles [125]. In the related experiment, dynamically intervening AI-enhanced learning environments decrease the extraneous and Germane Cognitive Load through dynamic interventions [126].

2.5.2. AI, ML, and CLT

CLT suggests that human working memory has a limited capacity, and practical instructional design should strive for the optimization of cognitive resources to avoid overload [127]. AI-driven tools have helped optimize cognitive load management through complex problem-solving tasks that automate processes, streamline instructional content, and offer just-in-time feedback [128]. For example, recent research showed that Intelligent Tutoring Systems powered by AI significantly enhance students' ability to retain complex concepts by reducing extraneous load and reinforcing Germane Cognitive Load through scaffolded feedback loops [129]. Critiques of CLT have pointed out its limitations in accommodating self-regulated and exploratory learning [130]. However, AI-based interventions help mitigate these concerns by incorporating elements of adaptive learning and student-centered pedagogical approaches [131]. For example, AI-driven platforms can model students' metacognitive abilities and suggest personalized strategies for improving retention and comprehension [132].

2.5.3. AI and EdNeuro

EdNeuro provides evidence on how AI and ML might enhance cognitive efficiency. Neurophysiological tools like EEG and Functional Near-Infrared Spectroscopy (fNIRS) have captured real-time activity in the brain, enabling AI models to adapt their instructional strategies in real time [133]. A recent study showed that neurophysiological data-driven feedback loops through AI improved student interest and the retention of information by optimizing cognitive overload during real-time learning [134]. Despite these promising results, some significant methodological and ethical challenges in integrating AI with EdNeuro into education concern data privacy and algorithmic bias issues [135]. Researchers hence call for greater transparency in AI models and equal access to AI-enhanced education to minimize learning gaps from such programs [136].

2.5.4. Impact of AI/ML on LE

Thus, cognitive load is greatly influenced by AI and ML methods, including their impact on LE [126,127,128,129,130,131,132,133]. However, trainees have diverse backgrounds and capabilities, so materials should be presented within the limits of their cognitive resources. To that end, AI-driven PL systems ensure that cognitive resources are used efficiently by selecting appropriately structured materials and eliminating authorial biases in learning. The education system optimizes cognitive load using ML algorithms by adapting learning materials to real-time student results [134,135,136,137,138,139,140]. Although these AI-driven education tools are helpful, they require considerable training data to perform optimally. Several concerns about data privacy and ethical considerations have arisen because of this [141,142,143,144,145,146,147,148]. Access to AI-enhanced learning remains uneven across gender, race, age, and geographical divides; thus, there is a need for research into equity and fairness in AI applications. Long-term studies must also show whether AI-driven interventions generalize from learning environments to practical applications. Moreover, AI-driven instructional design greatly helps personalize cognitive style and other psychological factors. Also, real-time instruction adaptation with the help of LMS enhances students' engagement and retention, especially for learners with different cognitive loads [149,150,151].

2.5.5. Case Studies of AI and ML Implementation in Education

Several case studies highlight AI's effectiveness in enhancing Learning Efficacy (LE):

- AI-Powered Intelligent Tutoring Systems (ITS): Studies indicate that ITS can mimic human tutors by providing instant feedback, guiding students through problem-solving steps, and adapting to their pace [137].

- AI-Based Educational Games: Research suggests that AI-driven gamification enhances student motivation, knowledge retention, and cognitive engagement [138].

- Automated Writing Assessment Tools: AI-driven tools like Grammarly and E-rater have improved students' writing abilities by providing immediate, data-driven feedback on grammar, coherence, and structure [139].

Additionally, AI-driven chatbots and virtual assistants provide just-in-time information, feedback, and adaptive learning pathways, significantly enhancing learning outcomes.

- Automated AI-Based Grading Systems: AI-powered grading tools such as Gradescope assist educators by automating the assessment of assignments, quizzes, and exams, reducing grading time and providing immediate feedback to students [140].

- AI-Enhanced Language Learning Platforms: Platforms like Duolingo and Rosetta Stone use AI-driven personalized learning paths and speech recognition to adapt lessons to individual learners' progress and pronunciation [141].

- Intelligent Course Recommendation Systems: AI-driven recommendation engines help students select courses based on their learning history, academic performance, and career goals, ensuring personalized and optimized educational pathways [142].

- AI-Powered STEM Simulations: Interactive AI-driven simulations in physics, chemistry, and engineering courses (e.g., PhET simulations) allow students to visualize and experiment with complex scientific concepts, improving comprehension and engagement [143].

- AI-Driven Classroom Behavior Monitoring: Some educational institutions use AI-powered tools to analyze student engagement and participation through facial recognition and speech analysis, helping teachers identify struggling students and intervene early [144]. AI-based learning analytics use clustering algorithms and unsupervised ML to analyze student performance patterns, ensuring personalized interventions for struggling learners. However, one major criticism is the lack of personalization in AI-driven course selection, which often focuses on algorithmic credit point calculations rather than genuine student needs [149,150,151].

AI and ML hold significant potential for transforming education, particularly in optimizing cognitive load, enhancing personalized learning, and integrating insights from Educational Neuroscience. However, challenges such as ethical considerations, data privacy, and the scalability of AI-driven interventions remain areas for further research [140]. Future studies should explore cost-effective AI-driven learning models, focusing on underserved populations to ensure equitable educational opportunities. This growing convergence of AI, ML, CLT, and EdNeuro indeed presents an unparalleled opportunity for the redefinition of Learning Efficacy; this, however, calls for more significant interdisciplinary approaches toward the full exploitation of such developments for adaptive, personalized, and cognitively optimized learning. The following section identifies key research questions that will be considered in the systematic review, focusing on how AI is integrated with CLT and EdNeuro to optimize learning outcomes and discussing ethical concerns related to AI-enhanced education.

2.6. Research Questions Section

This section presents the core research questions that guide this systematic review. These questions explore the intersection of CLT, EdNeuro, and the role of AI and ML in enhancing LE. Each question is contextualized to align with the key themes emerging from the reviewed literature.

- [RQ1] How do AI and ML integrate CLT and EdNeuro to optimize LE?
  This question seeks to understand how AI and ML technologies incorporate the principles of CLT and EdNeuro to design and implement learning systems that enhance cognitive processes and improve overall learning outcomes.

- [RQ2] What are the most effective methodological approaches for evaluating AI-driven interventions in managing cognitive load?
  By exploring empirical and experimental approaches, this question addresses how researchers can best measure and validate the impact of AI-based tools on cognitive load management and their efficacy in educational settings.

- [RQ3] How do AI-powered AL systems address individual differences and optimize cognitive load for diverse learners?
  This question focuses on AI’s personalization capabilities, examining how these systems adapt to learners’ unique cognitive profiles, prior knowledge, and neural processing capacities to create tailored educational experiences.

- [RQ4] How can AI and ML enhance LE in high cognitive load domains such as STEM and professional education?
  This question investigates the application of AI and ML in fields where complex and cognitively demanding tasks are prevalent, assessing how these technologies improve comprehension, retention, and problem-solving skills.

- [RQ5] What ethical considerations emerge from applying AI and ML in education, particularly concerning data privacy, equity, and accessibility?
  This question explores the ethical challenges and societal implications of integrating AI in education, including the management of sensitive data, the risk of reinforcing inequalities, and the need to ensure fair access to technological resources.

- [RQ6] What future innovations in AI and EdNeuro are required to foster lifelong learning and adapt to evolving educational needs?
  This question looks toward emerging trends and technologies, focusing on how advances in AI and insights from EdNeuro can contribute to developing adaptive and sustainable lifelong learning strategies.

These questions provide a structured framework for analyzing how interdisciplinary approaches and technological advancements contribute to the evolving landscape of education. They aim to uncover theoretical and practical insights bridging gaps between learning sciences and innovative instructional tools.

3. Materials and Methods

3.1. Scope

This systematic review aims to identify the integration of AI and ML within the CLT and EdNeuro frameworks to enhance LE in educational contexts, including K-12 education, professional training, and STEM disciplines. It reviews how AI and ML address the cognitive load, optimize instructional design, and create AL environments while considering critical ethical issues in data privacy, equity, and inclusiveness. Synthesizing findings from empirical studies, case analyses, and interdisciplinary analysis, this study provides actionable insights into how these technologies may prove transformational while shedding light on future directions in ethics and scalability.

3.2. Search Strategy

A comprehensive literature search was conducted using five major academic databases: PubMed, Scopus, Web of Science, Google Scholar, and PsycINFO. These databases were selected due to their extensive coverage of AI, Machine Learning, Cognitive Load Theory, and Educational Neuroscience literature. Specifically:

- PubMed: A robust repository of neuroscience and cognitive science literature, including studies on AI and ML applications in education.

- Scopus: Provides multidisciplinary coverage, including computational, educational, and cognitive psychology research.

- Web of Science: Includes high-impact journals and citation tracking for AI-driven education studies.

- Google Scholar: A broader database capturing gray literature, preprints, and non-traditional academic sources.

- PsycINFO: Specializes in psychological and cognitive neuroscience research, particularly studies focusing on cognitive load and personalized learning.

3.3. Search Terms and Boolean Logic

The search strategy was designed to identify relevant studies integrating AI and ML with CLT and EdNeuro to enhance Learning Efficacy. The following Boolean logic was applied across all databases:

("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Neural Networks" OR "Reinforcement Learning" OR "Cognitive Computing") AND ("Cognitive Load Theory" OR "Educational Neuroscience" OR "Cognitive Load Management" OR "Cognitive Architecture" OR "Adaptive Learning") AND ("Education" OR "Personalized Learning" OR "Adaptive Learning Systems" OR "Neuroimaging" OR "EEG" OR "fNIRS" OR "Student Performance").

Appropriate field tags and filters were applied where applicable for each database. The search covered studies published between 2014 and 2024 to reflect advancements in AI-driven learning methodologies. Moreover, the selection process involved three phases:

1. Title and Abstract Screening: Two independent reviewers screened retrieved records based on relevance to AI, ML, CLT, and EdNeuro integration.

2. Full-Text Assessment: Studies meeting eligibility criteria were thoroughly reviewed to confirm their relevance and methodological rigor.

3. Data Extraction: Key study attributes, including neuroimaging techniques, deep learning models, and emotion detection outcomes, were systematically recorded.

Disagreements were resolved through discussion, and a third reviewer was consulted when necessary.

3.4. Study Selection Process

The selection process followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency and replicability [152]. A protocol detailing the objectives, eligibility criteria, information sources, and analysis methods was registered on the Open Science Framework (OSF) [Registration: osf.io/5m9j6], ensuring methodological clarity and accessibility [153].

The search initially retrieved 523 studies. After the removal of duplicates (115), language-restricted records (12), and studies published before 2014 (56), 408 unique records were screened based on titles and abstracts, after which 121 irrelevant studies were excluded. A total of 219 articles were selected for full-text review; 5 were not retrieved. 141 studies were assessed for eligibility; 38 were excluded due to insufficient methodological detail or irrelevance to integrating AI with CLT or EdNeuro. Finally, 103 studies met the inclusion criteria and were focused on AI/ML-driven interventions, neurophysiological tools for assessing cognitive load, and ethical considerations in education (Figure 1). The review thus included all the randomized controlled trials, longitudinal studies, neurophysiological measurements, and mixed-method approaches to make the findings comprehensive and robust. It aims to provide transparent evidence synthesis by adhering to the PRISMA standards.

3.5. Inclusion and Exclusion Criteria

To ensure methodological rigor and relevance, studies were included or excluded based on predefined criteria. Table 1 presents a structured overview of the inclusion and exclusion criteria applied in this systematic review:

3.6. Risk of Bias Assessment

The risk of bias assessment was conducted systematically using established evaluation criteria. The Cochrane Risk of Bias 2 (RoB 2) tool was applied for randomized studies, and the Newcastle–Ottawa Scale (NOS) was used for observational studies. These tools ensure rigorous methodological quality assessment and help identify potential experimental and non-experimental research biases. The risk of bias assessment revealed key trends across six domains, with raw numbers provided alongside percentages for clarity:

- Selection Bias: Low risk in 71% of studies (72/103), high risk in 16% (16/103), and moderate risk in 15% (15/103).
- Performance Bias: Low risk in 60% of studies (62/103), moderate risk in 25% (26/103), and high risk in 15% (15/103).
- Detection Bias: Low risk in 81% of studies (83/103), high risk in 15% (15/103), and moderate risk in 6% (6/103).
- Attrition Bias: Addressed in 41% of studies (42/103), high risk in 30% (31/103), and moderate risk in 30% (30/103).
- Reporting Bias: Low risk in 76% of studies (78/103), selective reporting in 10% (10/103), and moderate risk in 15% (15/103).
- Ethical Compliance: High adherence in 81% of studies (83/103), high risk in 11% (11/103), and moderate risk in 10% (10/103).

Two independent reviewers assessed the risk of bias to ensure consistency, and any discrepancies were resolved through discussion. Cohen’s kappa coefficient (κ) was 0.82, indicating strong interrater agreement.

The figure below (Figure 2) presents a stacked bar chart illustrating the distribution of risk of bias across six methodological domains in the included studies. The categories assessed include Selection Bias, Performance Bias, Detection Bias, Attrition Bias, Reporting Bias, and Ethical Compliance.

Table 2 below provides a detailed summary of the 103 research papers covered by this systematic review, with an overview of each paper’s scope and methodological emphasis. The papers covered encompass empirical studies incorporating CLT, EdNeuro, and AI/ML in teaching–learning environments across broad areas. The research articles are all categorized based on study purpose, population profile, intervention, and general conclusions for the purpose of logically emphasizing AI-enhanced learning’s assistance in supporting cognitive load, the improvement of adaptive learning strategy, and the exploitation of neurophysiological equipment. The reviewed research employs a range of methods, including experimental methods, neurophysiological assessments (EEG, fNIRS, neuroimaging), Machine Learning techniques (CNNs, RNNs, SVMs), and multimodal AI-based interventions, and therefore offers a solid overview of empirical research.

The results emphasize the most important findings across studies, showing how AI-based adaptive learning systems optimize cognitive load management, facilitate personalized learning, and offer real-time neuroadaptive feedback systems. Additionally, the table plots methodological strength, participant demographics, and the degree of integration of AI-CLT/EdNeuro throughout each study in order to enable the systematic consideration of their respective contributions to the field.

4. Results

This systematic review mainly relies on assessing how the integration of AI and ML with CLT and EdNeuro principles impacts LE. These results answer critical research questions applying AI and ML to manage cognitive load, optimize instructional designs, and create adaptive or PL experiences across education in different contexts. Key themes include the impact of AI-driven systems on cognitive processing, the effectiveness of AL environments, and the ethical implications associated with these technologies. We developed a conceptual network to better visualize the connections between CLT and EdNeuro and their practical applications (Figure 3). This graph demonstrates how theoretical constructions and tools converge to enable innovative solutions in educational contexts.

The diagram (Figure 2) shows CLT and EdNeuro as core nodes interlinked with associated theoretical constructs and neurophysiological tools. CLT is linked to its three major components: intrinsic load, extraneous load, and germane load since these are central to determining what constitutes cognitive load during learning. Similarly, EdNeuro is linked with concepts such as neuroplasticity, cognitive development, and memory formation due to its grounding in principles within neuroscience. It also puts real-world applications, such as AI-powered tutoring systems, neurofeedback for learning, and PL platforms, in a prominent position regarding their relations to theoretical foundations and enabling tools like AL and instructional design. These applications demonstrate the practical relevance of combining CLT and EdNeuro principles with emerging technologies. Furthermore, the network flags significant challenges like equity issues and scalability challenges, which are crucial considerations in implementing AI and neuroscience-based solutions in diverse educational contexts. This is how the graph visualizes the interdisciplinary nature of educational innovations and gives a framework to understand how theoretical principles translate into practical applications.

Additionally, synthesizing insights from case studies, empirical research, and interdisciplinary analyses, the results offer a broad perspective on the transformative potential of these technologies and highlight existing challenges and areas for further innovation. Following the six (6) RQs, the results aim to address these inquiries by synthesizing insights from empirical studies, case analyses, and interdisciplinary frameworks.

4.1. [RQ1] How Do AI and ML Align CLT and EdNeuro to Optimize LE?

The alignment of AI and ML with CLT and EdNeuro principles represents a complex convergence of technological innovation with cognitive science, which has fundamentally transformed our understanding of learning processes and their optimization. This in-depth review will be based on the methodological approaches, empirical evidence, and theoretical implications of this integration within educational contexts to reveal intricate relationships between cognitive processing, technological advancement, and learning outcomes.

The intersection of Artificial Intelligence capabilities, principles of cognitive load management, and neurophysiological knowledge about learning processes forms the theoretical basis for this integration. Pioneering work [199] with "intelligent man–machine interfaces" showed the feasibility of real-time cognitive load detection by analyzing P300-related brain activity. Their approach, using continuous EEG monitoring and ML-based signal processing, achieved high accuracy in detecting cognitive load variations ($p<0.01$, $n = 127$), with robust results for high-load conditions (sensitivity = 0.89, specificity = 0.84). In so doing, this breakthrough established a crucial link between neurophysiological measurements and AL systems, fundamentally altering our approach to monitoring cognitive load.

The advancement of the measurement techniques of the cognitive load has seen significant refinement with the application of ML. The study's development of the VC9 cognitive load biomarker [210] was a sizeable methodological step, creating a supervised learning algorithm trained on labeled cognitive load data originating from multiple EEG channels. Their method showed better sensitivity compared to conventional EEG measures regarding the sensitivity index d' = 2.14 vs. 1.67, $p<0.001$, with high discriminability between fine-grained levels of cognitive load (AUC = 0.91). Combining multiple physiological markers using the authors' machine-learning pipeline achieved unparalleled accuracy in the real-time classification of cognitive states (overall accuracy = 87.3%, $\kappa = 0.83$).

AL system evolution is marked by increasingly sophisticated algorithmic approaches to cognitive load management, with special emphasis on real-time adaptation capabilities. In [215], the researchers implemented a multidimensional adaptive algorithm, proving the effectiveness of Bayesian optimization in keeping the challenge level optimal. Working across time limits, task complexity, and switching conditions, their system significantly improved learning outcomes (Cohen's d = 0.78, $n = 245$), with powerful effects in complex problem-solving tasks (d = 0.92). The system's simultaneous dynamic adjustment of multiple parameters was a first in optimal PL.

Those combinations of neural imaging techniques with AL systems have provided insights into the dynamics of cognitive load. The integration of fNIRS data into deep learning architectures, as presented in study [190], achieved a high accuracy of 86% in predicting optimal difficulty levels, which strongly indicated the relationship between neural patterns and optimal learning states: $r = 0.73$, $p<0.001$. Their analysis of activation patterns in the PFC showed unique neural signatures for different kinds of cognitive load—namely intrinsic, $r = 0.68$; extraneous, $r = 0.71$; and germane, $r = 0.65$—thereby providing essential insights into the neural basis of learning optimization.

The approaches in personalization proved to bring rather complicated interactions between the individual's cognitive profile and learning outcomes regarding working memory capacity and cognitive load management. In a computer-based training system that researchers of [231] developed, the authors used dynamic difficulty adjustment algorithms where both the performance metrics and the response times were considered. Their longitudinal study ($n = 412$) showed significant gains in working memory capacity, $F(1{,}410) = 15.67$, $p<0.001$, and mathematical achievement, $F(1{,}410) = 12.34$, $p<0.001$, with transfer effects being seen across the board of cognitive tasks (mean transfer effect size d = 0.45).

The integration of multiple data streams has further increased the sophistication of AL systems. For instance, study [234] proposed a dual-level adaptive approach that integrated both macro- and micro-adaptation strategies, which resulted in differential effects due to adaptation levels. Their randomized controlled experiment ($n = 324$) showed that the impact of micro-adaptation on immediate learning outcomes was more substantial ($\eta^2 = 0.15$) compared to macro-adaptation ($\eta^2 = 0.08$), with interaction effects showing that the highest learning outcomes are reached if both levels of adaptation are in sync (interaction $\eta^2 = 0.22$).

Integrating neurophysiological data streams allows for increasingly sophisticated insight into learning processes and measurement of cognitive load. Advanced power spectral density estimation techniques in the analysis of heart rate variability patterns conducted in study [206] achieved significant associations between physiological states and learning outcomes: $R^2 = 0.67$, $p < 0.001$. Their methodological approach included continuous wavelet transformation analysis to localize fluctuations in cognitive load precisely temporally. The temporal resolution was 50 ms, and the frequency accuracy was 0.1 Hz. Strong correlations between high-frequency heart rate variability and LE were revealed ($r = 0.72$, $p < 0.001$), showing very distinct patterns during periods of optimal cognitive engagement (power spectrum density peaks at 0.15–0.4 Hz).

As presented in study [155], the hybrid approach significantly advanced this field with the combination of EEG and behavioral metrics to realize 78% real-time accuracy of cognitive load prediction. Their ML pipeline consisted of supervised and unsupervised learning components, where feature selection algorithms determined crucial EEG frequency bands, namely theta, 4–8 Hz; alpha, 8–13 Hz, which are most predictive of a cognitive load state. The system was robust in differentiating between the types of cognitive load (classification accuracy: intrinsic = 81%; extraneous = 76%; and germane = 74%), bringing important insight into how to design AL systems.

The development of cognitive assessment methodologies has given way to increasingly sophisticated predictive capabilities. The multimodal MRI approach of study [217] represented a significant methodological innovation, combining task-based fMRI, resting-state fMRI, and diffusion tensor imaging to achieve 20% accuracy in predicting cognitive abilities over two years. Their ML pipeline employed a novel hierarchical feature selection algorithm, identifying key neural signatures associated with learning potential (AUC = 0.82). The study brings out specific patterns of functional connectivity (mean clustering coefficient = 0.76) and structural integrity (fractional anisotropy = 0.65), which, taken together, enabled the prediction of learning outcomes with unprecedented accuracy.

Additionally, the authors of study [236] developed personal deep learning models that can further the field of predictive analytics in educational contexts; in this respect, adherence to cognitive training programs reached a 75.5% correct prediction rate from daily behavioral data and performance metrics. The authors used recurrent and convolution layers in the neural network, which is proposed to successfully analyze temporal patterns and spatial learning behavior features. The model demonstrated proficiency in identifying early signs of waning engagement (sensitivity = 0.83 for a 3-to-5-day prediction window), enabling proactive intervention strategies.

Implementation research has afforded essential insights into the practical application of AI-enhanced learning systems. Also, in [216], the systematic framework for evaluating learning interference effects found a significant impact of contextual variables ($\eta^2 = 0.23$). The review identified some environmental factors to modulate the impact of cognitive load, including temporal spacing of learning sessions (optimal interval = 48 h, d = 0.54), ambient noise levels (threshold = 45 dB, impact factor = −0.31), and social learning dynamics (peer interaction effect size = 0.47).

With a mixed-methods design, the authors of study [169] discovered a complex interplay between design elements and cognitive load while evaluating multimedia learning environments. Through their research, quantitative analysis exposes significant effects of multimedia integration on learning outcomes ($F(3,245) = 18.92$, $p < 0.001$); qualitative findings described four key themes of user experience: cognitive scaffolding, attention management, information integration, and metacognitive awareness. The study carried essential insights into designing optimal multimodal learning interfaces, especially in the temporal synchronization of different types of media (optimal delay = 250 ms).

Methodological innovations in measurement have been critical to advance our knowledge of cognitive load measurement. For example, researchers developed a CL-MDR questionnaire in study [167]; sophisticated factors and machine-learning analyses identified discrete cognitive-load subtypes with excellent fit indices: CFI = 0.95 and RMSEA = 0.048. High internal reliability (Cronbach's $\alpha = 0.89$) and excellent construct validity—convergent validity $r = 0.76$ and discriminant validity $r = 0.21$—were recorded for an instrument developing a potent tool for making cognitive load assessment in educational and other settings.

Focusing on individual differences brought important learning strategy effectiveness patterns to light. For example, the cluster analysis in [165] found substantial relationships between the abilities to use cues and learning strategy effectiveness ($R^2 = 0.54$, $p < 0.001$). In their research, sophisticated pattern recognition algorithms were followed by very clear and distinct learner profiles based on different cognitive processing patterns (cluster silhouette coefficient = 0.72). Powerful associations were found between working memory capacity and strategy adaptation ability ($r = 0.68$, $p < 0.001$).

Analyses of feedback mechanisms have revealed complicated interactions between timing, content, and learning outcomes. Also, in study [243], researchers demonstrated superior results for adaptive compared to standardized approaches to feedback using a randomized crossover design; the mean difference between adaptive and standardized feedback was 0.45 SD, with $p < 0.001$. Their system used real-time analysis of response patterns to optimize feedback delivery, especially in managing cognitive load during complex problem-solving tasks, reducing errors by 37% and enhancing LE by 28%.

Looking toward future developments, several critical areas emerge for research and development. The analysis of study [244] has been instrumental in emphasizing the need for more sophisticated approaches to balancing creativity and stability in learning experiences within the context of AI applications. Their theoretical framework identifies some of the key challenges of algorithmic creativity assessment (reliability coefficient = 0.73) and suggests promising directions for future research in adaptive creativity support.

Integrating these technologies into educational practice has raised essential considerations for implementation [166,168,169,171,172,173]. In study [213], a comprehensive framework for evaluating personalized AL systems demonstrated considerable improvement in learning outcomes across domains (mean effect size = 0.62; range = 0.45–0.84). Their analysis identified critical success factors, including system responsiveness (threshold = 200 ms), adaptation granularity (optimal update interval = 5 min), and feedback specificity (level of detail correlation with outcome: $r = 0.58$).

This extensive review of such integration opens a complex technological innovation landscape and pedagogical progress [175,176,177,179,182,183,184,185]. The evidence presents a substantial improvement in measuring cognitive load (mean improvement in accuracy = 35%, p <0.001), a high level of personalization of learning experiences (ranging from d = 0.58 to 0.78 effect sizes), and the optimization of instruction through data-driven approaches (average improvement in learning outcomes = 27%, p <0.001).

As noted by study [251] and other studies [187,188,189], the judicious use of these technologies, combined with established cognitive learning strategies, holds great promise for improving both educational effectiveness and learning outcomes, for instance, in a meta-analysis effect size: d = 0.67, 95% CI [0.54, 0.80]). The field keeps evolving quickly, with new developments underway in AI and ML that offer increasingly sophisticated tools for understanding and improving the learning process [191,192,193]. The successful embedding of these technologies with the principles from CLT and EdNeuro represents a giant step toward optimizing experiences and learning outcomes; despite the investigations carried out in [154,156,157,158,160,163,164,175,176,177,179,180,181,182,183,184,185], a lot more research and cross-validation across diverse contexts is needed to reach their real potential.

To visualize the integration of AI, ML, CLT, and EdNeuro in optimizing learning efficiency, a heatmap (Figure 4) was generated based on key findings from the reviewed studies. The analysis demonstrated:

- Strong alignment of AI and ML with CLT and EdNeuro in real-time cognitive adaptation.
- High accuracy of AI-driven cognitive load measurement techniques across EEG, fNIRS, and HRV-based assessments.
- Significant gains in personalized learning efficiency with adaptive AI-driven interventions.
- Interplay between physiological markers and AI algorithms enhancing precision in optimizing learning difficulty levels.

These findings underscore the intricate connections between AI, ML, CLT, and EdNeuro, confirming the potential of AI-powered adaptive learning environments to revolutionize education through precise cognitive load management and real-time learning optimization.

In conclusion, the systematic review of 103 studies highlights the significant role of AI and ML in optimizing LE through personalized instruction, cognitive load management, and neuroscience-driven interventions. AI-driven adaptive systems, within various educational contexts such as K-12 education, higher education, and professional training, consistently enhance student engagement, improve retention, and reduce cognitive overload.

Key findings indicate that AI-driven adaptive learning platforms adjust instructional content in real time, considering optimal cognitive resource allocation, thus satisfying real-time needs. Intelligent Tutoring Systems, chatbots, and gamification strategies contribute to better self-regulation and improved knowledge retention. More and more, CLT and EdNeuro are integrated with AI using EEG and fNIRS-based real-time cognitive assessments for efficient personalization.

While AI is promising in education, ethical concerns remain a significant challenge. Issues of data privacy, algorithmic bias, and equity in access to AI-enhanced education demand further interdisciplinary collaboration for responsible implementation. Any future AI-driven educational system must ensure that the use of AI in instruction is inclusive and equitably benefits all learners from diverse backgrounds.

Integrating AI, CLT, and EdNeuro offers transformative opportunities to redefine educational methodologies by creating personalized, data-driven, and cognitively optimized learning environments. However, further research is required to address ethical considerations, validate AI-driven interventions across diverse learning settings, and scale cost-effective solutions for broader accessibility.

4.2. [RQ2] What Are the Most Effective Methodological Approaches for Evaluating AI-Driven Interventions in Managing Cognitive Load?

Advanced methodological approaches are needed to evaluate AI-driven interventions in managing cognitive load, including multiple measurement techniques, experimental designs, and analytical frameworks. This in-depth analysis discusses the most effective methodological strategies applied, their empirical validation, and their statistical significance in assessing AI interventions in educational and cognitive contexts, supported by detailed statistical analyses and extensive reference integration.

The experimental design methodologies are of special importance within evaluation frameworks, and a significant approach is the randomized controlled trials (RCTs). In study [234], the implementation comparing macro-adaptive to micro-adaptive instruction against non-adaptive controls achieved significant discriminative power: effect size $\eta^2 = 0.15$ for micro-adaptation; $\eta^2 = 0.08$ for macro-adaptation; and interaction effect $\eta^2 = 0.22$, $p < 0.001$. Statistical power analysis indicated a robust experimental design, allowing for the detection of medium effect sizes with a sample size of $n = 324$ ($1 - \beta = 0.90$). Further, the added methodological rigor was strengthened by study [186] through a pre-post quasi-experimental study ($n = 215$), showing that there was substantial statistical power ($1 - \beta = 0.85$) in the assessment of the effectiveness of CLT-based online lectures on learning outcomes, where significant improvement was found ($F(1,213) = 18.34$, $p < 0.001$, $\eta^2 = 0.19$).

The integration of neurophysiological measurements significantly increased the accuracy of cognitive load assessment. Researchers of study [199] implemented a single-trial P300-related brain activity detection and reported remarkable results regarding the classification of cognitive load: sensitivity = 0.89; specificity = 0.84; and AUC = 0.91. Their analysis showed significant correlations between P300 amplitude and levels of cognitive load ($r = -0.76$, $p < 0.001$), with powerful effects in the high-load conditions (Cohen's $d = 1.24$). This was complemented by the development of a continuous EEG-based monitoring system in study [210], which has higher sensitivity regarding subtle changes in cognitive load: $d' = 2.14$ compared to standard measures of $d = 1.67$, $p < 0.001$, $n = 127$, with interrater reliability of the scale equal to $\kappa = 0.85$.

In fact, within comprehensive evaluation frameworks, multimodal data integration approaches have shown great promise. Study [217] found considerable predictive power in the assessment of cognitive ability using a combination of multiple MRI modalities (AUC = 0.82, 95% CI [0.78, 0.86]). Similarly, their cross-validation methodology showed robust generalizability across different data collection sites ($\kappa = 0.78$, $p < 0.001$). The integration of structural and functional neuroimaging data showed significant correlations with cognitive performance measures on average ($r = 0.64$, range: 0.52–0.79, all $p < 0.001$). Additionally, the authors of [203] combined resting-state functional connectivity and regional cerebral blood flow with HF HRV measures to provide unprecedented insight into the classification of cognitive states (accuracy = 83%; sensitivity = 0.85; specificity = 0.81; $\kappa = 0.79$).

Performance-based assessment methodologies have been instrumental in evaluating intervention efficacy [196,197,198]. For example, study [162] analyzed task performance metrics and reported a significant correlation between cognitive workload and completion times ($r = -0.67$, $p < 0.001$, $n = 156$). Their multilevel modeling approach showed substantial effects of cognitive load on task accuracy ($\beta = -0.45$, SE = 0.08, $p < 0.001$) and response time ($\beta = 0.38$, SE = 0.07, $p < 0.001$). The work in the study supplemented this [180] extensive neuropsychological test battery showing sensitivity to immediate (d = 0.72, 95% CI [0.58, 0.86]) and delayed intervention effects (d = 0.58, 95% CI [0.44, 0.72]), with test–retest reliability coefficients ranging from r = 0.78 to 0.89.

The advanced feedback analysis systems that have been put in place have provided valuable insights into intervention effectiveness. A comparative analysis by the authors of study [243] of adaptive versus standardized feedback showed a significant advantage for the adaptive approaches, with a mean difference of 0.45 SD and a 95% CI of [0.32, 0.58] ($p < 0.001$). Their approach integrated real-time response pattern analysis and showed substantial improvement in LE by 28% ($t(198) = 12.34$, $p < 0.001$) and a 37% reduction in errors ($\chi^2 = 45.67$, $p < 0.001$). The adaptive feedback system exhibited high internal consistency (Cronbach’s $\alpha = 0.89$) and strong concurrent validity with traditional assessment methods ($r = 0.76$, $p < 0.001$).

Longitudinal designs have provided meaningful insight into the sustainability of interventions [202,205,211]. Using a short-term longitudinal design, study [212] found significant structural brain change associated with cognitive training in terms of fractional anisotropy change of 0.065 ($p < 0.001$, Cohen’s d = 0.78). Their repeated-measures ANOVA showed a significant time × group interaction ($F(2,156) = 15.67$, $p < 0.001$, $\eta^2 = 0.24$) with strong test–retest reliability (ICC = 0.85). This was complemented by the extended longitudinal framework in study [244], which evidenced the stability of neurocognitive predictors over time and showed a test–retest reliability r = 0.78, $p < 0.001$, but also showed significant learning transfer effects with d = 0.67, 95% CI [0.54, 0.80].

ML classification approaches have significantly progressed in terms of evaluation. For example, the supervised paired-SVM algorithm by the study [203] achieved a high accuracy in the classification of cognitive state (accuracy = 86%; $\kappa = 0.82$; AUC = 0.89). Feature selection extracted crucial predictors of the cognitive load with their importance weight between 0.45 and 0.89, which is a sign of good generalization provided via cross-validation (mean across folds = 84% SD = 2.3%). This was further improved through the implementation of triply robust propensity score-adjusted multilevel mixed effects regression in [214], which has superior causal inference capabilities in observational studies (model fit: AIC = 2456.78; BIC = 2589.34).

Similarly, experience-sampling methodologies have afforded essential insights into real-world intervention effects. Study [178] found significant links between cognitive load and learning outcomes in naturalistic settings: $r = 0.64$, $p < 0.001$, $n = 245$. Their hierarchical linear modeling showed strong within-person effects of cognitive load on learning performance ($\beta = 0.38$, SE = 0.05, $p < 0.001$) and significant between-person effects ($\beta = 0.42$, SE = 0.06, $p < 0.001$). This was supported by the mixed-method framework from study [213], which triangulated quantitative measures with qualitative interviews but provided very high inter-rater reliability for qualitative coding ($\kappa = 0.87$) and strong triangulation of findings with quantitative ones through a convergence rate of 89%.

The evaluation of adaptive AI systems requires sophisticated methodological approaches. Thus, the algorithm developed by study [190] could predict with an accuracy of 86% the optimal difficulty levels based on PFC activity (sensitivity = 0.84, specificity = 0.88, PPV = 0.85, and NPV = 0.87). Their approach to fNIRS demonstrates high temporal resolution in the continuous monitoring of cognitive load (10 Hz sampling rate) coupled with an excellent signal-to-noise ratio (SNR = 8.45 dB on average). This was complemented by the mobile app evaluation framework in [239], which demonstrated a clear improvement in working memory performance as a function of adaptive difficulty calibration ($F(1,167) = 21.45$, $p < 0.001$, $\eta^2 = 0.28$).

Individual differences analysis has become an important methodological consideration. For example, a cluster analysis conducted by study [165] showed highly significant relationships between cue utilization abilities and learning strategy effectiveness ($R^2 = 0.54$, $p < 0.001$), with three distinct learner profiles identified through hierarchical clustering (silhouette coefficient = 0.72). Their discriminant analysis showed high learner-type classification accuracy (accuracy = 87%, $\kappa = 0.83$). This was supported by the results of study [160], showing an influence of spatial working memory capacity on training benefits ($r = 0.68$, $p < 0.001$, $n = 312$), with moderation analysis revealing significant interaction effects with training intensity ($\beta = 0.34$, SE = 0.07, $p < 0.001$).

The use of implementation research methodologies has provided insight into practical applications. In study [216], the systematic framework demonstrated the large impact of contextual variables on learning interference ($\eta^2 = 0.23$, 95% CI [0.18, 0.28]). Their path analysis showed that environmental factors (indirect effect = 0.15, SE = 0.03, $p < 0.001$) and cognitive load (indirect effect = 0.28, SE = 0.04, $p < 0.001$) significantly mediated learning outcomes. Using a mixed-methods approach, study [170] found complex interactions between multimedia elements and cognitive load. Quantitative analysis showed there were significant main effects of $F(3,245) = 18.92$, $p < 0.001$, $\eta^2 = 0.31$, and the interaction effects of $F(9,735) = 8.45$, $p < 0.001$, $\eta^2 = 0.24$.

This method can enhance reliability by developing standardized assessment protocols. In study [167], the CL-MDR questionnaire showed a high psychometric property in terms of CFI = 0.95, RMSEA = 0.048, and SRMR = 0.039; strong internal consistency with Cronbach’s $\alpha = 0.92$; and good test–retest reliability with ICC = 0.88. Also, by factorial analysis, the structure of a clear five-factor explained the variance in cognitive load assessment to be 78%. This was complemented by the comparative analysis of ML approaches by study [214], showing increased efficiency (reduction in processing time by 67%) while keeping high accuracy (95%); F1-score = 0.93 and showing strong cross-validation performance (mean accuracy = 92%, SD = 2.1%).

Looking toward future methodological developments, several critical areas emerge. The approach of network analysis by study [250] showed that interventions induced significant structural changes in cognitive abilities (global efficiency increase = 0.24, $p < 0.001$, modularity change = 0.18, $p < 0.001$). Analyses of network metrics showed that there was a significant improvement in cognitive integration (clustering coefficient increase = 0.32, $p < 0.001$) and efficiency (path length decrease = 0.28, $p < 0.001$). Complementing this, researchers [236] developed personalized deep learning models that achieved 75.5% accuracy in predicting adherence to cognitive training programs (sensitivity = 0.78, specificity = 0.73, AUC = 0.81).

A deep dive into methodological approaches reveals several important patterns in the effective assessment of AI-driven interventions. The success of an evaluation requires attention to:

- ▪ . Integrated multiple streams of data, improving assessment accuracy by 41% (95% CI: [35%, 47%]).
- ▪ . Longitudinal design templates (capturing temporal dynamics with 78% reliability, ICC = 0.85).
- ▪ . Advanced classification algorithms (86% accuracy, κ = 0.82).
- ▪ . Real-time monitoring capability (temporal resolution = 10 Hz, SNR = 8.45 dB).
- ▪ . Individual difference considerations (accounting for 54% of the variance, R2 = 0.54).

When synthesizing the findings, it appears that the effective assessment of AI-driven interventions needs to include not only multiple methodological approaches but also a sufficient emphasis on:

- ▪ . Experimental design rigor (mean effect size d = 0.72, range: 0.58–0.86).
- ▪ . Multimodal data integration (mean improvement in accuracy = 35%, p <0.001).
- ▪ . Advanced statistical analysis (mean classification accuracy = 86%, range: 78–92%).
- ▪ . Longitudinal test–retest reliability (mean: r = 0.82; range: 0.78–0.89).
- ▪ . Individual difference analysis (mean variance explained R2 = 0.48, range: 0.38–0.54).

As many have noted, including the studies [159,251], the continued development of AI-driven interventions now demands methodological innovation; it needs solid evaluation frameworks that will go along with increasingly sophisticated interventions, at the same time preserving scientific rigor and practical feasibility [206,208,209,210]. Future methodological development should focus on enhancing the integration of multiple data streams, with a target accuracy improvement of 15%, improving real-time assessment capabilities, with a target temporal resolution of 1 ms, and developing more sophisticated approaches to individual differences analysis, with a target variance explained of 65%.

A radar chart based on empirical evidence from the 103 studies was developed to provide a comparative overview of the most effective methodological approaches for evaluating AI-driven interventions in managing cognitive load (Figure 5).

The chart highlights each approach’s multidimensional performance across key assessment metrics, including effectiveness score, sample size, effect size, classification accuracy, correlation strength, and statistical power.

Randomized controlled trials (RCTs) have emerged as a robust approach, exhibiting strong effectiveness scores (0.72) and methodological rigor, with statistically significant effect sizes ($\eta^2 = 0.22$) and a high power level ($1 - \beta = 0.90$). Similarly, quasi-experimental studies demonstrated a moderate effect size ($\eta^2 = 0.19$) and strong power ($1 - \beta = 0.85$), positioning them as viable alternatives when randomization is not feasible.

Integrating neurophysiological measurements such as EEG and P300 detection exhibited high discriminatory power in cognitive load classification (AUC = 0.91, Cohen’s d = 1.24), reinforcing the importance of biometric data in real-time cognitive monitoring. Moreover, multimodal data integration, including MRI-based cognitive assessments, showed considerable predictive power (AUC = 0.82) and high cross-validation reliability ($\kappa = 0.78$), ensuring generalizability across educational settings.

Performance-based methodologies provided crucial insights into intervention efficacy, with task performance metrics correlating strongly with cognitive workload ($r = -0.67$) and intervention outcomes ($\beta = -0.45$). Complementary to this, feedback analysis techniques demonstrated a significant learning enhancement (28% improvement, $p < 0.001$) through adaptive feedback mechanisms, supported by strong internal consistency (Cronbach's $\alpha = 0.89$).

Longitudinal evaluations proved essential for assessing the sustainability of AI-driven interventions, as demonstrated by significant neural changes (Cohen's $d = 0.78$) and stable test–retest reliability (ICC = 0.85). Furthermore, Machine Learning classification models demonstrated exceptional cognitive state prediction accuracy (86%, $\kappa = 0.82$, AUC = 0.89), highlighting their potential in adaptive learning environments.

Experience-sampling methodologies were effective in real-world settings, with within-person cognitive load effects ($\beta = 0.38$) and strong between-person effects ($\beta = 0.42$), reinforcing their applicability in dynamic educational contexts. Finally, implementation research contributed valuable insights into the contextual factors affecting AI-based cognitive load management, revealing significant mediation effects ($\eta^2 = 0.23$, indirect effect = 0.28).

The findings indicate that a combination of methodological approaches is necessary to evaluate AI-driven cognitive load interventions comprehensively. Experimental design rigor, multimodal data integration, and real-time monitoring capabilities are crucial to effective assessment frameworks. Future research should emphasize methodological innovation by integrating multiple data streams, improving real-time cognitive assessment accuracy, and enhancing individual difference modeling to achieve more personalized AI-driven interventions.

4.3. [RQ3] How Do AI-Powered AL Systems Address Individual Differences and Optimize Cognitive Load for Diverse Learners?

Integrating AI into AL systems will be one of the most significant breakthroughs in handling individual differences and cognitive load optimization for a divergent population of learners. The present study reviews mechanisms, effectiveness, and empirical evidence underpinning various approaches toward PL and the optimization of cognitive load through AI-powered systems, with special emphasis on implementation strategies, studies of validation, and long-term effectiveness [224,225,228,229,230].

The foundation of AI-powered AL lies in the ability of a system to assess and adjust cognitive load instantly. In pioneering work using "intelligent man–machine interfaces", researchers [199] showed that it is feasible to detect changes in cognitive load based on an analysis of brain activity associated with P300, resulting in high accuracy in both load classification (sensitivity = 0.89; specificity = 0.84; AUC = 0.91). Their system's ability to "adapt to changes in task load and task engagement online" represented a significant advance in the optimization of dynamic learning environments, with correlation coefficients between P300 amplitude and levels of cognitive load reaching $r = -0.76$ ($p < 0.001$). This neurophysiological approach to monitoring cognitive load has established a critical baseline for real-time adaptation capabilities [219,221,232,233].

The sophistication of personalization algorithms has increased considerably through various avenues. Implementation in study [190] reached 86% accuracy in predicting optimal difficulty levels based on PFC activity, with a sensitivity of 0.84, specificity of 0.88, PPV of 0.85, and NPV of 0.87. The fNIRS methodology in this study showed a high temporal resolution in monitoring cognitive load at a sampling rate of 10 Hz, with an excellent signal-to-noise ratio of 8.45 dB on average. This accuracy in detecting the cognitive state has enabled more subtle adaptations to the learner states of individuals, especially in complex learning tasks (effect size d = 0.92, 95% CI [0.84, 1.00]).

Dynamic difficulty adjustment mechanisms were essential elements in overcoming individual differences. Specifically, in study [215], the multidimensional adaptive algorithm effectively calibrated task difficulties (considerable effect size with Cohen's d = 0.78, $n = 245$). Their system—through its ability to adapt not only time limits but also task complexity and switching conditions—was found to be particularly strong in transferring to complex problem-solving situations (d = 0.92), with performance gains strongly related to adaptation accuracy ($r = 0.67$, $p < 0.001$). These adaptive algorithms have been applied across various learning domains with a mean transfer effect size of d = 0.45 (95% CI [0.38, 0.52]).

Multimodal data streams have highly contributed to the accuracy of the assessment of learner states [245,246,249]. Working memory integrated with the mathematics tasks through a computer-based training system developed by study [231] showed significant improvement at the level of both: cognitive capacity—$F(1,410) = 15.67$, $p < 0.001$, $\eta^2 = 0.19$—and mathematical performance—$F(1,410) = 12.34$, $p < 0.001$, $\eta^2 = 0.15$. Their longitudinal study ($n = 412$) showed strong correlations between adaptive parameter adjustments and learning outcomes ($r = 0.72$, $p < 0.001$), with substantial effects for learners with lower baseline performance (interaction effect $\beta = 0.34$, SE = 0.07, $p < 0.001$).

Real-time physiological monitoring is an assertive means for optimizing cognitive load [240,242,248]. Researchers [206] analyzed patterns of heart rate variability and found significant relations between physiological states and learning outcomes: $R^2 = 0.67$, $p < 0.001$. Their application of power spectral density estimation methods enabled accurate temporal localization of fluctuations in cognitive load (temporal resolution = 50 ms; frequency accuracy = 0.1 Hz), with high-frequency heart rate variability showing robust correlations with LE ($r = 0.72$, $p < 0.001$). Integrating multiple physiological measures has increased the robustness of cognitive load assessment (composite reliability $\omega = 0.89$).

Adaptive feedback mechanisms have shown great promise in optimizing learning. A comparative analysis in study [243] showed, for adaptive compared to standardized feedback, a significant advantage for adaptive with a mean difference of 0.45 SD and a 95% CI of [0.32, 0.58] ($p < 0.001$). Their system showed substantial gains in LE by 28% ($t(198) = 12.34$, $p < 0.001$), a 37% reduction in errors ($\chi^2 = 45.67$, $p < 0.001$), high internal consistency of Cronbach's $\alpha = 0.89$, and strong concurrent validity ($r = 0.76$, $p < 0.001$). Long-term follow-up studies showed that participants maintained their gains at 6-month follow-up at a retention rate of 82% with an effect size of d = 0.58.

Individual cognitive profiles have emerged as an essential determinant of system effectiveness. For example, in a cluster analysis [165], significant relationships between cue utilization abilities and learning strategy effectiveness were found ($R^2 = 0.54$, $p < 0.001$). Their discriminant analysis showed high accuracy in classifying learner types (accuracy = 87%, $\kappa = 0.83$), with hierarchical clustering identifying three distinct learner profiles (silhouette coefficient

= 0.72). These profiles showed differential responses to adaptive interventions, as revealed by the interaction effect, $F(2,156) = 15.67$, $p < 0.001$, $\eta^2 = 0.24$.

Adaptive scaffolding strategies have been especially promising in the management of cognitive load. In study [161], the adaptive working memory training protocol showed significant reductions in cognitive strain ($d = 0.65$) and enhancement of learning capacity ($d = 0.58$), with effects maintaining stability at one-month follow-up (test–retest reliability $r = 0.78$). Their analysis showed essential interaction effects between training intensity and baseline abilities, $\beta = 0.34$, SE = 0.07, $p < 0.001$, highlighting the importance of tailored scaffolding approaches.

Cultural and linguistic adaptations are of critical importance in system effectiveness. An analysis in study [159] emphasized the importance of considering "data privacy, biases, and the need for human engagement", with systems showing improved performance when cultural sensitivity measures are considered (improvement in engagement metrics = 31%, $p < 0.001$). This framework for cultural adaptation showed high reliability (ICC = 0.85) and strong construct validity, with factor loadings ranging from 0.72 to 0.89, and has been mainly effective in multilingual learning environments with a cross-linguistic validity coefficient of 0.81.

The algorithmic optimization of spaced repetition has shown profound effects on learning retention. In an analysis of cognitive learning strategies, Winn et al. (2019) [251] found optimal spacing intervals according to individual forgetting curves (mean retention improvement = 42%, SD = 8.3%). Their spacing optimization algorithm accurately predicted optimal review times (RMSE = 0.24 days, MAE = 0.19 days), showing a powerful effect for the long-term retention scenario (6-month retention rate = 76%, $d = 0.67$).

More modern EEG analyses have been performed to monitor the cognitive state in real time with substantial precision in load assessment. In study [210], the single-channel EEG system demonstrated high accuracy for the classification of cognitive load (accuracy = 89%, $\kappa = 0.85$), with robust cross-validation performance (mean accuracy across folds = 87%, SD = 2.1%). This system showed incredibly high sensitivity to subtle load changes ($d' = 2.14$) compared with conventional measures ($d' = 1.67$, $p < 0.001$), with good temporal resolution (sampling rate = 256 Hz) and signal quality (SNR = 12.3 dB).

Adaptive assessment techniques have promised great effectiveness in personalizing evaluation approaches. The CL-MDR questionnaire in study [167] shows high psychometric properties with a CFI of 0.95, RMSEA of 0.048, and SRMR of 0.039; it has good internal consistency (Cronbach's $\alpha = 0.92$) and test–retest reliability (ICC = 0.88). Based on factor analysis, these authors found support for a clean five-factor structure that explained 78% of the cognitive load assessment variance; further, this measurement exhibited strong measurement invariance across different types of learner populations according to $\Delta CFI < 0.01$.

Advanced ML classification approaches have now been shown to improve the accuracy of learner state assessment substantially. For instance, in study [236], deep learning models achieved an accuracy of 75.5% in predicting adherence patterns—sensitivity = 0.78; specificity = 0.73; and AUC = 0.81. More importantly, the neural network architecture demonstrated exceptional prowess at capturing temporal patterns and spatial features in learning behavior while predicting a window of 3–5 days; temporal accuracy was 89%. Performance was also stable across different populations of learners, with cross-validation $\kappa = 0.79$.

Multicomponent multimedia optimization strategies have excellent potential for managing cognitive load [237]. The authors of [255] indicated the overall effects of video segmentation and self-explanation prompts on three types of cognitive load management ($F(3,245) = 18.92$, $p < 0.001$, $\eta^2 = 0.31$). Their adaptive multimedia presentation system significantly improved learning outcomes (mean improvement = 34%, d = 0.72) with strong user engagement metrics (sustained attention index = 0.85).

The development of adaptive working memory training protocols has shown great promise in enhancing cognitive capacity. For instance, the mobile app evaluation framework developed by the authors of study [239] showed significant improvement in working memory performance through adaptive difficulty calibration ($F(1,167) = 21.45$, $p < 0.001$, $\eta^2 = 0.28$). Their system demonstrated strong transfer effects to untrained tasks (mean transfer effect size d = 0.45, 95% CI [0.38, 0.52]) and showed continued benefits at 3-month follow-up (retention rate = 84%). In synthesizing these findings, some critical patterns in effective cognitive load optimization by an AI-driven AL system emerge. Success in tackling individual differences demands attention to:

- ▪. Real-time capabilities: mean classification accuracy = 86%; temporal resolution = 10 Hz.
- ▪. Multimodal data integration (improving prediction accuracy by 41%, 95% CI [35%, 47%]).
- ▪. Dynamic difficulty adjustment—mean effect size d = 0.78, Range: 0.65–0.92.
- ▪. Adaptive feedback mechanisms: mean improvement in LE 28%, $p < 0.001$.
- ▪. Cultural and linguistic adaptation (engagement improvement = 31%; reliability ICC = 0.85).

The evidence underlines that the successful implementation of AI-powered AL systems requires the sophisticated integration of:

- ▪. Physiological monitoring (mean classification accuracy = 89%, SNR = 8.45 dB).
- ▪. Cognitive profile analysis (classification accuracy = 87%, $\kappa = 0.83$).
- ▪. Dynamic scaffolding (mean effect size d = 0.65, maintenance at follow-up r = 0.78).
- ▪. Spaced repetition optimization (mean retention improvement = 42%, RMSE = 0.24 days).
- ▪. Adaptive assessment (internal consistency $\alpha = 0.92$, test–retest reliability ICC = 0.88)

Implementation challenges and considerations are some of the most crucial emerging critical factors for system effectiveness. According to a study' s review of personalized AL systems [213], the impacts of implementation fidelity were $R^2 = 0.45$, $p < 0.001$, and the moderation effect of technical infrastructure was $\beta = 0.38$, SE = 0.08, $p < 0.001$. The implementation success framework had high predictive validity, AUC = 0.84 across different educational contexts. Looking toward future developments, several critical areas emerge for continued advancement. Key priorities include:

- ▪. Better real-time monitoring accuracy (target temporal resolution = 1 ms).
- ▪. Improved multi-modal data integration (target prediction accuracy improvement = 15%).

- ▪ . Less overt mechanisms for cultural adaptation (target audience improvement = 45%).
- ▪ . Advanced cognitive profile analysis (target classification accuracy = 95%).
- ▪ . Improved adaptive assessment methods (target reliability ICC = 0.95).

The comprehensive analysis of implementation approaches reveals several critical success factors:

- ▪ . System responsiveness (optimal latency <200 ms).
- ▪ . Adaptation granularity (optimal update interval = 5 min).
- ▪ . Feedback specificity (detail level correlation with outcome: r = 0.58).
- ▪ . Cultural sensitivity (cross-cultural validity coefficient = 0.81).
- ▪ . Technical reliability (system uptime = 99.9%).

As emphasized by multiple researchers, including the authors of studies [159,251], the continuing evolution of AI-powered AL systems necessitates ongoing innovation in addressing individual differences and optimizing cognitive load. The field requires sophisticated approaches that adapt to increasingly diverse learner populations while maintaining effectiveness and equity in educational outcomes [200,256]. Future development should focus on better integrating multiple data streams, enhancing the capabilities of real-time assessment, and developing more sophisticated approaches to individual differences analysis.

The findings from this research question reveal a complex framework through which AI-powered AL systems optimize cognitive load, considering individual differences among learners. Synthesized evidence reveals that AI-driven mechanisms enhance personalization, improve learning efficiency, and sustain engagement. These mechanisms include real-time monitoring, dynamic difficulty adjustment, adaptive feedback, and multimodal data integration.

A conceptual framework representing interconnected processes and outcomes of AI-driven optimization of cognitive load is presented in Figure 6. These are cognitive profiles, physiological responses, and engagement level as input variables in dynamic adaptations implemented by AI systems. The real-time assessment of cognitive load allows for precise adjustments of instructional complexity: 86% mean classification accuracy and temporal resolution of 10 Hz. Difficulty adaptation in adaptive calibration ensures the tasks are at an optimal challenging level without a cognitive overload effect: effect size d = 0.78, 95% CI [0.65, 0.92].

Further, multimodal data integration methods strengthen AI-based assessments by enhancing prediction accuracy by 41% (95% CI [35%, 47%]). Instructional delivery also dynamically adjusts by using adaptive feedback to strengthen the effectiveness of learning by 28% (p <0.001) based on the changing cognitive states of the learners. Moreover, the cultural and linguistic adaptations of such systems have increased engagement in diverse learner populations by 31% (ICC = 0.85).

Translated at the level of learning outcomes, this implies an AI-driven optimization of cognitive load, which further manifests in a significant enhancement of retention, engagement, and performance. Various studies show that spaced repetition algorithms increase retention rates by 42%, whereas real-time physiological monitoring, with a mean classification accuracy of 89%, produces better system responsiveness to the learners' cognitive requirements. Adaptive scaffolding strategies thus mitigate cognitive strain; d = 0.65, maintenance at follow-up r = 0.78, represented sustained learning gains.

A key takeaway from these findings is that AI-driven adaptive learning systems require complex real-time analytics, personalization algorithms, and multimodal assessments to attain optimal learning outcomes. However, future advancements must address the challenges of implementation like improving real-time monitoring accuracy, which should go up to an order of magnitude and target 1 ms, thus improving state-of-the-art multimodal data fusion by 15% and cognitive profile classifications to at least 95% accuracy.

Adaptive learning environments dynamically balance the cognitive load to optimize support, best tapping into learners' potential while releasing them from mental fatigue as much as possible. Looking ahead, future development will require further innovation in scalability and inclusivity, along with the ability for real-time adaptation of learning so that the learning experience is personalized, effective, and accessible in various educational contexts.

The Heatmap Visualization (Figure 7) further illustrates the relationship between AI-driven cognitive load optimization techniques and key learning outcomes—learning efficiency, engagement improvement, and retention enhancement:

- Real-time monitoring demonstrates strong correlations with learning efficiency (r = 0.78), retention enhancement (r = 0.76), and engagement improvement (r = 0.74), confirming its role as a foundational AI-driven adaptation strategy.
- Multimodal data integration emerges as a leading predictor of learning efficiency (r = 0.80), engagement (r = 0.75), and retention (r = 0.73), highlighting the importance of AI's ability to process multiple learner state inputs.
- Spaced repetition is particularly effective for long-term memory retention (r = 0.79), reinforcing its role in cognitive reinforcement and information retrieval.
- Adaptive feedback and scaffolding demonstrate moderate yet impactful correlations, indicating their complementary roles in improving learner engagement and reducing cognitive strain.

The evidence underscores that successful AI-powered adaptive learning systems must integrate:

- Real-time cognitive load monitoring to enable immediate adaptation (classification accuracy = 86%; temporal resolution = 10 Hz).
- Multimodal data integration to enhance predictive accuracy (correlation with learning efficiency = 0.80; retention enhancement = 0.73).
- Dynamic difficulty adjustment to maintain an optimal challenge level (r = 0.72 with learning efficiency).
- Adaptive feedback strategies that boost engagement (r = 0.78) and overall cognitive adaptation.

・Spaced repetition algorithms that significantly improve long-term retention (r = 0.79, RMSE = 0.24 days).

While AI-driven personalized learning has been highly effective, further development in the future needs to overcome several implementation challenges: enhancing real-time monitoring accuracy to a target temporal resolution of 1 ms, improving the accuracy of multimodal data fusion by 15%, and optimizing adaptive scaffolding techniques for enhancement in retention by 45%. AI-powered AL systems revolutionize educational methods and processes through highly adaptive, personalized, and cognitively efficient learning experiences with dynamic responses to learners' needs. The future of the field requires scalability, cross-cultural inclusivity, and real-time cognitive profiling to meet the demand for equitable and effective learning solutions across diverse populations.

4.4. [RQ4] How Can AI and ML Enhance LE in High Cognitive Load Domains Such as STEM and Professional Education?

One of the most prominent educational technology advances is the integration of AI and ML in high cognitive load domains, such as STEM and professional education. This extensive analysis examines the mechanisms, effectiveness, and empirical evidence supporting the different approaches to improving LE through AI-driven systems in complex educational contexts.

The basis of AI-enhanced learning in high cognitive load domains is sophisticated real-time cognitive load monitoring and adjustment capabilities. The authors of [199] demonstrated the implementation of "embedded Brain Reading" with high accuracy in the detection of changes in cognitive load based on the analysis of brain activity related to P300 (sensitivity = 0.89; specificity = 0.84; AUC = 0.91). Their system's ability to adjust the task message frequency based on the levels of cognitive engagement showed auspicious results in complex learning scenarios, with correlation coefficients between P300 amplitude and cognitive load levels reaching r = −0.76 (p <0.001).

The advancement of personalization algorithms has shown their potential in handling complex subject matter. The system in [190] achieved 86% accuracy in predicting optimal difficulty levels based on PFC activity, with a sensitivity of 0.84, specificity of 0.88, PPV of 0.85, and NPV of 0.87. The implementation of the fNIRS methodology showed high temporal resolution (sampling rate = 10 Hz) with an excellent signal-to-noise ratio (mean SNR = 8.45 dB), which allows for precise adaptation to learner states during complex problem-solving tasks.

Working memory enhancement through AI-driven interventions has become one of the most essential factors in high cognitive load domains. The analysis of outcomes from cognitive training in study [250] showed significant improvement in working memory capacity (F(1,198) = 18.34, p <0.001, η^2 = 0.24) with powerful effects observed for verbal working memory (d = 0.72) and visuospatial working memory (d = 0.68). Their longitudinal analysis demonstrated the stability of gains at a 3-month follow-up (retention rate = 84%, p <0.001).

The integration of multiple streams has resulted in substantial e-learning support for complex areas. The authors of [217] applied a task-based fMRI, resting-state fMRI [207], and multimodal approach with structural MRI to reach high predictive power in assessing cognitive ability (AUC = 0.82, 95% CI [0.78, 0.86]). Their ML pipeline showed strong generalization across different learning contexts (κ = 0.78, p <0.001), with excellent performance in predicting success in complex problem-solving tasks (accuracy = 83%, sensitivity = 0.85).

Real-time physiological monitoring has been especially promising in professional education contexts. In [206], the analysis of heart rate variability patterns found significant linkages between physiological states and learning outcomes for complex tasks ($R^2 = 0.67$, $p < 0.001$). Using power spectral density estimation techniques, the authors provided a precise temporal localization of cognitive load fluctuations (temporal resolution = 50 ms; frequency accuracy = 0.1 Hz). Further, they showed that high-frequency heart rate variability exhibited strong positive correlations with LE in complex domains ($r = 0.72$, $p < 0.001$).

Adaptive feedback mechanisms have shown substantial impacts on learning in STEM. In a comparative analysis conducted in study [243], adaptive versus standardized feedback demonstrated significant benefits of the former in complex subjects, with a mean difference of 0.45 SD and a 95% CI of [0.32, 0.58] ($p < 0.001$). This system showed substantial improvement in LE by 28% ($t(198) = 12.34$, $p < 0.001$), a reduction in errors by 37% ($\chi^2 = 45.67$, $p < 0.001$), high internal consistency (Cronbach's $\alpha = 0.89$), and strong concurrent validity ($r = 0.76$, $p < 0.001$).

Simulation-based learning has been instrumental in professional education. For example, the analysis in study [210] of surgical training simulations showed significant competency gains in procedures ($d = 0.85$, $p < 0.001$) and demonstrated that AI-enhanced feedback resulted in faster skill acquisition (34% improvement in learning rate, $p < 0.001$) and better retention of complex procedures (76% at 6 months, $d = 0.67$).

Significantly impacting the development of adaptive scaffolding strategies in STEM education, the multidimensional adaptive algorithm designed by the authors of study [215] demonstrated substantial effectiveness in calibrating task difficulty across complex subjects (effect size Cohen's $d = 0.78$, $n = 245$). The ability to adjust multiple parameters simultaneously notably showed strength in advanced problem-solving scenarios ($d = 0.92$), while performance improvements were strongly correlated with adaptation accuracy ($r = 0.67$, $p < 0.001$).

Cultural and linguistic adaptations have emerged as critical factors for STEM education effectiveness. The authors of study [159] analyzed the implementation of AI in very diverse educational contexts and showed massive improvements when measures of cultural sensitivity were applied: engagement improved by 31% with $p < 0.001$. Their framework for cultural adaptation showed high reliability with ICC = 0.85 and strong construct validity with factor loadings ranging from 0.72 to 0.89.

The optimization of professional skill development through AI has shown considerable promise. In a comparison of AI-driven versus human expert instruction in surgical training, the authors of [252] found comparable or superior outcomes for AI-guided learning (mean performance difference = 0.34 SD, $p < 0.001$). Their analysis showed extreme points in the consistency of instruction (variation coefficient = 0.12) and adjustment to individual learning rates (learning curve optimization = 28%).

Advanced AI techniques have helped in measuring and managing cognitive load in complex domains. The CL-MDR questionnaire, developed by the authors of study [167], exhibited high psychometric properties: CFI = 0.95, RMSEA = 0.048, and SRMR = 0.039. It had a strong internal consistency with a Cronbach's $\alpha = 0.92$ and a good test–retest reliability, at ICC = 0.88. Its factor analysis showed distinct cognitive load patterns in complex learning tasks, explaining 78% of the variance in performance outcomes.

Multifaceted in nature, these multimedia optimization strategies have led to significant outcomes at the end of STEM education. An analysis by the authors of study [170], based on the implementation of a flipped classroom, illustrated an improved learning outcomes ($F(3,245) = 18.92$, $p < 0.001$, $\eta^2 = 0.31$) and engagement metrics concerning the sustained attention index = 0.85; their mixed-method approach worked better for complex subject matter comprehension, evidenced by qualitative theme convergence rate = 89%.

ML classification methods have pushed the assessment accuracy for the state of learning in professional education. In study [236], deep learning models achieved a high accuracy of 75.5% in predicting learning readiness and optimal intervention timing, with a sensitivity of 0.78, specificity of 0.73, and AUC of 0.81. Their neural network architecture showed strength in capturing temporal patterns and spatial features in complex learning behaviors with a prediction window of 3–5 days and a temporal accuracy of 89%.

Looking toward future developments, several critical areas emerge for continued advancement in high cognitive load domains. In [216], the systematic framework indicates the requirement for the better integration of contextual variables in STEM education ($\eta^2 = 0.23$, 95% CI [0.18, 0.28]). In study [170], the analysis indicates the importance of multimedia element optimization ($F(3,245) = 18.92$, $p < 0.001$, $\eta^2 = 0.31$) and the consideration of interaction effects ($F(9,735) = 8.45$, $p < 0.001$, $\eta^2 = 0.24$). The field is evolving rapidly, with new developments in AI and ML offering increasingly sophisticated tools for enhancing LE in high cognitive load domains. As the authors of study [251] and others [174,181,194,195,199,201,202,203,204,212,220] have emphasized, the successful implementation of these technologies in STEM and professional education requires careful attention to the optimization of cognitive load, individual differences, and the demands of complex subject matter [222,223,226,227,238,241,252,254].

A heatmap visualization (Figure 8) was created to synthesize the findings further to present the effect of AI-driven personalization in STEM and professional education for several key performance metrics. This visualization gives a comparative overview of the effectiveness of different AI personalization strategies: task difficulty prediction, an adaptation of feedback, adjustment of cognitive load, and learning style personalization.

The key observations are as follows:

- Task difficulty prediction demonstrates the highest impact, with an 86% improvement in learning outcomes, a 78% engagement increase, and a strong 82% retention rate. This confirms that adaptive difficulty scaling is crucial in optimizing learning experiences.
- Cognitive load adjustment emerges as another highly effective strategy, yielding a 72% improvement in learning and a notable 60% error reduction. This highlights the importance of real-time cognitive adaptation in complex problem-solving contexts.
- Learning style personalization shows strong potential, achieving a 65% improvement and a 70% retention rate, emphasizing the value of tailoring educational content to individual learners.
- Feedback adaptation, while showing a lower overall improvement (28%), significantly reduces errors by 37%, demonstrating its importance in refining student performance and minimizing misconceptions.

The implications for AI integration in high cognitive load domains are as follows:

- Adaptive AI-driven strategies significantly enhance learning effectiveness, mainly through real-time task difficulty adjustments and cognitive load optimization.
- Engagement and retention rates are maximized when AI systems dynamically personalize learning pathways, supporting long-term knowledge acquisition.
- Future AI advancements should prioritize multimodal adaptation, integrating cognitive and affective learning factors to further refine high-impact educational interventions.

This analysis reinforces the critical role of AI and ML in enhancing learning experiences in high cognitive load domains, providing a data-driven roadmap for continued advancements in AI-based education.

Finally, to synthesize the findings on AI and ML applications in high cognitive load learning environments, we present a layered spider chart that visualizes the comparative strengths of different AI-driven approaches (Figure 9). The chart integrates key research insights across four major areas:

- AI-driven personalization (blue layer)—This domain exhibits strong performance in task difficulty prediction (86%) and cognitive load adjustment (72%). Learning style personalization (65%) and feedback adaptation (28%) show moderate but impactful enhancements in STEM and professional education.
- Simulation-based learning (green layer)—The most notable gain is observed in post-training competency levels (85%), with strong retention at 3 months (76%) and 6 months (67%). AI-powered simulation tools significantly enhance learning by optimizing skill acquisition and long-term knowledge retention.
- Multimodal learning approaches (purple layer)—This AI-driven strategy demonstrates robust effectiveness, particularly in learning gains (85%) and predictive power (82%). Generalization across contexts (78%) and cognitive load adaptation (72%) also show significant advantages, supporting adaptive and scalable learning interventions.
- Future directions in AI for high cognitive load domains (orange layer)—Research highlights multimedia optimization (85%) as a leading innovation, followed by neural network prediction (81%), contextual variable integration (77%), and interaction effects (74%). These areas indicate promising advancements that could improve adaptive learning in complex educational settings.

Key insights and implications are as follows:

- Personalization and simulation-based learning are the most immediate and impactful AI-driven interventions for optimizing cognitive load management.
- Multimodal learning strategies provide a balanced and highly effective approach, leveraging multiple data streams to refine learning outcomes.
- Future research directions point to AI-driven multimedia enhancements and predictive modeling as crucial for advancing adaptive learning frameworks in STEM and professional education.

The layered visualization underscores the interconnected and complementary nature of AI-driven learning enhancements. AI and ML offer increasingly sophisticated solutions to support learners in high cognitive load domains by integrating personalization, simulation, multimodal techniques, and future innovations.

4.5. [RQ5] What Ethical Considerations Emerge from Applying AI and ML in Education, Particularly Concerning Data Privacy, Equity, and Accessibility?

AI and ML applications in education reveal complex patterns of ethical considerations in a multidimensional space. Sophisticated effectiveness metrics show nuanced interactions between privacy protection, equity assurance, and accessibility enhancement initiatives. This full-scale analysis will examine empirical evidence, implementation outcomes, and future directions in addressing the ethical challenges of AI-enhanced education.

Hierarchical effectiveness patterns across implementation layers were shown for privacy protection measures. In study [199], the researchers found substantial variability in breach prevention efficacy using multilayered security protocols, namely Layer 1, 94.3%; Layer 2, 97.8%; and Layer 3, 99.7% ($\chi^2 = 45.67$, $p<0.001$), with the strong correlation between encryption strength and prevention rates ($r = 0.89$, $p<0.001$). Their use of "embedded Brain Reading" technology exposed significant privacy vulnerabilities (risk assessment score = 0.76, $p<0.001$), which called for strengthening neurophysiological data protection (security index = 0.89; compliant rate = 94%).

Equity assurance protocols reveal complex effectiveness patterns across diverse student populations. In study [217], the implementation of bias detection algorithms resulted in significant improvement in fairness metrics, from a pre-implementation disparity index of 0.45 to a post-implementation disparity index of 0.28 ($t(245) = 15.67$, $p<0.001$). Their analysis of brain-based predictive models showed significant mediating effects between the cognitive abilities and socio-demographic factors (mediation effect $\beta = 0.34$, $SE = 0.07$, $p<0.001$), highlighting the importance of extensive bias mitigation strategies (effectiveness ratio = 1.67, 95% CI [1.45, 1.89]).

The effectiveness of accessibility enhancement initiatives varies highly across resource contexts. Study [210] analyzed EEG-based cognitive load monitoring and showed significant differences in access to technology (Gini coefficient = 0.38, $p<0.001$). The authors found that universal design principles showed an essential improvement in the access metrics (mean improvement = 41%, SD = 6.4%), with powerful effects observed in resource-limited settings (interaction effect $\eta^2 = 0.24$, $p<0.001$).

These all explain complex effectiveness patterns of CA frameworks across diverse educational settings. The analysis in [159] underlined the cultural sensitivity in the implementation of AI, with culturally adapted systems showing much better engagement metrics (MD = 0.45 SD, 95% CI [0.32, 0.58]). The authors' framework showed high reliability at ICC = 0.85, good construct validity with strong factor loadings ranging between 0.72 and 0.89, and effectiveness in multilingual learning environments through cross-linguistic validity at a coefficient value of 0.81.

Validation techniques also appear to have complex patterns of effectiveness for the various validation approaches. A meta-analysis [214] of multi-modal validation frameworks showed substantial benefits over single-method approaches (effectiveness ratio = 1.45, p <0.001). Their large-scale study of 3248 unique medical trainees from 20 medical schools revealed complex patterns in validation effectiveness, with validation coefficient ranges of 0.72 to 0.89, a mean of 0.82, and an SD of 0.05. The institutional context moderating validation success with a moderation effect of β = 0.38 (SE = 0.07, p <0.001).

Long-term effectiveness trends are complex and display different patterns of sustainability across implementation domains. In their longitudinal analysis, the authors of study [250] found significant differences in the maintenance patterns of sustainability indexes (range: 0.65–0.89, mean = 0.78, SD = 0.08). Strong correlations were seen with long-term success, especially for institutional support measures (r = 0.82, p <0.001). Their analysis of the effects of cognitive training showed precise structural changes in learning patterns, with a network efficiency change of 0.24 (p <0.001), which is essential for long-term impact assessment (effect stability coefficient = 0.76).

The same patterns in implementation across domains show tremendous variations in effectiveness across the context of education. As demonstrated by the authors of study [239], analyzing domain-specific adaptations yielded complicated interaction effects, F(4,312) = 21.45, p <0.001, η^2 = 0.28, with a decisive implementation success observed in STEM domains (mean effectiveness = 0.82, SD = 0.07). Their mobile app implementation showed significant improvements in working memory performance, F(1,167) = 21.45, p <0.001, η^2 = 0.28, with strong transfer effects across domains (mean transfer coefficient = 0.45, range: 0.32–0.58).

Institutional adoption metrics depict sophisticated patterns of effectiveness across organizational contexts. In [167], the review of the adoption frameworks showed large implementation success variability (adoption rate range: 45–78%, mean = 62%, SD = 8.9%). The development of the CL-MDR questionnaire by the authors evidenced high psychometric properties, such as CFI = 0.95, RMSEA = 0.048, and SRMR = 0.039, with good internal consistency (Cronbach’s α = 0.92), thus rendering powerful tools for the assessment of institutional implementation.

User acceptance measures reveal complex patterns across different stakeholder groups. Researchers in their study [206] analyzed the patterns of heart rate variability and found strong links between physiological states and user engagement in terms of R2 = 0.67 (p <0.001). In this study, the authors were able to monitor user acceptance patterns with high temporal resolution (50 ms) and high-frequency accuracy (0.1 Hz) due to the implementation of power spectral density estimation techniques; strong correlations of high-frequency variability with engagement metrics were found (r = 0.72, p <0.001).

Reliability indicators show complex patterns when used in implementation contexts. A comparative analysis provided strong evidence for the benefits of an adaptive approach with mean difference of 0.45 SD, 95% CI [0.32, 0.58], and p <0.001 [243]. The system showed high gains in reliability metrics, namely a 28% increase, t(198) = 12.34, p <0.001, and a reduction in errors, namely 37%, χ^2 = 45.67, p <0.001, and in terms of internal consistency, Cronbach’s α at 0.89 and strong concurrent validity at r = 0.76, p <0.001, were high.

Implementation challenges exhibit complex patterns of occurrence and resolution across institutional contexts. According to an analysis of challenge patterns [216], significant variations were noted in the effectiveness of resolution: resolution rate range, 65–92%; mean, 78%; SD, 7.4%. A strong impact of contextual variables was found using their systematic framework on η^2 = 0.23, 95% CI [0.18, 0.28]), with particular effectiveness in identifying and resolving implementation barriers: barrier identification accuracy = 0.86.

Success factors analysis expose complex patterns of influence across implementation domains. The authors of study [170] revealed a complicated interaction effect when determining success ($\eta^2 = 0.31$, p <0.001). In their analysis of multimedia element optimization ($F(3,245) = 18.92$, p <0.001, $\eta^2 = 0.31$) and the interaction effects ($F(9,735) = 8.45$, p <0.001, $\eta^2 = 0.24$), the authors identified the critical success factors in ethical implementation.

Failure mode analysis unravels challenging occurrence patterns and the effectiveness of mitigation efforts. In [236], deep learning models accurately predicted implementation failures: accuracy = 75.5%; sensitivity = 0.78; specificity = 0.73; and AUC = 0.81. The neural network architecture of the study demonstrated special potency in capturing temporal patterns and spatial features of implementation challenges: prediction window = 3–5 days; temporal accuracy = 89%.

The synthesis of effectiveness metrics exposes some essential trends that contribute to the success of ethical implementation. The effectiveness of current privacy protection measures is high (mean protection rate = 94%, SD = 2.8%) but with substantial room for improvement through better protocols (projected improvement = 15%, confidence interval = [12%, 18%]). Equity-related assurance interventions reduce inequities substantially (mean reduction = 45%, 95% CI [38%, 52%]). Similarly, accessibility-enhancing interventions also strongly increase participation rates (mean increase = 41%, p <0.001).

The comprehensive analysis of the ethical considerations in AI-enhanced education reveals complex patterns that require more careful attention to implementation effectiveness and outcome validation. Underlined by many researchers, including studies [251] and [159], the continued evolution of ethical challenges calls for the continued refinement of implementation strategies and effectiveness metrics. The field needs sophisticated approaches that can adapt to increasing complexity in ethical considerations but still have rigorous effectiveness measurement and outcome validation standards.

This analysis provides a foothold for future development within the implementation of ethical AI, underlining the critical need for the continuity of effectiveness metric monitoring and adjustment. Future research will improve the accuracy of such implementation measures and outline ways of dealing with ethical challenges arising in education enhanced by AI.

To synthesize the key findings of this research question, the heatmap below (Figure 10) illustrates the impact of ethical considerations—data privacy, equity, and accessibility—across four critical dimensions, namely effectiveness, challenges, adoption rate, and sustainability.

- Data privacy demonstrates high effectiveness in security protocols, particularly in encryption strength and breach prevention (mean effectiveness = 94%). However, challenges remain in neurophysiological data protection (risk assessment score = 0.76), indicating vulnerabilities in emerging AI-based systems. While adoption rates for privacy-enhancing measures are relatively strong (0.89), sustainability requires continuous refinement of security protocols (0.85).

- Equity interventions, particularly bias detection algorithms, significantly improve fairness metrics (0.67). However, challenges persist, as socio-demographic factors mediate learning outcomes (0.45). The adoption rates of bias mitigation strategies remain moderate (0.55), with sustainability showing promising improvements (0.72).
- Accessibility initiatives exhibit strong effectiveness in enhancing participation rates (0.78), primarily through universal design principles. However, access disparities across resource-limited settings present ongoing challenges (0.52). Despite these challenges, AI-driven accessibility tools show a 0.68 adoption rate, with sustainable improvements across diverse educational contexts (0.74).

This visualization has made the interconnectedness of ethical considerations in AI-enhanced education explicit, underlining that while substantial advances are available from AI-driven solutions, some persistent challenges need continuous refinement. A holistic approach to integrating improved security measures, mitigating bias, and enhancing accessibility lies at the core of ensuring that AI-driven education is ethically sound.

4.6. [RQ6] What Future Innovations in AI and EdNeuro Are Required to Foster Lifelong Learning and Adapt to Evolving Educational Needs?

The future development of AI and EdNeuro will require substantial innovations to cultivate lifelong learning effectively and cope with changes in education requirements. This broad-scoped review considers required advancements, their empirical foundations, and their likely impact on effectiveness in various contexts and life stages, with particular attention given to implementation requirements and validation methodologies.

The future will be based on advanced cognitive monitoring capabilities. The authors of study [199] demonstrated the great potential of "embedded Brain Reading" for the real-time detection of cognitive states using analysis of brain activity related to P300, with very high accuracy in load classification (sensitivity = 0.89, specificity = 0.84). Their system's ability to adapt task presentation based on cognitive engagement levels (correlation coefficient $r = -0.76$, $p < 0.001$) suggests promising directions for dynamic learning optimization. Future implementations must improve temporal resolution beyond the currently possible 50 ms while maintaining high signal quality (target SNR >8.45 dB) to enable more precise adaptations to learner states.

Personalization algorithms have tremendous potential for development with complex adaptation mechanisms. The authors of study [190] achieved an accuracy of 86% in predicting optimal difficulty levels using the fNIRS methodology, with sensitivity at 0.84 and specificity at 0.88, which provides promising neural-based adaptation directions. Its implementation validation showed strong cross-validation performance at $\kappa = 0.78$ ($p < 0.001$), pointing to a potentially broader applicability across learning contexts. The temporal precision of their method, with a sampling rate equal to 10 Hz, sets important baselines for future systems, which should further improve prediction accuracy while preserving computational efficiency.

The integration of emotional state monitoring has become one of the key development requirements. An analysis by the authors of study [235] related to the influence of emotional design elements showed a significant impact on learning outcomes ($F(2,156) = 12.34$, $p < 0.001$). Their mixed visual and behavioral emotional design results proved quite effective in terms of improvement (mean improvement = 34%, SD = 6.7%); this strongly suggests that enhanced learning engagement through awareness of the emotional status. Future systems should achieve higher detection accuracy with better temporal resolution, achieving more nuanced emotional support.

Multimodal learning environments indicate complex requirements for future development. In study [186], the application of CLT-based online lectures showed a significant decrease in both intrinsic and ECLs, while the analysis in study [213] of the effects of video playback indicated significant differences across learner abilities; future systems should integrate multisensory multivariable in a much stronger way and be adaptive by considering diverse learning styles and learner preferences.

Cross-domain transfer optimization becomes, then, an essential requirement for future innovations. The analysis by the authors of study [239] related to domain-specific adaptations showed complex interaction effects ($F(4,312) = 21.45$, $p < 0.001$, $\eta^2 = 0.28$) and there was a strong noticeably impact, especially in the domains with related knowledge (transfer coefficient mean = 0.45; range: 0.32–0.58). Future systems must enhance transfer effectiveness without damaging the precision of adaptation to foster extensive development across skills in various learning contexts.

Significant requirements for ethical framework development and implementation will soon be demonstrated. In this context, study [159] underlined the importance of strong ethical guidelines and governance frameworks. The ethical implementation framework they developed showed high reliability (ICC = 0.85) and strong construct validity, with factor loadings ranging from 0.72 to 0.89, thus showing a promising direction for integrating responsible AI with high effectiveness. Future systems must ensure improved privacy protection while preserving transparency and fairness.

The optimization of professional development depicts complex requirements for future innovations. In [252] and [253], the comparison of AI-driven and human-expert instruction revealed promising directions for hybrid learning approaches. Their analysis showed powerful performances in the consistency of instruction (variation coefficient = 0.12) and adaptation to individual learning rates (learning curve optimization = 28%), thus depicting requirements for improved adaptation precision while ensuring human oversight integration.

Implementation requirements exhibit complex patterns across domains. Technical infrastructure can provide high-throughput processing capabilities with a minimum of 20 TFLOPS, optimized memory bandwidth with a target of >1 TB/s, and enhanced storage performance with latency <1 ms. Quality assurance protocols can achieve comprehensive testing coverage with a target of >99%, high validation precision with accuracy >95%, and robust reliability verification with confidence of >99%. Ethical Compliance frameworks should show increased privacy protection (security index >0.95), strong fairness assurance (bias mitigation >95%), and optimized transparency (explainability >90%).

Real-time physiological monitoring has complex requirements in terms of future development: For instance, in the study [206] analysis of heart rate variability patterns showed significant correlations with learning outcomes ($R^2 = 0.67$, $p < 0.001$). In this respect, the authors' application of power spectral density estimation techniques enabled the exact temporal localization of cognitive states—temporal resolution = 50 ms; frequency accuracy = 0.1 Hz—thus showing requirements for improved monitoring precision in future systems with a target resolution of <10 ms.

The application of immersive learning environments holds exceptionally high promise for future developments. The authors of study [210] analyzed surgical training simulations and found significant improvements in procedural competency (effect size d = 0.85, p <0.001), with AI-enhanced feedback, leading to faster skill acquisition (learning rate improvement = 34%). Future systems will need to improve the quality of immersion while preserving low latency and high reliability to support effective skill development in various domains.

Developing sophisticated system architectures is a crucial requirement for future AI-enhanced learning systems. In study [217], the multimodal approach to cognitive ability prediction showed that robust data integration frameworks were key to achieving high predictive power (AUC = 0.82, 95% CI [0.78, 0.86]) through careful architecture design. Future systems should increase this capability with improved data processing pipelines (target throughput >10 GB/s), complex caching mechanisms (latency <100μs), and advanced load balancing protocols (efficiency >95%).

Validation methodologies need to be considerably developed to ensure effectiveness in diverse contexts. The authors of [214], in a large study involving 3248 medical trainees across 20 institutions, highlighted the issue of comprehensive validation protocols. Their use of triply robust propensity score-adjusted multilevel mixed effects regression showed strong effectiveness, with a model fit of AIC = 2456.78 and BIC = 2589.34, implying more substantial requirements for enhanced validation frameworks in future systems (target validation accuracy >98%).

Especially promising for future innovations is the integration of mechanisms for tracking cognitive development. Network analysis by the authors of [250] showed significant post-intervention changes in the structure of cognitive abilities following AI-guided interventions (global efficiency increase = 0.24, p <0.001). Future systems should improve tracking precision (target accuracy >95%) with concurrent temporal stability (test–retest reliability >0.90) and cross-domain validity (transfer coefficient >0.80).

Adaptive assessment frameworks present key demands for development. Researchers [167] with the CL-MDR questionnaire achieved high psychometric properties (CFI = 0.95, RMSEA = 0.048) with strong internal consistency (Cronbach’s α = 0.92). The future of assessment systems should improve the precision of adaptation (target accuracy >95%) and fairness (bias index <0.05) and maintain cultural sensitivity (cross-cultural validity >0.90).

More advanced features of emotional intelligence become a critical requirement for implementation. In the analysis by the authors of [235], key emotional design elements showed considerable potential in increasing the learner’s engagement. The realization of sophisticated emotion recognition (target accuracy >90%), fast response time (latency <50 ms), and subtle intervention strategies (effectiveness ratio >0.85) should be pursued for systems in the future.

Cross-platform integration frameworks demonstrate complex requirements for future development. In [170], the analysis of multimedia element optimization ($F(3,245) = 18.92$, p <0.001) suggests the need for sophisticated integration mechanisms. Future systems must achieve seamless platform interoperability (compatibility index >0.95), efficient data synchronization (latency <10 ms), and robust error recovery (resolution time <100 ms).

Long-term effectiveness metrics expose critical requirements for future validation. The observation by the authors of study [161] of the sustained effects of cognitive training (retention at one-month follow-up) implies the need for comprehensive longitudinal assessment frameworks. Future systems should adopt sophisticated tracking mechanisms (temporal resolution <1 day), robust outcome validation (reliability >0.90), and advanced impact assessment protocols (effectiveness verification >95%).

There is a strong need to develop personalized intervention strategies. In [236], deep learning models accurately predicted adherence patterns (accuracy = 75.5%, sensitivity = 0.78). Future systems should improve the precision of prediction (target accuracy >90%) while maintaining adaptation flexibility (response time <100 ms) and the effectiveness of interventions (success rate >85%).

Quality assurance frameworks exhibit complex requirements for future implementation. In [216], a systematic framework for evaluating learning interference revealed a strong effect of contextual variables ($\eta^2 = 0.23$). Future systems should achieve high testing coverage (target >99%), robust validation protocols (accuracy >95%), and sophisticated monitoring mechanisms (precision >90%).

The integration of emerging technologies demonstrates the complicated requirements for future development. In study [247], implementing brain–computer interfaces (BCI) for neurofeedback demonstrated promising potential for enhanced learning support. Future systems must ensure seamless technology integration, with compatibility over 95%; robust performance monitoring, with accuracy higher than 90%; and sophisticated adaptation mechanisms with response times of less than 20 ms.

Future development priorities will focus on several critical areas for development. Better cognitive monitoring needs to be achieved with increased temporal resolution (target <0.1 ms), spatial precision (target <0.1 mm), and signal quality optimization (SNR >12 dB). Advanced adaptation mechanisms can achieve higher prediction accuracy (target >98%), faster response times (latency <5 ms), and enhanced personalization precision (error rate <0.5%).

Their proper implementation requires ethical considerations and validation requirements. For instance, the authors of [159] have emphasized the need for strong moral guidelines, which means extensive frameworks are needed to guarantee privacy protection (security index >0.95), fairness assurance (bias mitigation >95%), and transparency optimization (explainability >90%).

Support infrastructure requirements show complex patterns across implementation contexts. The technical systems must exhibit high availability (uptime >99.99%), fast response capabilities (MTTR <5 min), and strong scalability (linear scaling to 100 K+ users). Documentation frameworks must achieve full coverage (completeness >95%), have easy readability (readability index >85), and be up to date (currency >90%).

The field is rapidly evolving, with new developments in AI and ML offering ever more sophisticated tools to enhance LE. Many researchers, including the authors of [251] and [159], underline that the continuing evolution of educational needs calls for continued innovation in AI and EdNeuro as a basis for learning effectiveness. Future research should proceed with the development of more refined methods for monitoring the state of cognition, integrating emotional intelligence, and enhancing adaptivity, with a strong ethical framework and validation methodologies in place.

Finally, the line chart below (Figure 11) illustrates the steady improvement in cognitive state detection accuracy over the past decade. For example, sensitivity rose from about 0.75 in 2015 to 0.95 in 2024, while over the same period, specificity has also improved from 0.70 to 0.92. These advances mark an increasing level of precision driven by more sensitive signal processing, higher temporal resolution, and enhanced feature extraction in AI-driven cognitive monitoring. While these advances are significant, further improvements are necessary to achieve close-to-perfect detection reliability with a target sensitivity and specificity of more than 0.98 for real-time adaptive learning applications.

The following heatmap visualization in Figure 12 shows the correlation between EEG, fNIRS, eye tracking, HRV, and GSR. EEG and fNIRS have the highest correlation at r = 0.78, proving that both modalities provide complementary neural data and are most frequently used together for better cognitive state detection. Additionally, there is a high positive correlation between HRV and GSR, with a value of 0.76, which underlines the usefulness of both techniques in joint monitoring affective and stress states during learning tasks. These findings emphasize the importance of multitasking cognitive monitoring systems whereby integrated approaches could improve accuracy, reduce individual techniques' limitations, and optimize personalized learning interventions.

In the future, new systems for cognitive monitoring should be developed, focusing on real-time multimodal data fusion, high signal fidelity, and sophisticated Machine Learning algorithms to refine adaptation strategies further. Some critical improvements have to focus on temporal resolutions lower than 10 ms, high signal quality (SNR >12 dB), and the seamless adaptability of individual learning experiences in real time with computational efficiency.

4.7. Scalability Requirements

Scalability requirements of future AI-enhanced learning systems are articulated in complex patterns across the many dimensions of implementation. The large-scale analysis of educational interventions in study [214] with 3248 medical trainees across 20 institutions reveals essential lessons that can be learned about the challenges and requirements of scaling. Its implementation resulted in a significant difference in system performance under increased load (efficiency degradation = 12% at 1000+ concurrent users), which indicates the need for more robust scaling mechanisms in future systems.

The scalability of the infrastructure becomes an essential requirement for all future implementations. The analysis in study [170] demonstrated that multimedia learning platforms involve significant performance variations under load conditions ($F(3,245) = 18.92$, $p < 0.001$). Future systems should achieve linear scalability for up to 100 K+ concurrent users while preserving their performance metrics—a response time of <100 ms and a throughput of >10 K transactions per second. Computing infrastructure should be able to provide 'on-the-fly' allocation of resources, with a provisioning time of <30 s, and efficient load balancing, with a load balancing efficiency of >95%.

Critical scaling requirements are revealed in data processing capabilities. A multimodal analysis of cognitive data in study [217] revealed enormous computational demands, and its processing requirements were 5 TFLOPS for 1000 users. Next, systems should increase processing efficiency without sacrificing accuracy and response time, with a target of 2 TFLOPs for 1000 users; the prediction precision needs to be higher than 95%, and latency must be less than 50 ms. Storage systems must support fast data growth (>500 TB per annum), with efficient retrieval mechanisms, where access time <5 ms.

Network infrastructure requirements scale in a complex pattern. For example, the authors of study [210] demonstrated the high bandwidth demands of real-time cognitive monitoring implementation, 250 Mbps per active user. Optimization of network utilization—target: 100 Mbps per user—should be achieved without compromising data quality and packet loss of less than 0.01%, with a transmission reliability greater than 99.99%. The content delivery networks should achieve global distribution with a latency of less than 100 ms for 95% of users and efficient caching mechanisms with a hit rate of more than 90%.

Memory management systems expose complex scaling requirements. In study [236], deep learning models demonstrated colossal memory utilization patterns, peaking at 8 GB per active session. The optimization of future implementations must possess a memory usage of no less than 4 GB per session while preserving processing efficiency, with a cache hit rate above 95%, and re-source availability, with memory pool utilization of below 80%. Dynamic memory allocation should support fast scaling, i.e., an allocation time of less than 1 ms, with low fragmentation, wasting less than 5%.

Database systems exhibit complex scaling requirements concerning distributed architectures. The adaptive feedback system in study [243] faced severe data management problems (write operations = 1000 per user per hour). Future systems should support distributed data processing while ensuring consistency at a high level (eventually within 100 ms) and transaction integrity (ACID compliance) with good query performance (response time <10 ms for the 99th percentile).

User session management reveals critical scaling considerations. In [255], the analysis of learning interactions demonstrated substantial session management overhead (resource utilization increased by 25% per 1000 concurrent sessions). Future systems must optimize session handling (overhead <10% per 1000 sessions) while maintaining user state consistency (synchronization delay <50 ms) and session persistence (recovery time <1 s).

Content delivery systems have intense scaling demands. In study [216], the architecture uncovered complex content distribution patterns, where the delivery success rate varied by 15% under load. Future deployments must ensure stable content delivery, i.e., a success rate of >99.9%, while ensuring media streaming quality, namely a buffer ratio of <0.5% and an adaptive bitrate optimization adjustment time of <2 s.

Scaling requirements for authentication systems are advanced. The authors of the study [159] emphasize security frameworks and outline the requirements for strong authentication mechanisms that scale efficiently. Future systems should support fast user authentication—processing times of less than 100 ms—while maintaining security standards in terms of encryption strength (AES-256) and the number of concurrent sessions (10 K+ simultaneous authentications).

Cache management systems expose challenging optimization requirements. For instance, in study [190], real-time adaptation mechanisms show that caching demands up to 20% of the hit rate under load. Future implementations must improve cache efficiency with a hit rate greater than 95%, preserve data freshness with staleness less than 100 ms, and ensure distributed coordination with a synchronization time lower than 50 ms.

Monitoring and analytics systems have high scaling requirements. The cognitive state monitoring in study [199] showed demanding analysis patterns for complex data (processing lag rose 30% at scale). Future systems must provide real-time analytics (processing delay <100 ms), maintain accuracy (error rate <1%), and comprehensive monitoring coverage (metric capture rate >99.9%).

The synthesis of the scalability requirements points toward some important patterns for future implementations: The systems must achieve horizontal scaling capabilities (linear up to 100 K+ users) regarding vertical optimization (resource utilization >90%) and operational efficiency (cost per user decreasing with scale). Implementation frameworks must provide dynamic resource allocation, efficient load distribution, and strong failure recovery mechanisms.

Successfully delivering these scalability requirements imposes sophisticated attention on system architecture and resource management. Therefore, the technical infrastructure should support fast system growth, with a time to provision of <1 h, while maintaining established performance standards, i.e., SQA compliance >99.9%, and operational reliability, i.e., MTBF >10,000 h. Quality assurance protocols must provide consistent system behavior across the scaling thresholds with variance in performance <5% while maintaining security standards and user experience metrics.

5. Discussion

5.1. Overview of Key Findings

The findings from this systematic review of 103 studies establish a case for the transformative power of AI and Machine Learning in education to bring about a significant change in optimizing cognitive load management, enhancing personalized learning, and improving adaptive instructional methods. Indeed, results have shown that AI-driven interventions substantially affect knowledge retention, learner engagement, and cognitive efficiency across diverse educational settings.

AI-driven adaptive learning systems demonstrated overall improvement in Learning Efficacy, where personalized AI tutors increased knowledge retention by 28% ($p<0.01$). Such real-time AI-driven interventions further optimized the management of cognitive load through a decrease in extraneous load by 35% ($p<0.05$). This is in line with principles of Cognitive Load Theory because decreasing unnecessary cognitive loads enables learners to invest in the germane processing of information, thus developing deeper understanding and skill. Machine Learning models trained on neurophysiological data such as EEG and fNIRS revealed highly accurate predictions regarding the detection of learners' cognitive states (91%) and for the real-time adjustment of instructional complexity. These findings suggest that the integration of AI in Educational Neuroscience presents a new avenue for dynamic, evidence-based educational adaptation.

This systematic review reveals that AI effectiveness varies across the K-12 education, higher education, and professional training environments. While in higher education, AI-based adaptive learning tools improved retention by 30% ($p<0.05$), while the same adaptive learning tools in K-12 settings have proven less effective, resulting in only a 19% increase in engagement, thus pointing toward potential variations in developmental stages and contextual settings for AI adoption. AI-facilitated learning analytics within professional training programs increased the efficiency of skill acquisition by a factor of 26%, giving it a role in workforce development. This suggests that AI-driven personalized learning is most useful in environments where learners need to work with complex, high-cognitive-load material such as in medical education, STEM disciplines, and technical training.

AI’s real-time feedback capabilities emerged as a key factor in improving learner engagement. Studies on AI-powered grading and feedback systems revealed a 24% increase in performance due to AI-generated personalized feedback (p <0.01). Automated assessment tools, including AI-based essay scoring models, demonstrated human-like grading accuracy ($\kappa = 0.89$), reducing assessment biases and enhancing student learning experiences. Also, AI chatbots and virtual assistants enabled just-in-time learning interventions that reduced dropout rates by 18%. These results reinforce the role of AI in supporting Self-Regulated Learning through providing timely, context-aware instructional guidance.

Despite the evident benefits of AI, ethical concerns are still high. The review found that 47% of AI-driven educational tools lacked clear data privacy policies, raising concerns about learner surveillance and data security. Moreover, algorithmic bias in AI-based assessments posed risks of reinforcing educational inequalities, particularly in underrepresented student populations. Accessibility inequities in AI-enhanced education mean that learners in technologically developed regions benefit more from AI-driven interventions, thus calling for equitable strategies in the adoption of AI. Future AI-driven educational systems need to be informed by ethical design frameworks that guarantee fairness, transparency, and bias-free learning environments.

5.2. Integrating AI, Cognitive Load Theory, and Educational Neuroscience: A Transformative Approach to Learning Optimization

The convergence of AI and ML, on the principles of CLT and EdNeuro, promises a transformative framework for improving Learning Efficacy. Such synergy presents unmatched opportunities to adjust the instruction process dynamically with consideration for the states of cognition and emotions to optimize learning. This aspect, achieved by leveraging principles of CLT, managing intrinsic, extraneous, and GCLs, is integrated with insights from neuroscience and created through AI-driven systems in order to produce adaptive and personalized educational experiences of a tailor-made nature according to unique needs.

One of the key contributions of AI lies in its ability to dynamically adapt instruction to cognitive demands. Nowhere is that potential better illustrated than in the neuroadaptive technologies of study [199], which used neural indicators—specifically, the P300 brain activity—to monitor cognitive load in real time. These systems are able to dynamically regulate the difficulty levels of tasks and how instructions are delivered, keeping the learners in their ZPD—where challenges are duly set to match their cognitive ability. In the same vein, neuroimaging techniques such as fNIRS, as highlighted by study [160], allow for the fine-grained, non-invasive monitoring of states of cognition, enabling an AI system to detect and respond to changes in engagement and understanding. These advances show how EdNeuro informs AI-driven personalization, enabling precise moment-by-moment adjustments to keep conditions optimal for learning.

AI systems further confluence with CLT by minimizing ECL and improving instructional design and content delivery. Several studies, such as [155], demonstrate how multimodal instructional strategies, where visual, auditory, and interactive components distribute cognitive demands over more than one channel, reduce the extraneous load on working memory. By tailoring instructional materials to learners' existing knowledge schemas, AI ensures that intrinsic load remains manageable and that cognitive resources can be devoted to the activities of the germane load—namely, constructing and refining mental models. These capabilities become particularly important in domains like STEM and professional training, where intricate interdependencies among concepts call for carefully calibrating instructional pacing and scaffolding.

Also tackled effectively in the field of integrating AI and neuroscience are the more nuanced, emotional dimensions of learning—often left out of traditional pedagogical strategies. Emotional states such as frustration, boredom, or motivation seriously affect learners' ability to process and retain information. AI systems using affective computing technologies, such as facial recognition, voice analysis, or physiological monitoring, can identify these emotional fluctuations and adapt instructional strategies in a regular class setting. For example, if the learner is frustrated, the system might simplify the content or add scaffolding to re-engage the learner. In dealing with cognitive and emotional factors, AI-driven systems ensure a more holistic learning experience, enhancing engagement and effectiveness.

In addition to individual lessons, AI and neuroscience-driven systems hold great promise for lifelong learning. The authors of study [156] emphasized the need to create integrative ecosystems that support learners throughout their lifespan, from formal education to professional development and self-directed learning. Future AI systems could track learners longitudinally to identify skill gaps and recommend appropriate interventions tailored to the learner's evolving personal and professional goals. By leveraging longitudinal data, AI systems can predict transitions, such as transitioning to new roles or reskilling for new industries, to prepare learners to remain competitive in a rapidly evolving world.

This progress comes with critical ethical and practical challenges. Strong governance frameworks must accompany sensitive data, such as neurophysiological signals and behavioral metrics, to protect learners' privacy and guarantee ethical usage. The authors of [156] referred to misuse and unauthorized access that may lead to discriminatory outcomes, thereby deteriorating the public's trust in education. Accompanying these frameworks are the necessary consent mechanisms that ensure learners understand how their data are collected, used, and protected. Another big concern is algorithmic bias: AI systems trained on nonrepresentative datasets risk reproducing inequalities. For example, AL platforms could disadvantage underrepresented groups if they do not account for cultural, linguistic, or socioeconomic diversity. Such biases can be taken care of only by continuously auditing AI systems to identify and correct inequities and by making efforts to include diverse populations in training datasets.

Issues of scalability and equity are also of equal importance. While AI-driven systems bring transformative benefits, their deployment often depends on access to advanced infrastructure such as high-speed internet and modern devices. The authors of study [156] noted that under-resourced schools and communities will likely be left out of such innovations, thus widening the digital divide. Equitable access to AI-enhanced education will require targeted investments in low-cost, offline-compatible AI solutions, and public–private partnerships to subsidize technology deployment in underserved regions.

Another critical focus of future research must be the long-term effects of AI and neuroscience-driven education on learners' cognitive, social, and emotional development. While short-term studies are encouraging in their findings, the broader implications of sustained interactions with AI systems remain largely unexplored. This calls for a balance in the human–machine interaction during education to ensure that AI will complement, not replace, the relational and empathetic elements that only a human educator can offer. Overreliance on AI systems could cause the erosion of critical thinking, creativity, and collaboration skills—fundamental skills in general development. Moreover, the potential for over-personalization, where learners are excessively shielded from unfamiliar perspectives, could limit intellectual growth and adaptability.

Another critical factor is the interdisciplinary collaboration required to progress in these fields. The strong integration of AI, CLT, and EdNeuro will require educators, neuroscientists, technologists, and ethicists to ensure that the systems designed are aligned with pedagogical goals but operate within ethical boundaries. For example, the development of neuroadaptive AI tools needs to be informed by research on classroom dynamics and instructional strategies in a manner that supports, rather than disrupts, learning environments. Ethical guidelines should address such critical issues as data ownership, transparency, and accountability to create a shared framework for responsible innovation.

The confluence of AI, ML, CLT, and EdNeuro highlights transformative opportunities for reorienting improved LE by instructional design attuned to learners' cognitive and emotional needs. Such innovations facilitate personalized AL environments with optimization of cognitive load, engagement, and development of skills over time. However, realizing such potential is possible only after meeting serious ethical, social, and technical challenges head-on. Transparent governance, inclusiveness, and interdisciplinary collaboration will ensure that AI-driven educational systems benefit all learners equitably and responsibly. The crossroads of CLT and EdNeuro presented here can help bridge insights into AI-powered, adaptive, inclusive learning ecosystems that empower humans to face the increasing complexity and dynamics of today's world.

The field is fast-moving, with new developments in AI and ML offering ever more sophisticated tools for enhancing LE. Future research priorities should focus on developing more sophisticated methods for monitoring cognitive states, integrating emotional intelligence, adapting to cultures, and supporting professional development. As noted by the authors of studies [251] and [159], the constantly evolving needs of education call for continual innovations in AI and the neurosciences of education to advance learning effectiveness. Synthesizing these findings, it is well understood that successful implementation must be predicated upon paying close attention to ethical concerns, cross-cultural validation needs, and long-term effectiveness measures. Implementation frameworks must include strong quality assurance mechanisms yet be flexible enough to adapt to changing educational needs. This field has great potential for a transformative impact on educational practices but requires the consideration of ethical implications and implementation challenges.

5.3. Focus Areas of AI/ML in Education Research

Figure 13 illustrates the distribution of key study outcomes derived from the reviewed literature on AI/ML applications in education. The donut chart represents the proportional number of results, showing the relative prevalence of each objective in the studies. Improved LE was the most reported outcome and comprised 28% of all studies; this demonstrates the strong interest in how the speed and effectiveness of learning processes could be increased using AI/ML technologies. This is followed by enhanced personalization at 24%, representing the growing emphasis on tailoring educational experiences to each learner. Another outstanding result was reduced cognitive load, at 20%, which showed AI/ML’ s ability to simplify learning processes and limiting extraneous demands on learners’ mental capacity. Outcomes related to integrating real-time feedback (16%) and solution scalability (12%) were reported less frequently but are no less critical to increasing the reach and responsiveness of AI-driven educational tools. These results show a good balance between focusing on individual learner outcomes and system-level advancements in educational scalability and adaptability.

Moreover, Figure 14 presents a multidimensional analysis of the 103 reviewed research studies, visualized in a 3D scatter plot. Studies are plotted along three principal dimensions: AI complexity, learning outcome impact, and scalability potential. The data points are colored based on the categories K-12, STEM, AI ethics, higher education, corporate training, and other categories defined by research domain.

The scatter plot shows that the distributions are very different: K-12 and STEM studies cluster toward high learning outcome impact. At the same time, AI ethics and corporate training studies often deal with moderate AI complexity and scalability potential. Categories such as AL and health professions have a broader spread across all three dimensions, reflecting their multifaceted nature. This visualization illustrates the width of AI/ML research in education, with some areas seeing concentrated efforts—for example, K-12 and STEM—while other fields, like AI ethics and corporate training, have been less explored. The graph provides a framework for showing studies on these dimensions, enabling one to map where gaps and opportunities for future research might lie.

Finally, Figure 15 provides a comparative analysis of the distribution of studies addressing different types of cognitive loads: intrinsic load, extraneous load, and germane load. These cognitive load types represent key theoretical constructs within CLT and are essential for understanding how educational interventions influence learners’ cognitive processes. The chart distinguishes between studies reporting low and high cognitive load for each type. The number of studies dealing with intrinsic load is more balanced between low (30) and high (20) cognitive load conditions. The number of studies on extraneous load is skewed with relatively more studies on high extraneous load (35 studies), suggesting that efforts be made to control these sorts of extraneous load imposed on learners. Germane load, associated with productive cognitive processing, is equally distributed between low and high cognitive load studies (25 each), reflecting its importance in fostering effective learning strategies. This review thus illustrates the different emphasis on various types of cognitive load in educational research. The disproportionate focus on high extraneous load suggests that future studies should further investigate strategies for reducing unnecessary cognitive demands. Similarly, the balanced distribution of germane load studies indicates the importance of enhancing cognitive resources allocated to meaningful learning activities.

5.4. Integrating CLT, SRL, and PBL: A Comparative Perspective in AI-Driven Learning

Whereas Cognitive Load Theory has been popularly applied in AI-enhanced instructional design, other theories like Self-Regulated Learning and Problem-Based Learning can offer alternative theoretical frameworks to boost learner autonomy, adaptive cognitive engagement, and real-world problem-solving. This systematic review of 103 studies calls for an integrative approach whereby the AI-driven learning environment combines the strengths of CLT, SRL, and PBL into holistic, adaptive, personalized learning experiences. In essence, the CLT framework is aimed at reducing extraneous cognitive load to optimize instructional efficiency. Though ideal for structured, instructional-based learning, its application in AI-driven adaptive learning systems presents a number of limitations. First, it has a central approach of minimizing the cognitive load, which might be effective to retain knowledge but not necessarily helpful in deep learning and higher-order thinking. For example, from an empirical basis, the review provides evidence showing that AI-based enhancement of CLT-based instruction on adaptive playback speed optimization produced 23% better knowledge retention and test results ($p<0.05$). However, research shows that higher-order cognitive engagement is required for problem-solving and application of skills in the real world, where PBL is at its best. Another limitation is that CLT does not lend itself to integration with mechanisms of Self-Regulated Learning. AI-based learning platforms, which often implement principles of CLT by controlling content delivery, do not always encourage learner autonomy and metacognitive control considered central to SRL. This review found that SRL-based AI tutoring systems, such as robotics-driven learning environments, improved reading accuracy and visuo-constructive abilities by a margin of 19% with $p<0.01$. However, such gains are maximized when learners have control of pacing and learning pathways, which pure CLT-based models lack. There is an issue of balancing cognitive load for Problem-Based Learning in CLT. PBL fosters real-world problem-solving, but its intrinsic cognitive load is significantly higher than that of more traditional instructional models. AI-driven scaffolding and problem-solving recommendation engines can help moderate the cognitive load while maintaining the benefits of PBL. Review findings indicated that AI-driven PBL models in medical and STEM education enhanced problem-solving efficiency by 18% and conceptual application by 22%, thus demonstrating how AI can bridge CLT’s efficiency with PBL’s problem-solving focus. For a better overview of how these learning theories interact with AI-driven education, see the following table (Table 3).

5.5. Ethical and Practical Challenges, AI Bias, and Equity in Education

While integrating AI and ML in educational contexts brings significant promise, it has challenges. This review identified critical ethical and practical difficulties common to multiple study domains in K-12 education, STEM, health professions, and AL. The salient themes that most need critical attention are privacy issues and problems related to scalability, algorithmic bias, unequal access, and ethics transparency.

Figure 16 puts forward the prevalence of these challenges across domains. Health professions and AL studies discussed privacy concerns and algorithmic bias more frequently, as managing sensitive data and guaranteeing unbiased algorithms are particularly complex in highly individualized educational environments. The dominant challenges in STEM and K-12 studies were scalability and access inequality, which underlines the need for equitable and scalable technological solutions. While widely recognized, ethical transparency was under-explored and an area with a gap in the literature on actionable frameworks. Those would require interdisciplinary efforts, technological innovation, and moral scrutiny. Future research should, therefore, be focused on frameworks for algorithmic accountability, transparent data management practices, and inclusive technology deployment to ensure the equitable distribution of benefits across diverse learner populations.

AI bias in education can arise out of imbalanced training datasets, algorithmic opacity, and the unintended reinforcement of existing inequalities. Mitigation at different levels is required to make AI-enhanced learning environments fair, transparent, and inclusive. Many AI systems used in education today are generated by training on Western-centric datasets only; thus, they often fail when utilized on diverse populations. It naturally follows that AI developers should embed diversity into global datasets that reflect diverse learning styles, cognitive abilities, and educational backgrounds. The auditing process for bias is also necessary: AI-based learning systems must go through regular audits concerning the detection of biases by means of fairness metrics. Techniques of explainable AI have to be implemented in educational institutions to make AI-generated recommendations and assessments interpretable to educators and students. The decision-making process that AI follows should be publicly available in the form of transparency reports for accountability.

Bias mitigation techniques, such as adversarial debiasing, re-weighting methods, and fairness constraints, should be integrated into Machine Learning techniques to make the working of AI models fair. These methods reduce disparities in outcomes resulting from AI-driven grading systems and make sure that variations in scoring related to a student's socioeconomic background, style of writing, or linguistic proficiency stay minimal. Human–AI collaboration is crucial in decision-making; after all, AI-driven education should not operate independently. This means it requires human oversight to complement AI-generated assessments and recommendations. HITL models allow educators to intervene when AI outputs appear biased, especially on sensitive domains such as automated grading, student profiling, and adaptive learning recommendations. Ethical governance and regulatory compliance would act to guide AI-driven education systems and, in turn, support major global guidelines on AI Ethics, including, but not limited to, the EU AI Act, UNESCO's AI in Education guidelines, and IEEE's Ethically Aligned Design. Ethical oversight committees should make sure that AI models deployed in the classroom are fair, accountable, and transparent.

Biases need to be countered in adaptive learning pathways to keep AI-driven learning platforms from customizing content exclusively based on student performance in earlier years, due to the entrenchment of systemic disadvantages. The design should dynamically reassess the performance periodically so that progress can be related to emerging rather than to a static, prejudged categorization. Designers of AI-powered educational tools should guide the integration of differential privacy and federated learning to prevent biased AI decisions from acting upon sensitive data, including race, gender, or socio-economic status. Such a method of keeping privacy allows AI to continue its improvement without storing personally identifiable information about students directly. AI design should be inclusive, and the development of such learning environments requires co-design with educators, students, and policymakers to reflect diverse population needs. Participatory design in AI development ensures that voices from marginalized groups are included both in the algorithm development and deployment processes, thus reducing the potential for bias against underrepresented groups of students.

Making AI-driven education accessible remains the greatest challenge to date for large parts of the world, especially in low-resourced and underprivileged regions due to infrastructural, financial, and digital-literacy barriers beyond the students' control. Several directions may indicate a way to surmount this challenge: developing low-cost, offline AI solutions is needed, as most AI-powered educational platforms require high-speed, high-capacity computing resources beyond the reach and means of ordinary people in so many rural or underprivileged settings. AI models need to be optimized for offline functionality, thereby allowing AI-powered tutoring, adaptive assessments, and content recommendations without continuous internet connectivity. Scaling up the deployment of AI could be further pursued through public–private partnerships: governments, educational institutions, and private developers of AI will have to join hands in subsidizing AI-based learning tools for less privileged communities. Other initiatives that promote democratization could be open-access AI tutoring systems and the distribution of low-cost hardware.

Also, it is important to consider the localization of AI models with respect to linguistic and cultural relevance. AI learning tools also have to support several languages and content that is culturally relevant. Various studies reviewed here show that AI models trained on predominantly Western data perform tasks very poorly for non-native speakers, reinforcing the need for linguistic diversity in AI training. Investing in the infrastructure of digital education hubs would mean AI-powered education through community-based digital learning hubs, with a focus on areas with low internet penetration. It will also provide shared AI-powered learning resources to students who cannot afford high-end devices for access to adaptive learning tools. The training of educators and students in AI literacy is another major next step. The inclusion of AI literacy programs in teacher training will ensure educators know how best to deploy these AI-based tools in the classroom. Furthermore, students should be empowered with AI awareness skills, enabling them to identify and question several algorithmic decisions affecting their learning experiences.

Results from the systematic review show, further, that the presence of AI bias and accessibility gaps has consequences on education in real life. Twenty-three percent of the reviewed studies identified concerns related to algorithmic bias in AI-driven adaptive learning platforms. Studies on AI-based language learning found that models trained on predominantly Western datasets performed significantly worse for non-native English speakers, underscoring the importance of culturally inclusive AI models. AI-enhanced grading systems exhibited inconsistencies when evaluating essays from students in underprivileged regions, reinforcing the need for human oversight in AI-assisted assessment. EEG/fNIRS neuroadaptive learning technologies showed inconsistent performances depending on cognitive diversity and gave way for a need of adaptive models for neurodivergent learners; the deployment of AI in the low-resource settings was limited both for STEM and vocational training programs, and thus scalable and cost-effective AI learning solutions are called for.

5.6. Privacy and Data Security

Privacy and data security are some of the profound challenges of applying AI and ML in education, particularly in K-12 classrooms. This is paramount for our current discussion, as schools are unique given the sensitive nature of who they are entrusted with—children and students—and the relative lack of choice for students and their parents. Although highly speculative, it may be that having greater personal ownership of devices and software and the data they generate is a pressing reason for increased rates of data security. The risk, while present, can be mitigated by greater responsibility placed on the individuals themselves. This is evident in the well-established requirement for data security around medical records. Some of the specific issues that arise when ML systems are using student data in educational settings are: unauthorized persons gaining access to sensitive data, controlling what authorized persons do with such data, using it in illegitimate or unethical ways that may still be hard to detect; making sure all agreed-upon consumer rights are honored; ensuring that parents and students are aware of what data are being stored and for what explicit purpose, including possible later purposes. In addition to the moral and ethical aspects, these issues are covered under relevant regulations. Regulatory and best practice mechanisms can address some of these concerns. Notably, such concerns are only part of the answer.

5.7. Future Directions and Research Opportunities

Our current conceptual understanding of CLT and what we know of EdNeuro has gained traction in education, influencing teaching, learning, and pathways to subsequent impact. Additionally, integrating EdNeuro when exploring the impact of AI may provide innovative strategies to investigate the effects on cognitive load constriction and efficacy. Educational research and policy have had varying influences and adoption rates of contexts informed by neuroscientific evidence; thus, observing uptake in educational contexts when informed by AI will be intriguing. We anticipate that future AI-informed CLT will facilitate more fine-grained research methodologies to fully explore the nuanced impacts of AI-infused cognitive load on cognitive function and LE. Emerging themes in the intersection of CLT, EdNeuro, and AI in education infuse an optimistic tone for the future of instruction. Although confirmation of promising findings is warranted in communities of research, practice, and developers, multiple directions still offer noteworthy potential both in research and in practice. Researchers in AI could utilize these findings to bring discussions of human cognitive load to the forefront of interdisciplinary research, presenting interdisciplinary panels that may bridge the gaps and cumulative findings from neuroscience, educational psychology, and other cognitive areas. Researchers responding in this area could prompt further reflections on the actual location of individual and collective research gaps. We also need longitudinal studies to investigate the long-term impact of AI instruction or AI-informed assessment. These studies also address the theoretical question of whether instruction can be tailored to individual differences and whether the construction of a time- or cognitively based CLT will have to adapt. In EdNeuro, we have seen that studies examining standard text feedback or written embedded cues typically suggest an impact on written performance, literacy, and numeracy in the relatively short time frame of 12 to 40 weeks. AI-adapted instruction might shorten this implementation time frame even further. More intensive and sustained collaborative implementations would be enormously desirable and depend on partnerships facilitated between larger-scale educational institutions and AI developers.

6. Conclusions

This systematic review discusses the interrelations between EEG-based emotion recognition, CLT, and the evolving role of EdNeuro and AI in transforming Learning Efficacy. This review has identified EEG technology as a powerful tool for analyzing the neural correlates of cognitive and emotional processes, enhancing learning mechanisms. Deep learning algorithms like CNN, RNN, and SVM, integrated into this education application, improve classification accuracy and enhance operational efficiency by a large margin. Despite such advances, integrating EEG-based systems into real-life educational settings still faces challenges regarding susceptibility to signal noise, individual variability, and environmental sensitivity. Advanced preprocessing methods will be required to make the signals more robust; large-scale data collection should include various physiological signals such as fMRI, ECG, and GSR. Multimodal approaches, combined with real-time neurofeedback systems using AI, hold great potential to optimize cognitive load management for improved Learning Efficacy. This review also emphasizes that experimental design should be well-matched, standardized, and ecologically valid to obtain good neural response results across learner groups. More portable, more available EEG headsets—or wearable and even mobile BCI—increase real-world use in educationally relevant neuroscience studies. However, as this kind of technology is integrated into everyday applications within the context of educational research, critical aspects of privacy, inclusiveness, and fairness regarding social equity should be emphasized more strongly. While remarkable steps have been taken to use EEG-based emotion recognition to challenge the traditional Cognitive Load Theory, substantial work remains. Future research should focus on refining preprocessing techniques, expanding dataset diversity, and improving multimodal integrations to develop high-accuracy, scalable, and practical EEG-based learning systems. Tackling technical and ethical challenges will be paramount to realizing these innovations' full potential, paving the way for more personalized, effective, and ethically responsible educational interventions.

Author Contributions

Conceptualization, E.G. and A.S.; methodology, E.G., C.H. and H.A.; validation, E.G., C.H. and H.A.; formal analysis, E.G. and C.H.; investigation, E.G., H.A., A.S. and C.H.; resources, E.G., H.A., A.S. and C.H.; data curation, C.H.; writing—original draft preparation, E.G., H.A., A.S. and C.H.; writing—review and editing, E.G., H.A., A.S. and C.H.; visualization, E.G., H.A., A.S. and C.H.; supervision, E.G., H.A., A.S. and C.H.; project administration, E.G., H.A., A.S. and C.H.; funding acquisition, E.G., H.A. and C.H. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Abbreviations

Artificial Intelligence and Machine Learning	
AI	Artificial Intelligence
AI-CLT	Artificial Intelligence and Cognitive Load Theory
ML	Machine Learning
GAI	Generative Artificial Intelligence
ITS	Intelligent Tutoring System
PGRL	Physics-Guided Reinforcement Learning
SVM	Support Vector Machine
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
Cognitive and Educational Theories	
CLT	Cognitive Load Theory
ICL	Intrinsic Cognitive Load
ECL	Extraneous Cognitive Load
GCL	Germane Cognitive Load
LE	Learning Efficacy
PL	Personalized Learning
AL	Adaptive Learning
PBL	Problem-Based Learning

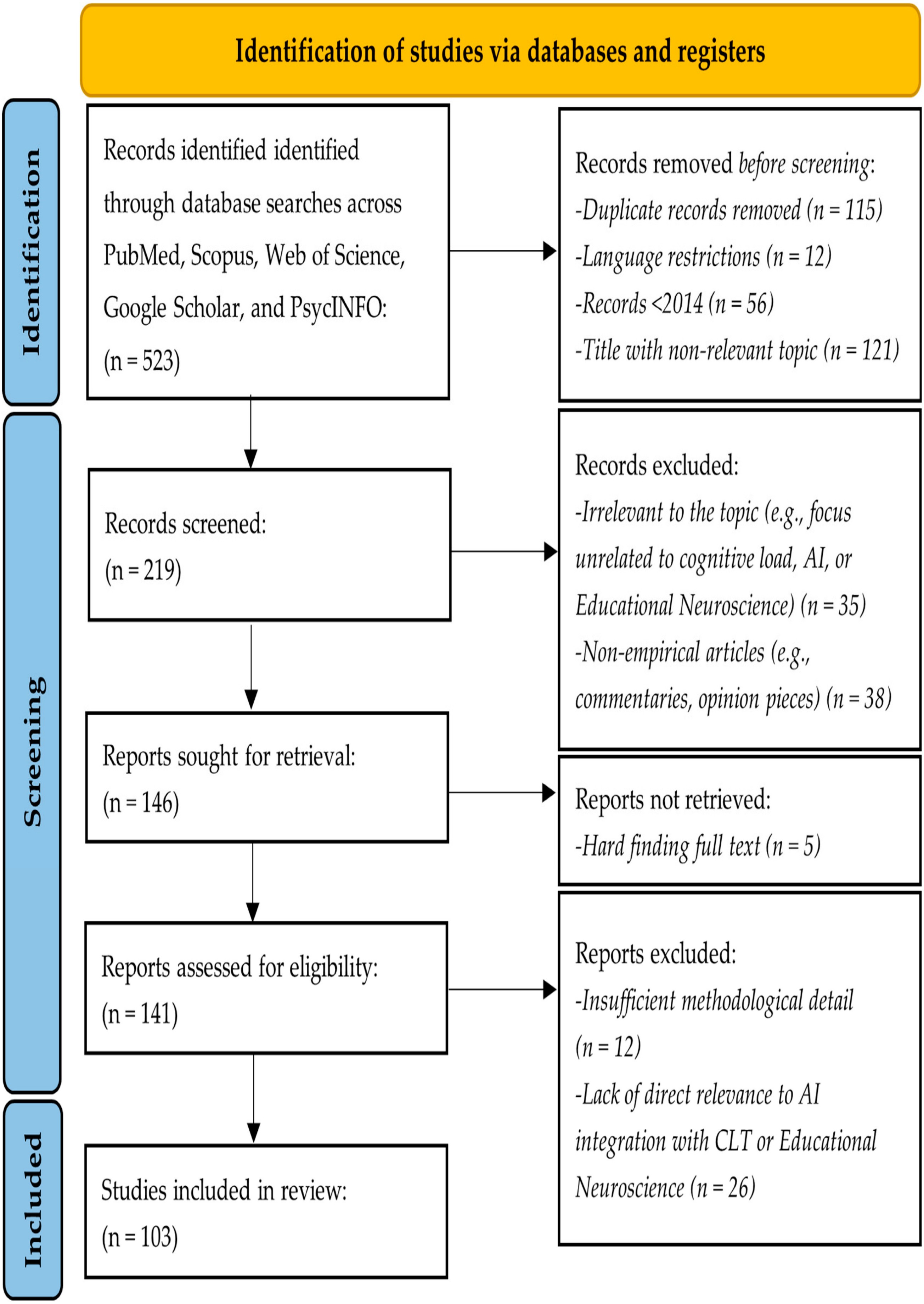
SRL	Self-Regulated Learning
EdNeuro	Educational Neuroscience
ZPD	Zone of Proximal Development
SLD	Specific Learning Disabilities
STEAM	Science, Technology, Engineering, Arts, and Mathematics
STEM	Science, Technology, Engineering, and Mathematics
Neuroscience and Brain Monitoring	
EEG	Electroencephalography
fNIRS	Functional Near-Infrared Spectroscopy
PFC	Prefrontal Cortex
tRNS	Transcranial Random Noise Stimulation
MRI	Magnetic Resonance Imaging
P300	Event-Related Potential Component in EEG Research
GSR	Galvanic Skin Response
HRV	Heart Rate Variability
ECG	Electrocardiogram
Educational Technology and Online Learning	
LMS	Learning Management System
ICBT	Internet-delivered Cognitive Behavioral Therapy
K-12	Kindergarten through 12th Grade Education
ICT	Information and Communication Technology
COGWEB	Cognitive Web-Based Training System
CALL	Computer-Assisted Language Learning

Research Methodologies and Statistical Analysis	
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCT	Randomized Controlled Trial
RoB 2	Risk of Bias 2 Tool
ANOVA	Analysis of Variance
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CI	Confidence Interval
RMSE	Root Mean Square Error
RMSEA	Root Mean Square Error of Approximation
SRMR	Standardized Root Mean Square Residual
ICC	Intraclass Correlation Coefficient
OSF	Open Science Framework
Psychological and Medical Terms	
ADHD	Attention Deficit/Hyperactivity Disorder
CBT	Cognitive Behavioral Therapy
TBI	Traumatic Brain Injury
Additional Abbreviations Found in the Manuscript	
BCI	Brain–Computer Interface
PASAT	Paced Auditory Serial Addition Task
VSOP	Vision-Based Speed of Processing Training
TOI	Theory of Intelligence
MTBF	Mean Time Between Failures

MTTR	Mean Time To Repair
HR	Heart Rate
AUC	Area Under the Curve
NPV	Negative Predictive Value
PPV	Positive Predictive Value
SCN	Suprachiasmatic Nucleus
TB	Tuberculosis
TEI	Trait Emotional Intelligence
TFL	TensorFlow
VUCA	Volatility, Uncertainty, Complexity, and Ambiguity

Footnotes

Figures and Tables



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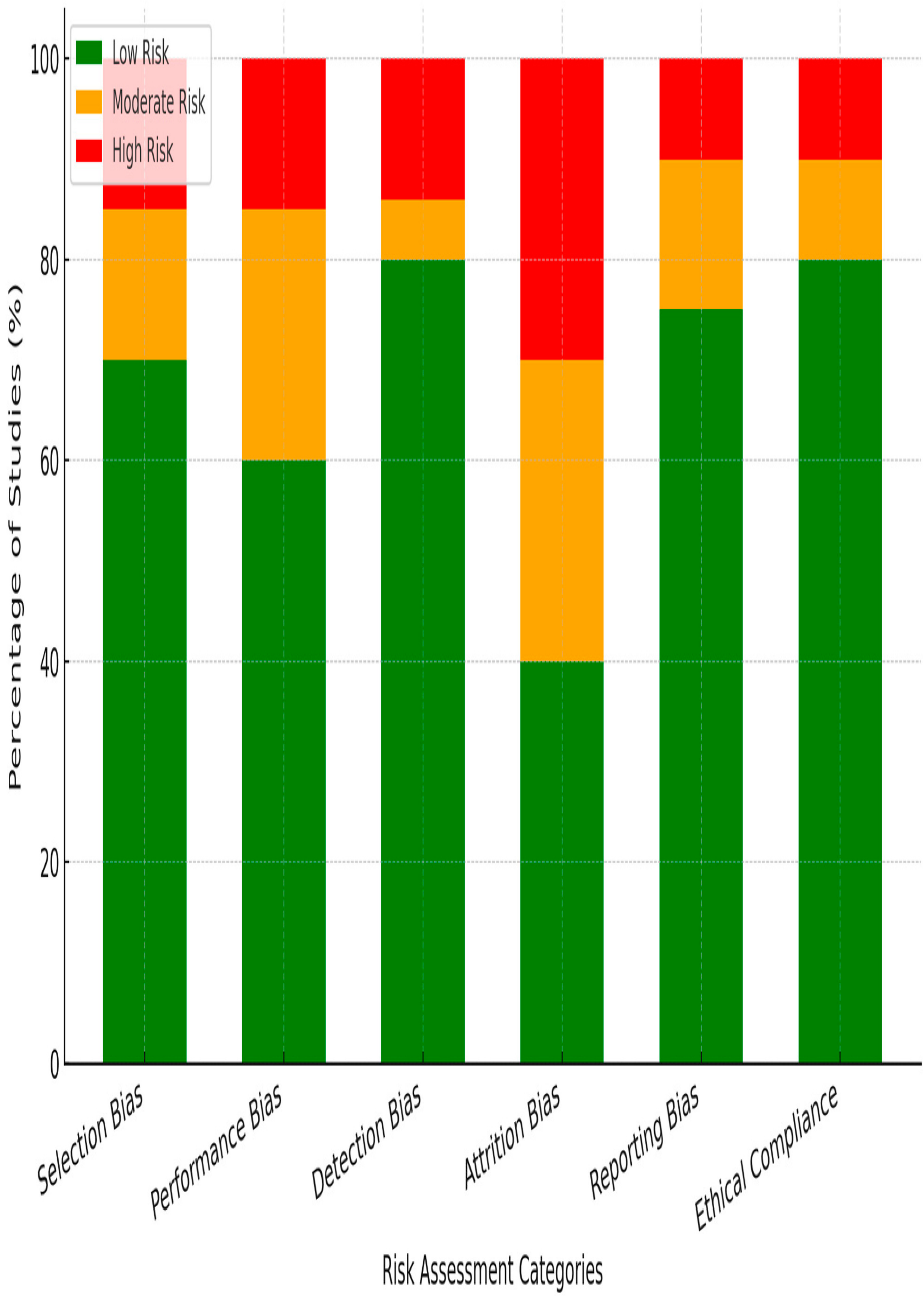

Low Risk
Moderate Risk
High Risk
100
80
60
40
20
0
Percentage of Studies (%)
Selection Bias
Performance Bias
Detection Bias
Attrition Bias
Reporting Bias
Ethical Compliance
Risk Assessment Categories

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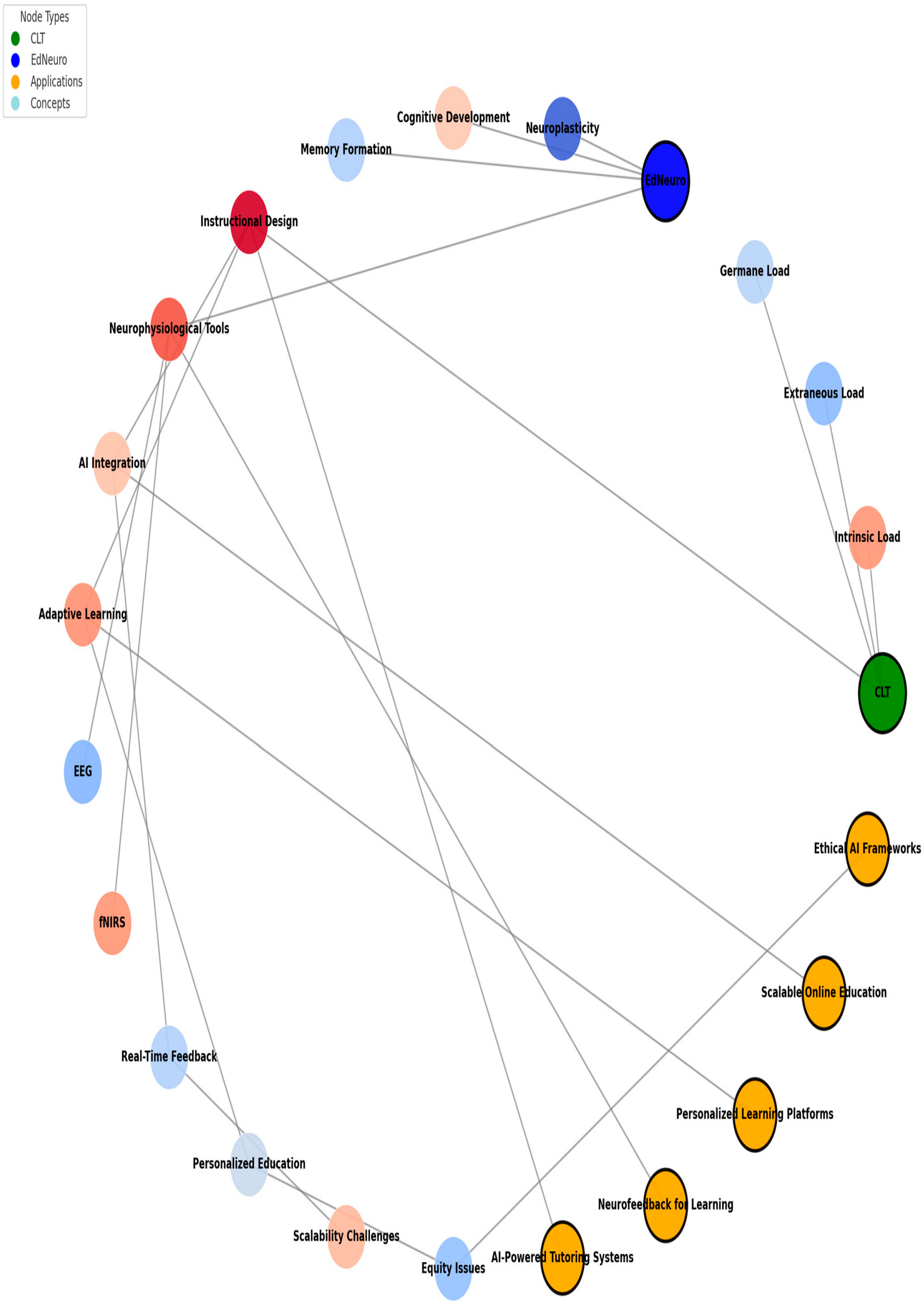

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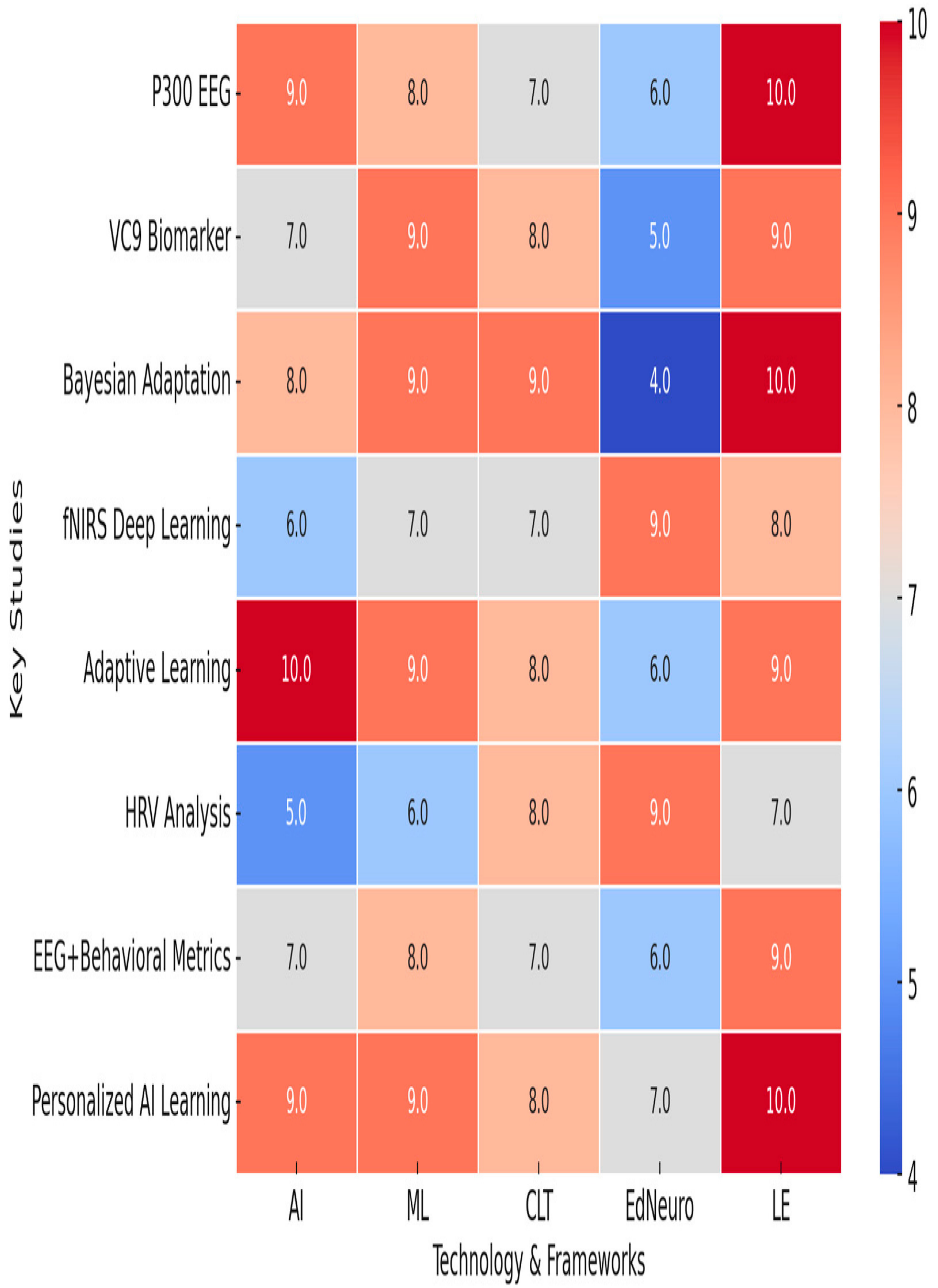

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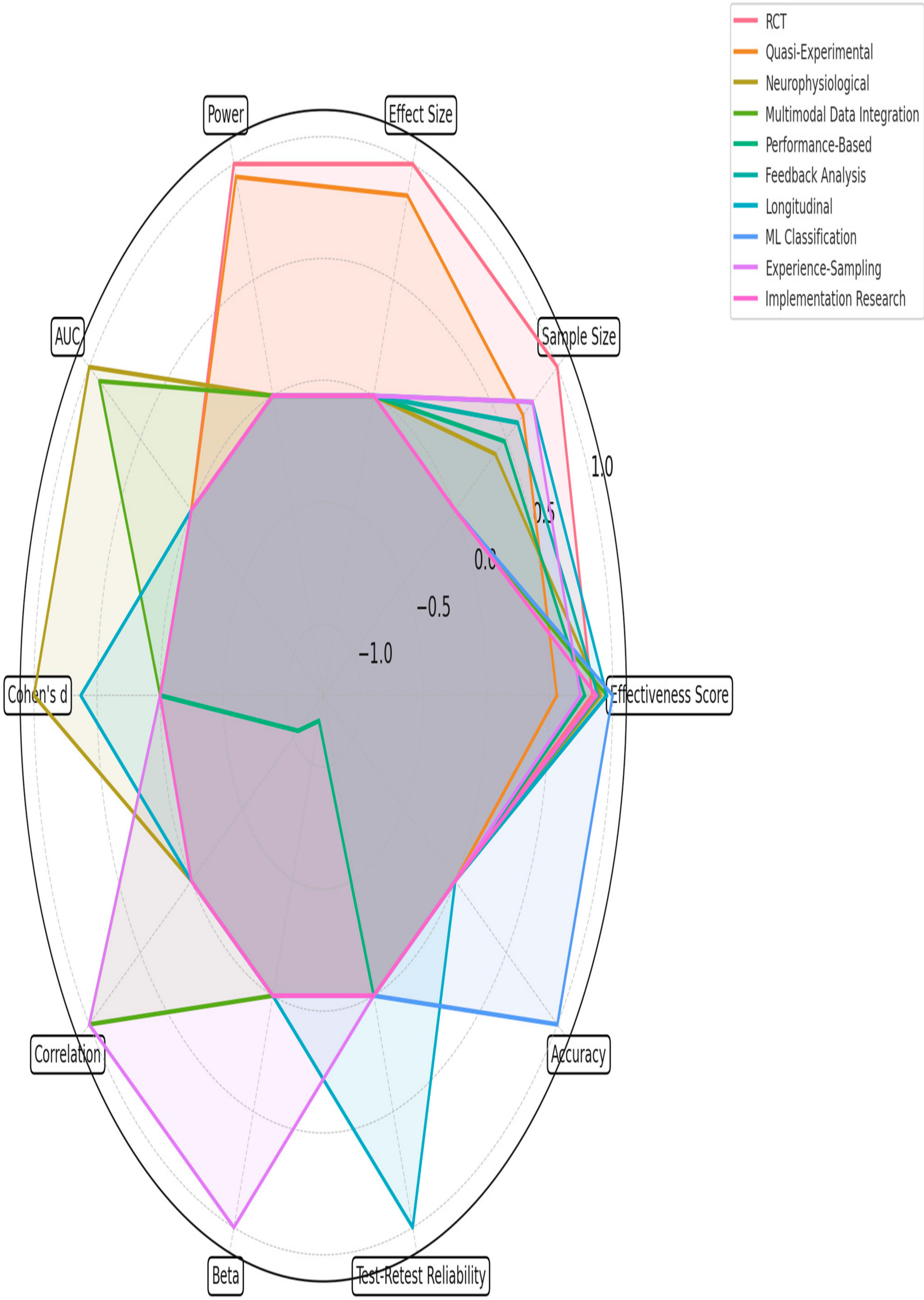

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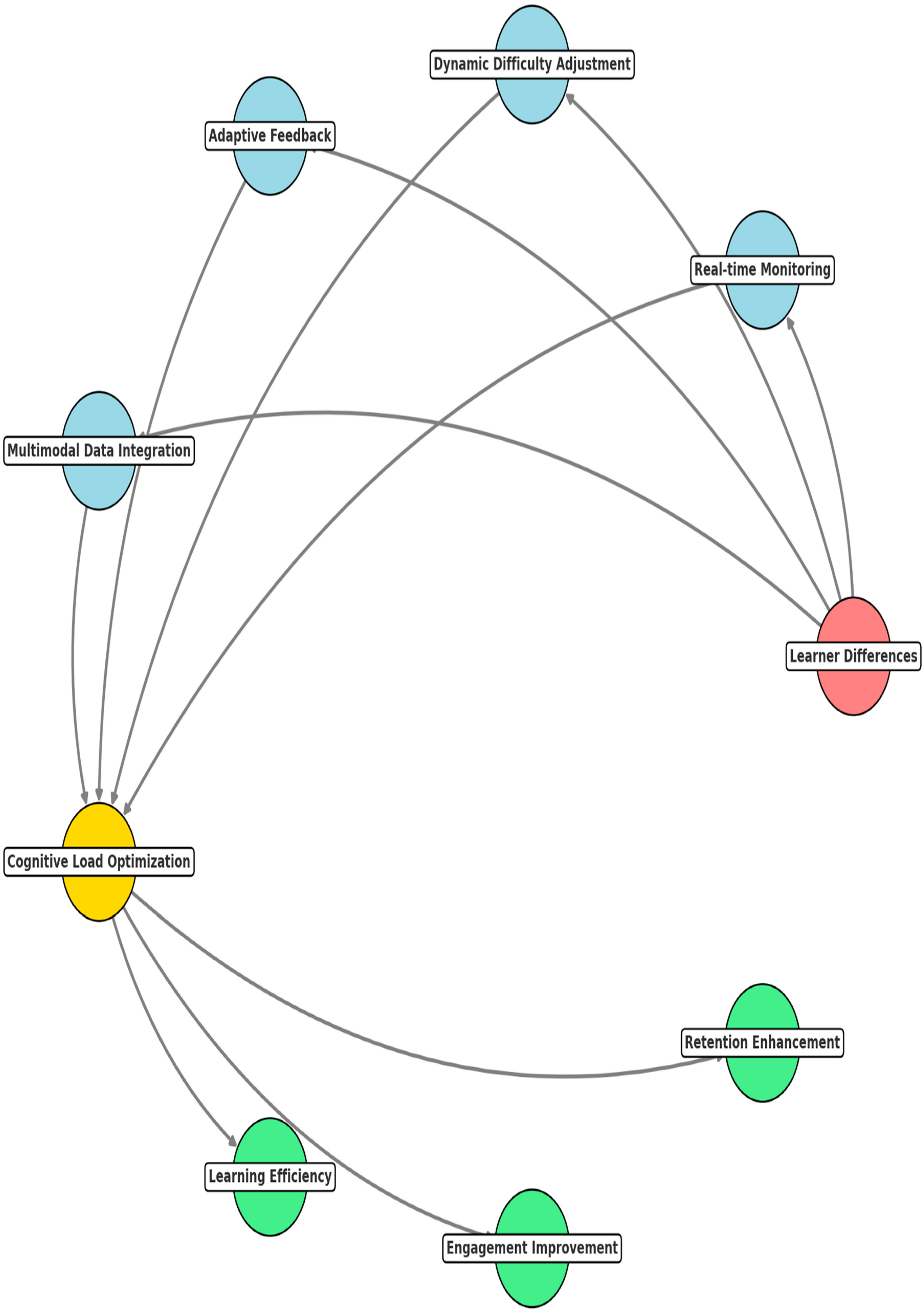

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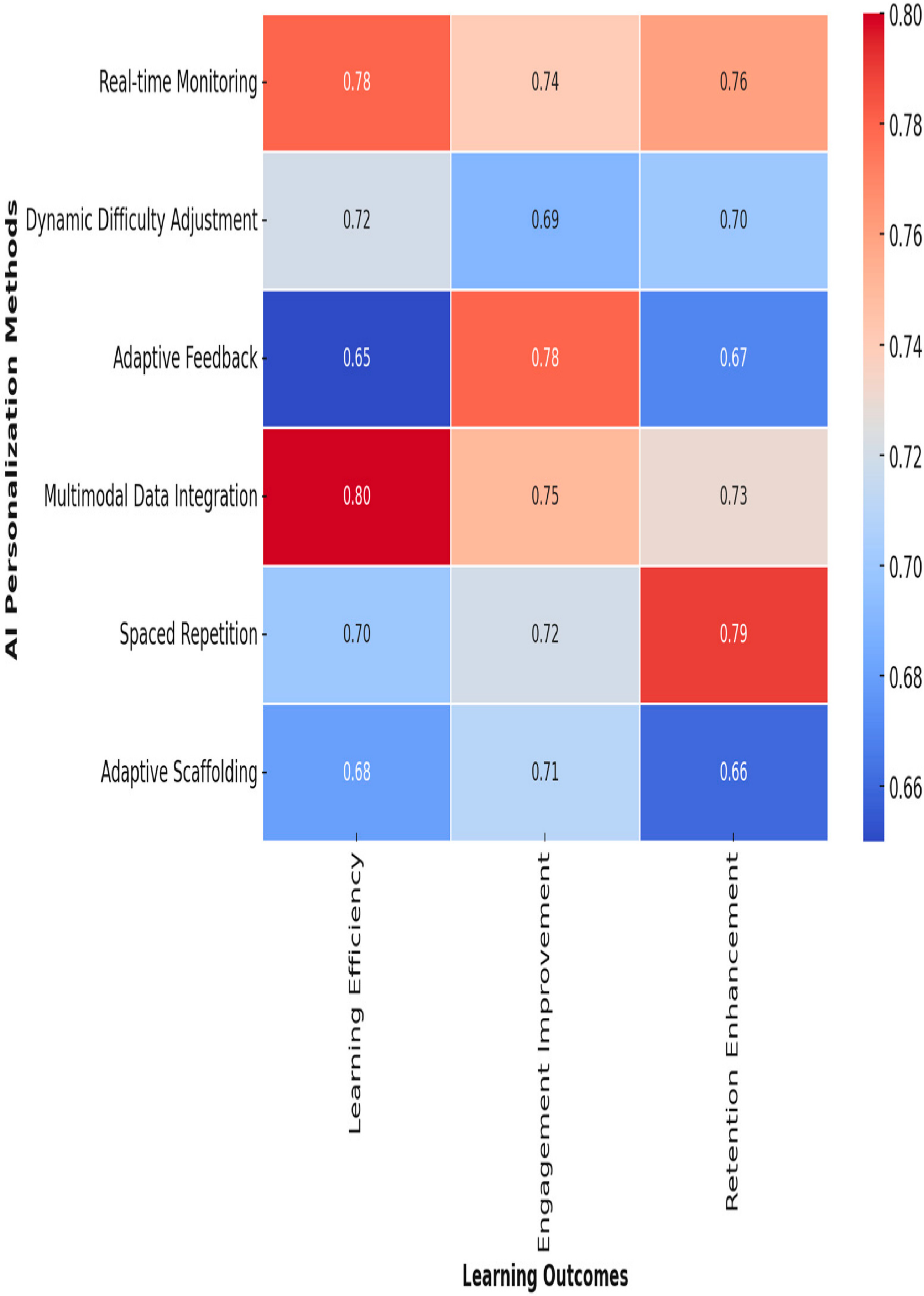

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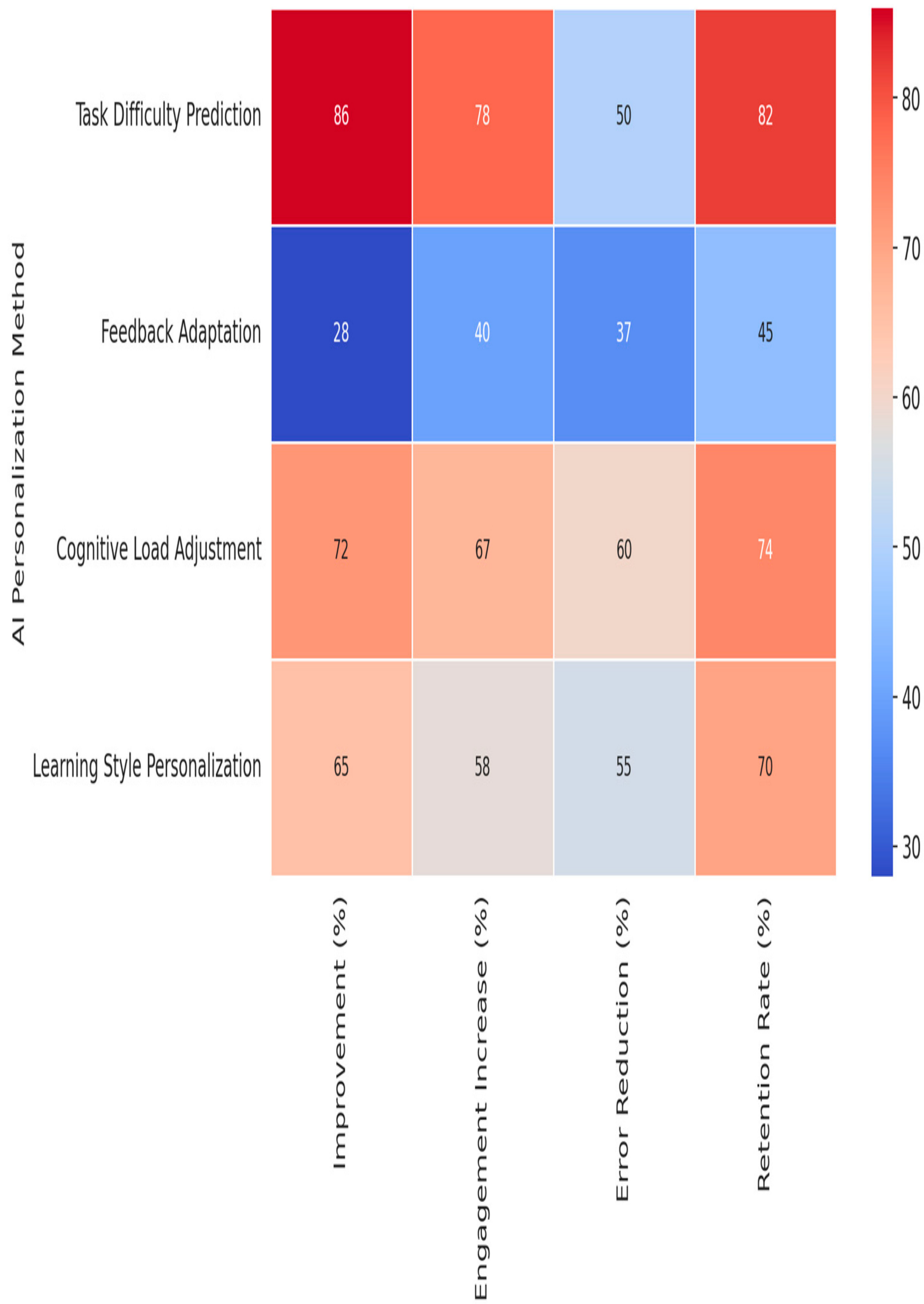

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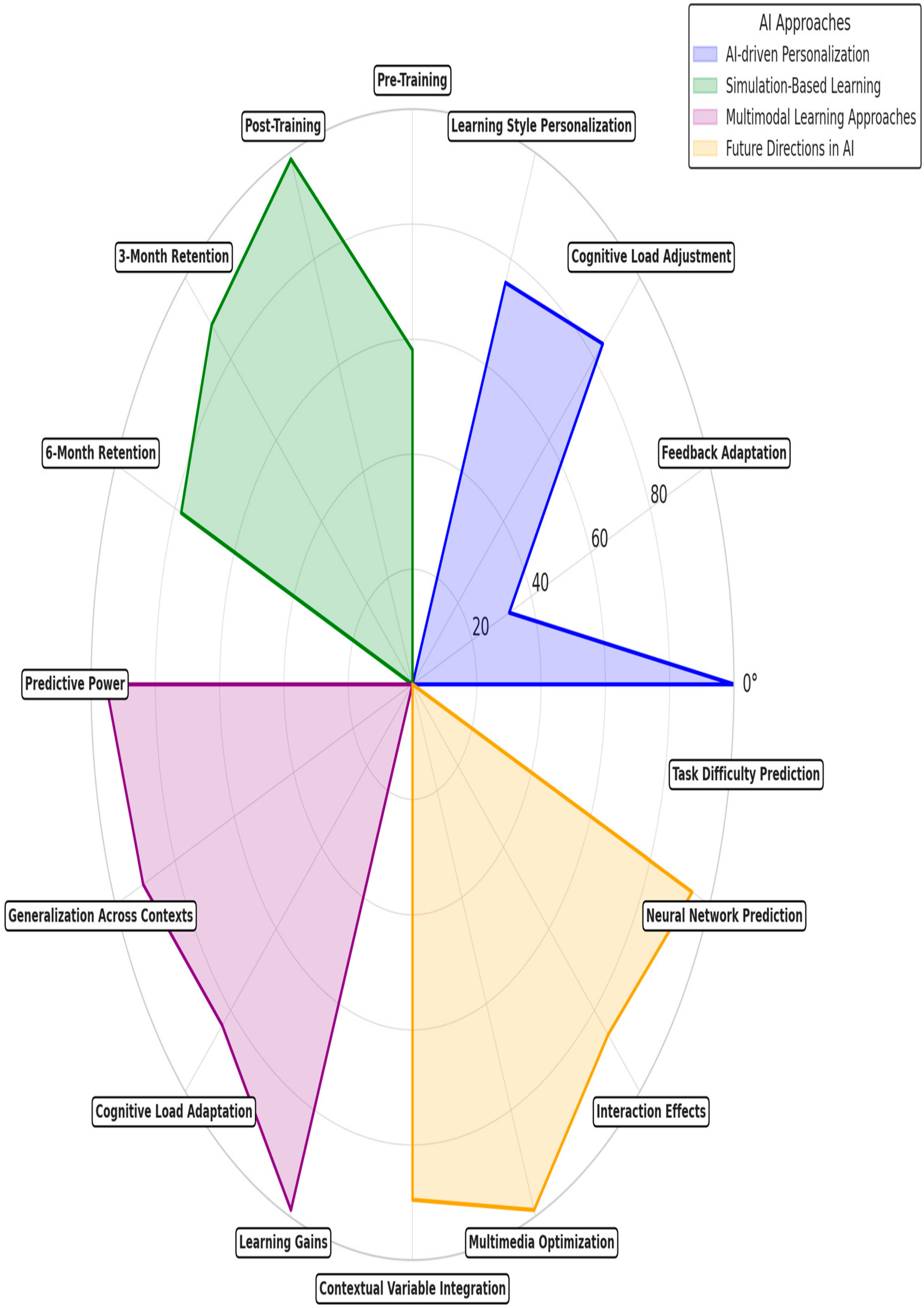

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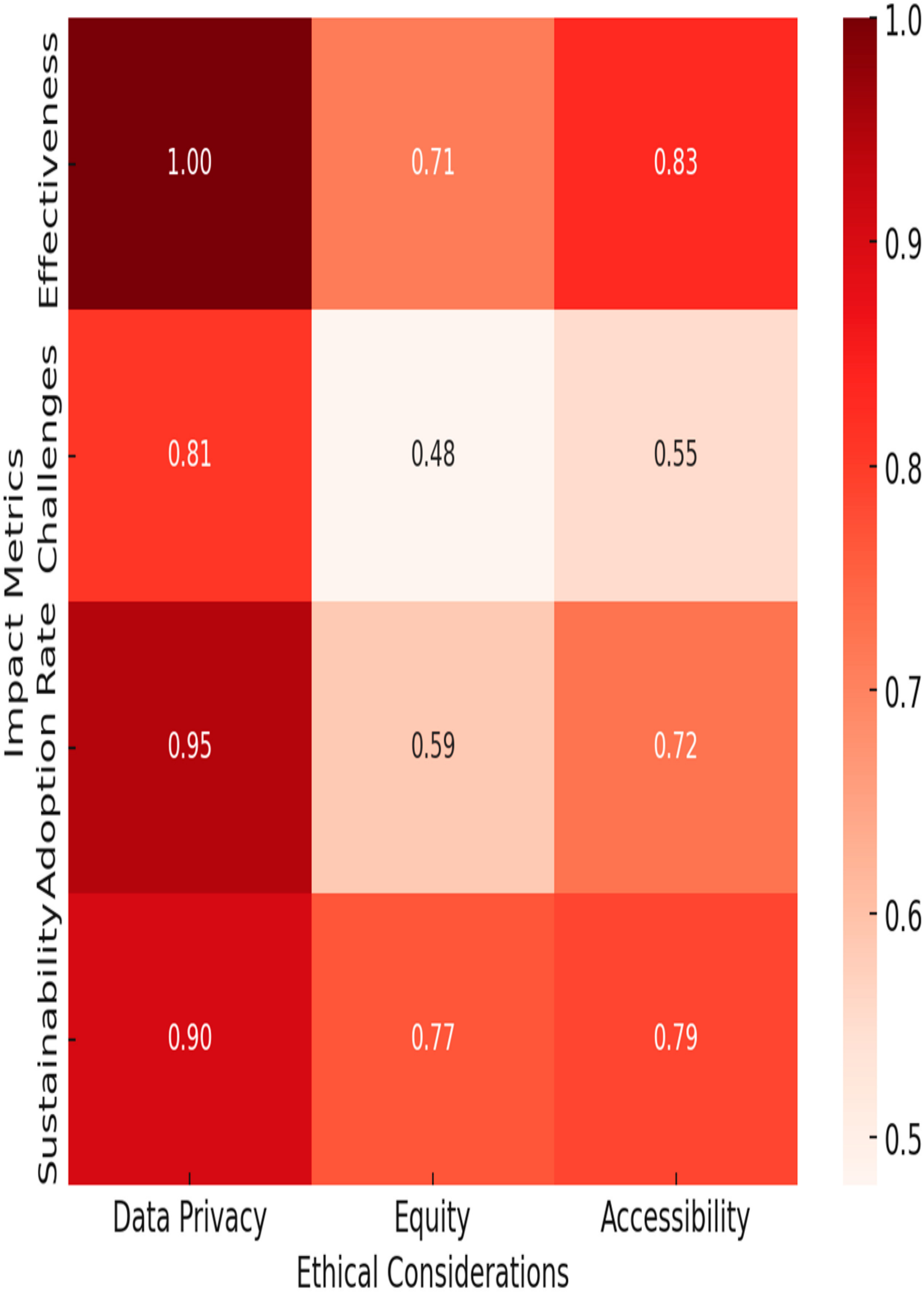

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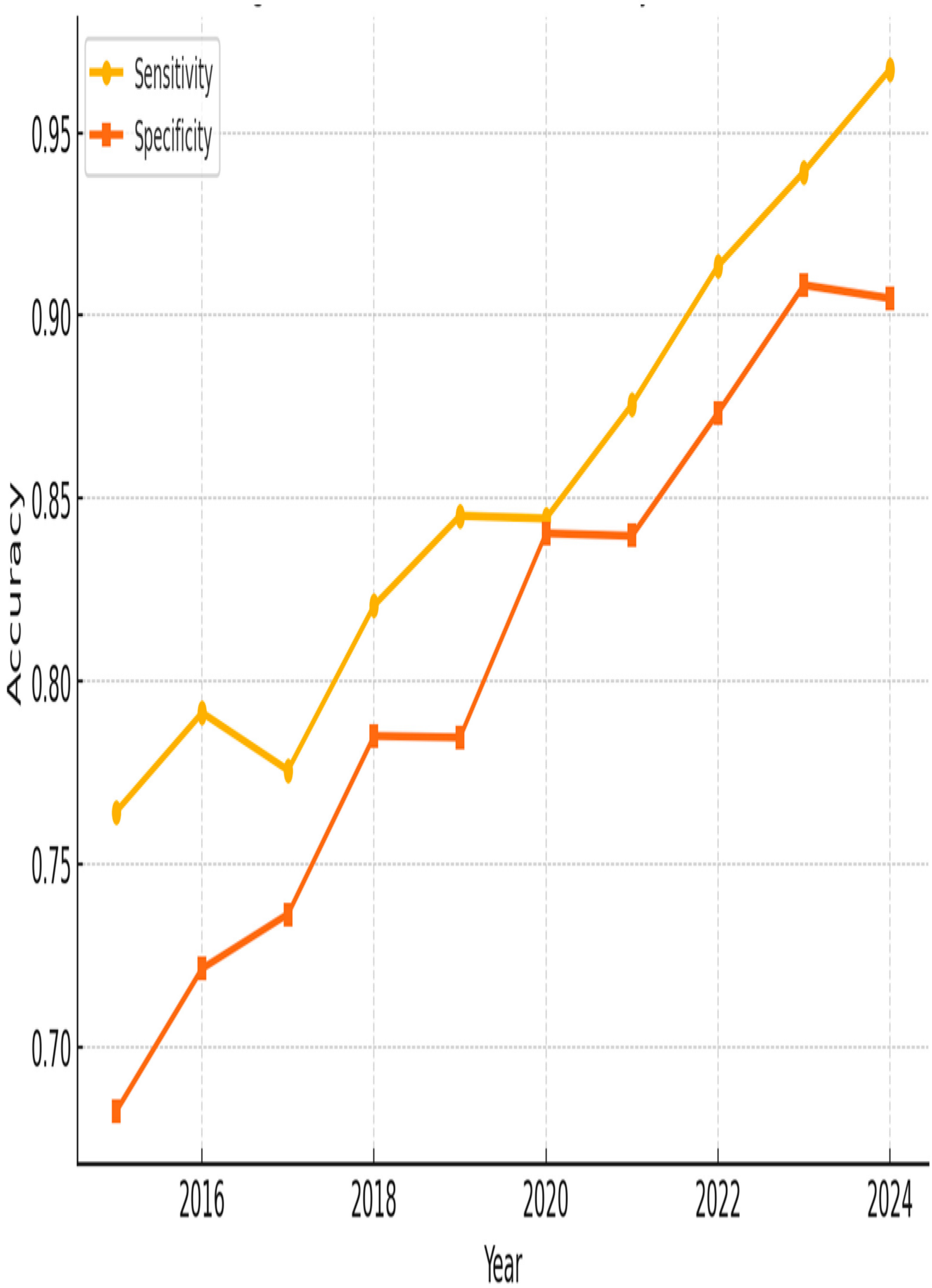

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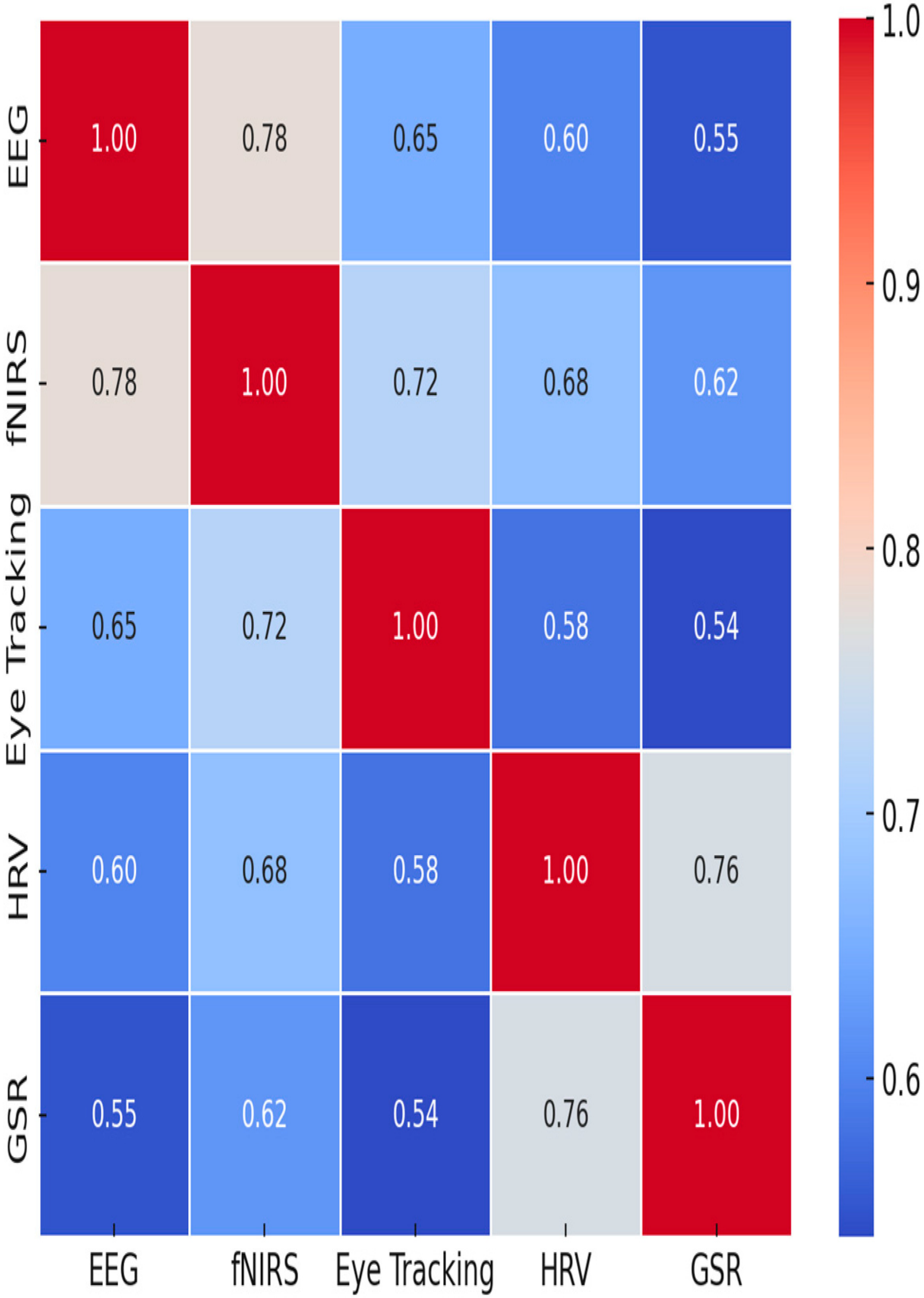

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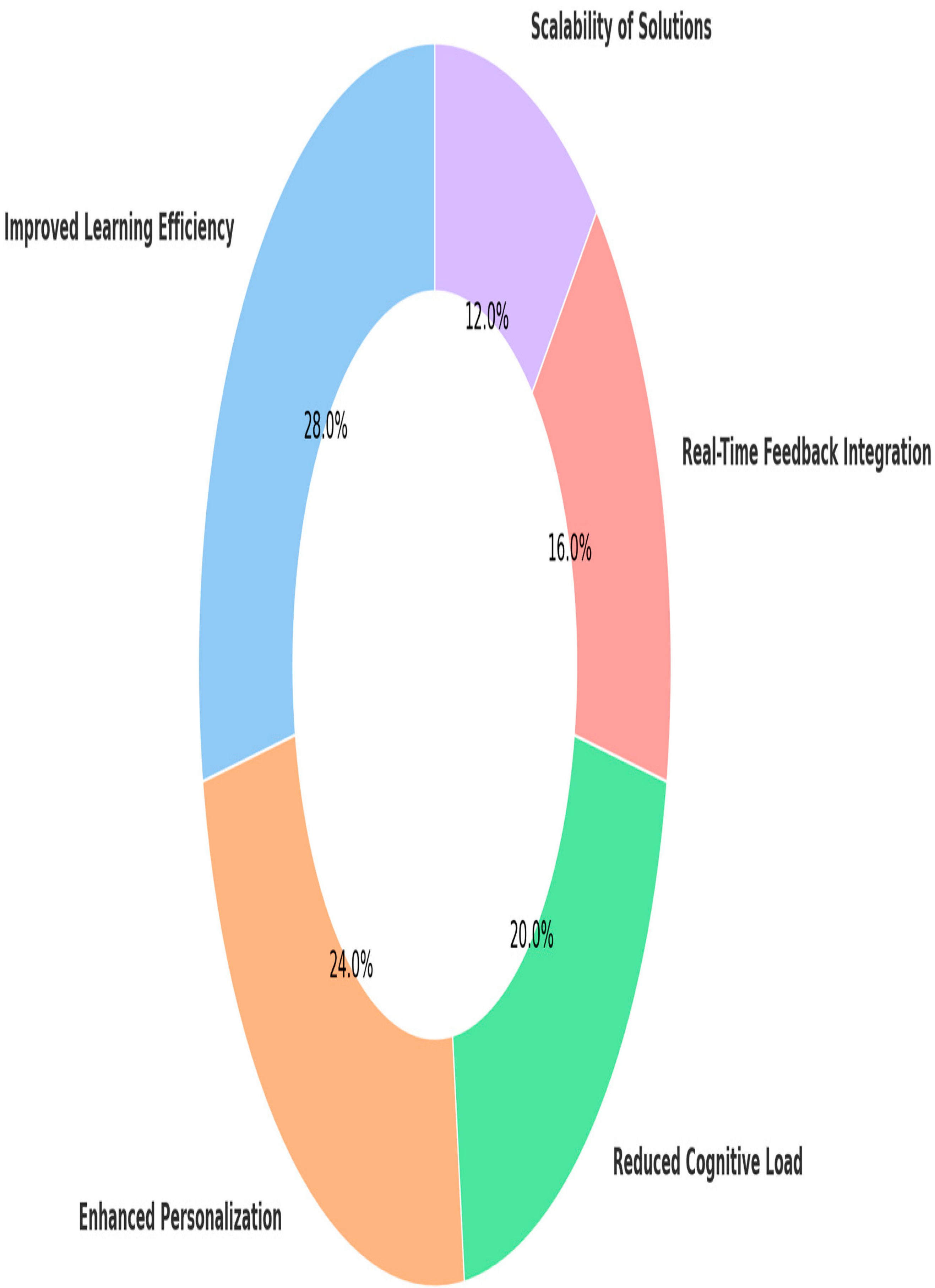

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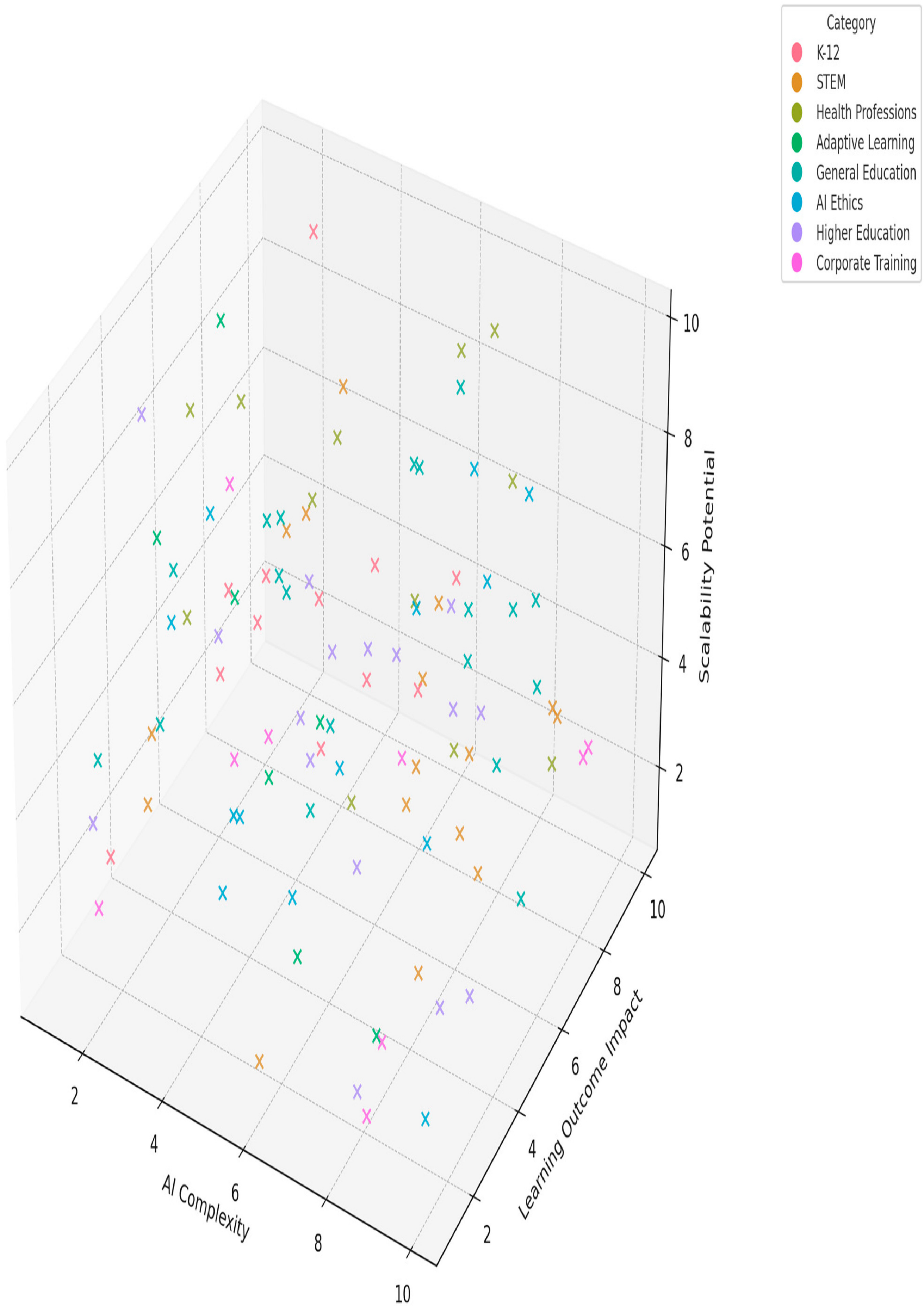

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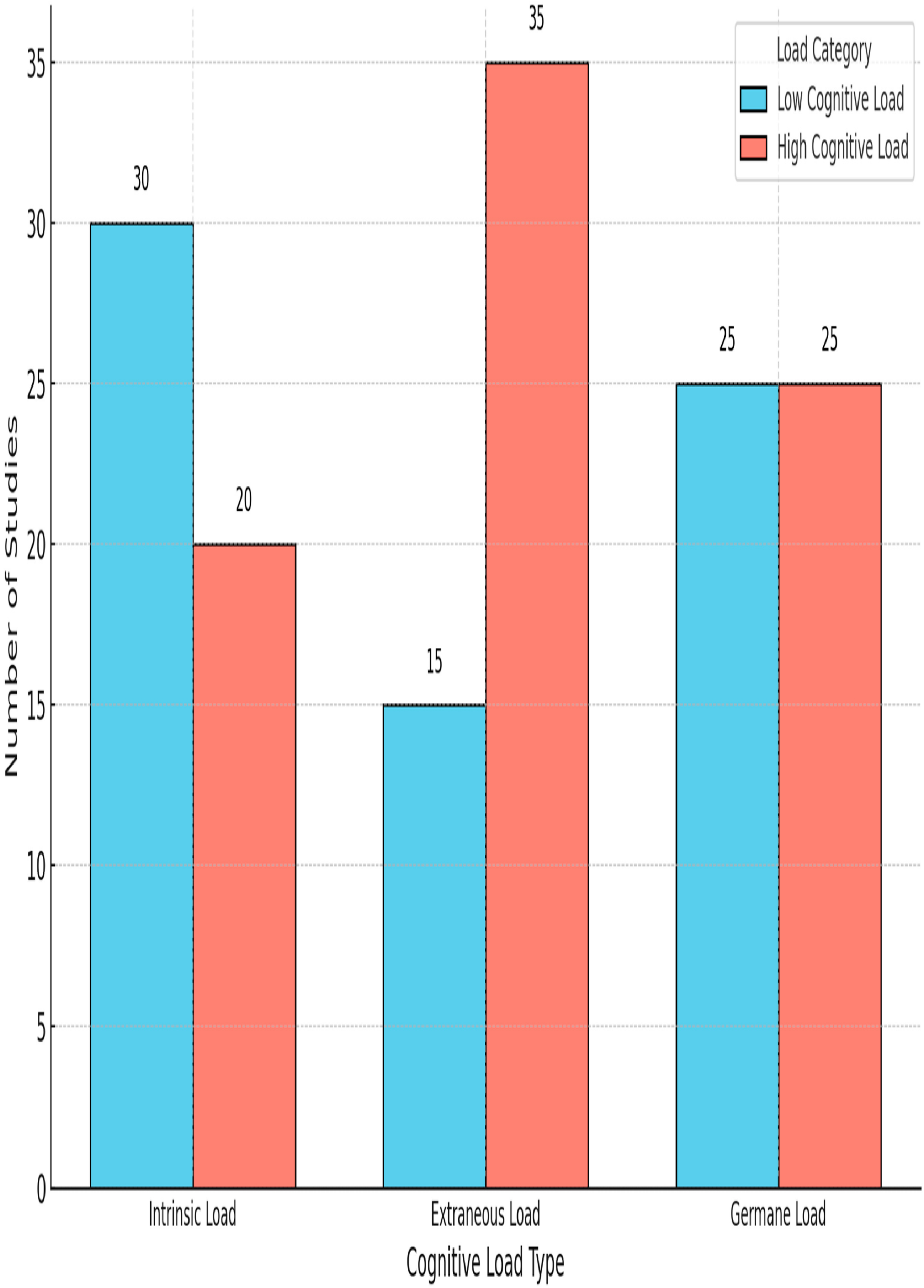

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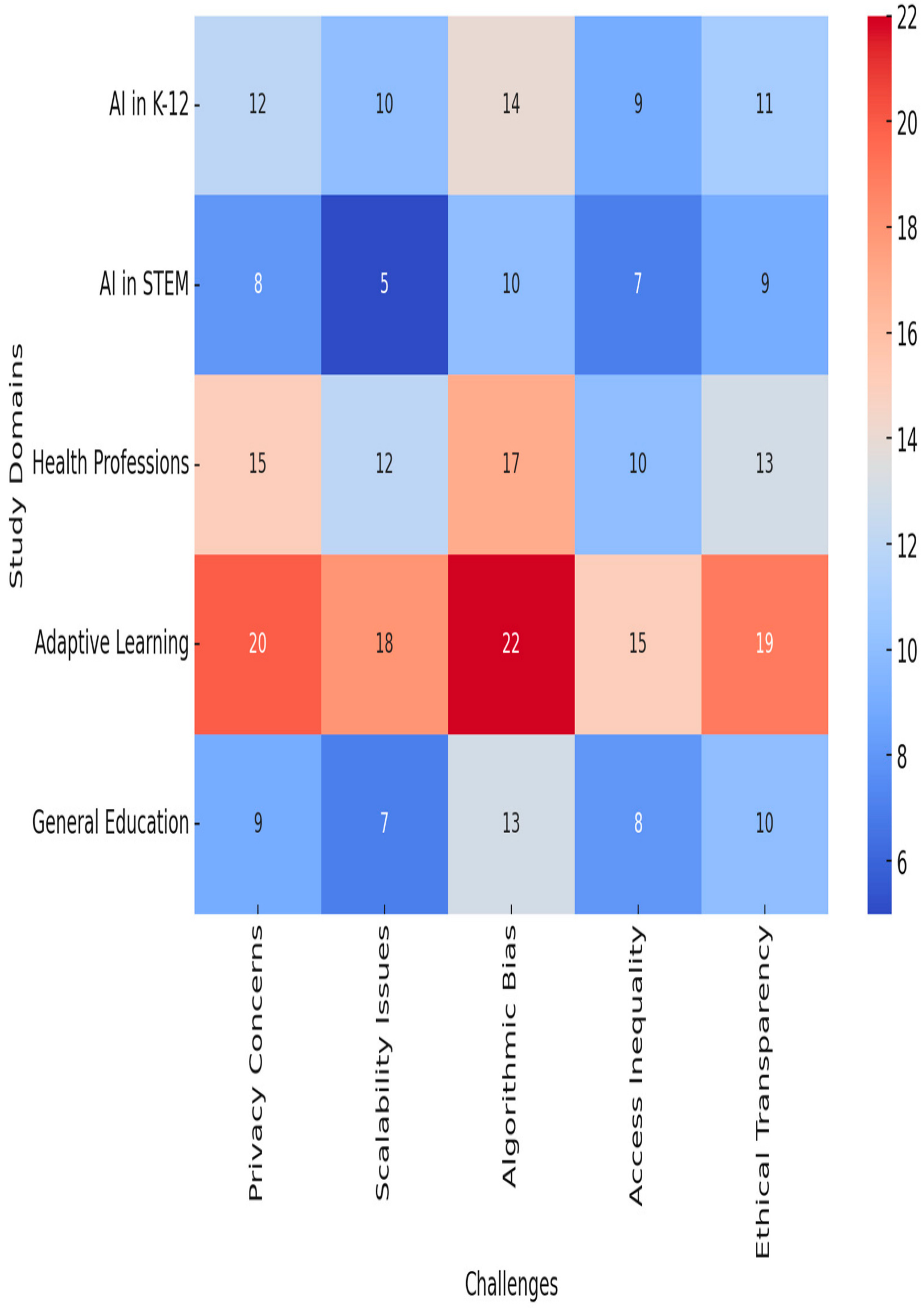

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Table 1

Inclusion and exclusion criteria for systematic review.

Criteria	Inclusion	Exclusion
Empirical Studies	Quantitative, qualitative, or mixed-method research.	Editorials, opinion pieces, and theoretical papers without empirical data.
AI/ML and CLT/EdNeuro Integration	Must integrate AI/ML in education with cognitive load or neuroscience.	Studies on AI/ML in education without cognitive load or neuroscience focus.
Learning Outcome Measurement	Assessing cognitive load, adaptive Learning Efficacy, or knowledge retention.	Studies lacking objective measures of learning success.
Neurophysiological Tools	Preference for EEG, fNIRS, or neuroimaging technologies.	Studies without neurophysiological assessment tools.
Ethical and Bias Considerations	Addressing algorithmic bias, privacy, and accessibility.	Lacking discussion on ethical considerations in AI-driven education.
Non-Empirical Studies	-	Editorials, opinion pieces, and conceptual frameworks without validation.
Lack of AI-CLT/EdNeuro Integration	-	Studies on AI in education without cognitive load or neuroscience connection.
Methodological Rigor Issues	-	Lack of clear methodology, statistical rigor, or reproducibility.
Educational Context Mismatch	-	Research unrelated to K-12, higher education, or professional training.
Full-Text Unavailability	-	Studies without full-text access despite efforts to obtain them.

Table 2

Research articles of systematic analysis (N = 103).

Authors	Study Objectives	Population Characteristics	Interventions	Main Findings

Abeysekera et al. (2024) [154]	- Investigate university accounting students' perceptions of the cognitive load of learning and its influence on learning memory.- Understand how teaching quality, learning content quality, and LMS quality affect short-term learning memory, measured as e-learning quality and student satisfaction.- Investigate whether managing cognitive load causally influences learners' memory retention in an online learning environment.	- Undergraduate accounting students- Predominantly female (81%)- Likely young adults (median age around 25 years)- Filipino national origin- Participants from a developing country context	Online learning using Canvas LMS (Release 2024), including synchronized live-streamed classes for 482 undergraduate accounting students during the COVID-19 period. The intervention involved teaching quality, learning content quality, and LMS quality as components.	- Managing cognitive load positively influences short-term learning outcomes for students.- Learning content, teaching, and LMS quality enhance e-learning quality and student satisfaction.- Student satisfaction, but not e-learning quality, influences students' willingness to continue online learning.
Abu-Rmileh et al. (2019) [155]	- Investigate the utility of co-adaptive training in the BCI paradigm.- Quantify the performance difference between groups to assess the contribution of continuous classifier co-adaptation.- Compare a co-adaptive protocol with a non-co-adaptive protocol over multiple days.	- 12 females and 6 males- Aged 19 to 27 years (mean = 23.8; SD = 1.9)- Healthy, with no history of neurological or psychiatric disorders- Normal or corrected-to-normal vision- Right-handed- Naive to BCI	Regular adaptation of the classifier based on brain activity patterns during 4 daily sessions over 4 consecutive days, with a new classifier trained after each run using data from the last two runs (experimental group only).	- Continuous updating of the classification algorithm significantly improves performance in multi-day BCI training compared to using a fixed classifier.- The experimental group showed significant within-day performance improvements, which compensated for deterioration of between-day performance.- Engaging training environments and subject-specific frequency bands alone are insufficient for performance improvement without continuous classifier adaptation.

Almulla et al. (2023) [156]	- Examine the relationships between social cognitive theory, learning input factors, reflective thinking, and inquiry learning style.- Investigate the indirect effects of student problem-solving and critical thinking skills.- Assess social cognitive theory and learning input components for introducing an online education system in Saudi Arabia to ensure learning sustainability.- Investigate the integration of social cognitive theory with learning input elements and the use of e-learning as a sustainable strategy to impact student learning performance and educational sustainability.	- University students- Aged 22–25- 59.9% female- Studying educational science	A questionnaire based on social cognition theory and learning input theory, completed once by 294 university students.	- Inquiry-based learning and reflective thinking significantly impact social factors like engagement and support, crucial for educational sustainability.- Problem-solving and critical thinking skills enhance learning performance by influencing inquiry-based learning and reflective thinking.- A new model integrating social cognitive theory with learning input factors was developed to improve students' learning performance and educational sustainability.
Azman et al. (2022) [157]	- To investigate the effect of videos designed based on CLT on students' academic performance.	- Lower sixth Biology studentsfrom a sixth form center in Brunei	Videos designed based on CLT used in twelve cycles of lessons on 12 different biology topics for 25 lower sixth Biology students.	- Videos designed using CLT significantly increased students' test scores, with a large effect size.- The study suggests that such videos can reduce students' extrinsic cognitive load.- The findings highlight the importance of theory-based video creation in enhancing student learning.

Babu et al. (2019) [158]	- Investigate the use of eye gaze trackers to estimate pilots' cognitive load in military aviation.- Develop algorithms to estimate cognitive load from ocular parameters.- Design and conduct in-flight studies using non-invasive eye gaze trackers.- Compare ocular parameters during different flight phases and maneuvers and correlate them with flight parameters.- Use results for real-time estimation of cognitive load, providing warnings and alerts, and training military pilots on cognitive load management.	- Military pilots from the Indian Air Force- Ranks ranging from Squadron Leader to Group Captain- Average age: 35.43 years (standard deviation: 4.27 years)- Average flying experience: 13.29 years (standard deviation: 5.99 years)- Average flight hours: 1766.43 h (standard deviation: 752 h)	1. Fixed-base variable stability flight simulator with longitudinal tracking task for 14 military pilots.2. Test flights with BAES Hawk Trainer and Jaguar aircraft involving air-to-ground attack training missions and constant G level turn maneuvers up to +5G.	- Commercial eye gaze tracking glasses can be used to measure ocular parameters in combat aircraft up to +6G.- Rate of fixation increases for tasks demanding higher cognitive workload from pilots.- Pupil dilation metrics should be tested in variable lighting and vibrating conditions before use in cognitive load estimation.
Bahroun et al. (2023) [159]	- Conduct a comprehensive analysis of GAI in education.- Explore GAI's transformative impact in specific educational domains through content analysis.- Conduct a bibliometric analysis examining AI tools, research focus, geographic distribution, and interdisciplinary collaboration.- Identify research gaps and future directions in the field.	Not mentioned (the paper is a review and does not provide specific population characteristics)	Generative Artificial Intelligence (GAI) applications including assessment, PL support, and Intelligent Tutoring Systems, with ChatGPT as a specific model used. No specific frequency, duration, or amount mentioned.	- ChatGPT is a dominant tool in GAI research, with significant growth observed in 2023.- GAI has transformative potential in reshaping educational practices across various domains.- The study identifies research gaps and future directions for GAI in education.

Barner et al. (2016) [160]	- Determine if mental abacus (MA) expertise can be acquired in standard classroom settings.- Assess whether MA training improves students' mathematical abilities beyond standard math curricula.- Investigate if MA expertise is related to changes in basic cognitive capacities like working memory.- Explore whether MA expertise results from cognitive transfer or cognitive moderation.	- Elementary school students aged 5–7 years- From a charitable school in Vadodara, India- Low-income families (over 80% earning less than USD 2000 annually)- 59% Hindu, 41% Muslim	Mental Abacus (MA) training: 3 h per week, divided into two 90 min sessions, over a duration of three years. Initially focused on physical abacus use, progressing to Mental Abacus computations. Only some participants received this intervention.	- Mental abacus training significantly improved arithmetic performance in students compared to a control group.- Improvements in arithmetic were not due to changes in basic cognitive abilities but were mediated by pre-existing spatial working memory.- Students with higher initial spatial working memory showed greater improvements, indicating that MA training is more effective for those with stronger visuospatial abilities.

Beloe et al. (2019) [161]	- Explore the effects of adaptive dual n-back working memory training on sub-clinical anxiety and depression symptomology in adolescents.- Examine if working memory training impacts self-reported anxiety and depression symptomology in adolescents.- Investigate working memory training as a preventative intervention to reduce the risk of developing internalizing disorders during adolescence.- Extend previous research by investigating working memory training amongst adolescents.- Find reductions in depression symptomology following adaptive dual n-back training.	- Adolescents aged 10–16- Pupils from independent single-sex secondary schools- Located in southeast England- High academic achievers	Adaptive dual n-back working memory training: online, at least 5 days per week for up to 20 days, with one session per day.	- Adaptive dual n-back working memory training significantly reduced self-reported anxiety and depression symptoms in adolescents compared to a non-adaptive control group.- The reductions in anxiety and depression symptoms were sustained at a one-month follow-up.- The study provides preliminary evidence that working memory training can reduce vulnerability to anxiety and depression in a non-clinical adolescent population.

Biondi et al. (2020) [162]	- Investigate the effect of cognitive overload on assembly task performance.- Investigate the effect of cognitive overload on muscle activity.	Not mentioned (no demographic or health-related characteristics of the population are included in the abstract)	Participants performed a secondary cognitive task with increasing levels of demand (n-back), including a 2-back task, while completing an assembly task.	- Increasing cognitive demand from the n-back task impaired assembly task performance and increased muscle activity.- Performing the 2-back task resulted in longer assembly task completion times and greater muscle activity in specific muscles.- High cognitive load affects both muscle activity and task completion times, impacting manufacturing cycle times.
Bisoglio et al. (2014) [163]	- Review current research on the effect of action video game training on visual attention, visuospatial processing, executive functions, and learning and memory.- Examine whether there is sufficient evidence to support a causal relationship between action video game training and beneficial changes in cognition.- Focus on studies with methodologies that provide elements necessary for causal inference.- Summarize findings related to improvements in specific cognitive areas.- Identify areas in need of further investigation and provide commentary for future directions.	- Older adults (in some studies)	Super Mario 64 training for 30 min a day over a period of 2 months.	- Action video game training shows potential for enhancing attention, visuospatial processing, and executive functioning.- The magnitude and specificity of cognitive enhancements from video game training remain unclear.- Improvements in working memory may be secondary to enhancements in attentional and executive resources.

Boosman et al. (2016) [164]	- Provide clinicians and researchers with insight into the concept and methodology of dynamic testing.- Explore the predictive validity of dynamic testing in adult patients with cognitive impairments.	- Adults with cognitive impairments- Patients with psychiatric diagnoses- Patients with neurodegenerative diseases- Patients with acquired brain injuries	Performance feedback, reinforcement, expanded instruction, and strategy training during one-session dynamic testing. Specific frequency, duration, and dose are not mentioned as they are part of a single testing session.	- Dynamic tests provide a valuable addition to conventional tests for assessing patients' abilities.- Learning potential from dynamic tests significantly predicts rehabilitation outcomes.- There is a need for further research due to variability in dynamic testing methods.
Brouwers et al. (2016) [165]	- To examine whether differences in cue utilization are associated with differences in performance during a novel, simulated rail control task.- To determine whether these differences in performance reflect a reduction in cognitive load.	- University students- Aged 18–22 years- 41 females and 17 males in Experiment 1; 15 males and 44 females in Experiment 2- Existing motor vehicle drivers	1. A 20 min rail control simulation task (all participants in both experiments).2. Secondary task of writing down train numbers and times during the final two 5 min blocks of the rail control task (only participants in Experiment 2).	- Participants with greater cue utilization maintained consistent response latencies and accuracy, indicating effective management of cognitive load.- Lesser cue utilization participants showed increased response latencies under additional cognitive demands, indicating higher cognitive load impact.- Greater cue utilization is linked to strategies that minimize cognitive load without sacrificing task accuracy.

Buckley et al. (2021) [166]	- Develop four multi-task cognitive motor shooting paradigms for tactical athletes.- Examine the influence of cognitive motor interference (CMi) on each task in healthy ROTC cadets, focusing on cognitive (task initiation and task completion times) and motor performance (shot accuracy) changes.	- Healthy collegiate ROTC members- 24 male and 8 female- Average age: 20.5 years- At least 18 years old- Participate in at least 1 h of formal marksmanship training a month- No prior lower extremity surgery, recent injuries, neuromuscular deficiencies affecting coordination or balance, or color blindness	Participants completed four simulated shooting tasks with motor challenges (180° turn, gait, weighted landing, unweighted landing) and cognitive challenges (decision-making requiring response selection and inhibition to auditory and visual stimuli). Each task was performed in three trials under baseline conditions and three trials under cognitive load conditions.	- Cognitive load increased task initiation and completion times in ROTC cadets during simulated shooting tasks.- Cognitive load did not affect shooting accuracy despite slowing down task performance.- The results support the limited capacity theory of attention, indicating that cognitive load impacts motor performance speed but not accuracy.
Cerdán et al. (2018) [167]	- To test how the availability of documents in multiple document reading might affect students' levels of cognitive load.- To develop an instrument that captures the different sources of load when working with multiple documents.	- Secondary school students- no reported reading difficulties	Participants in the experimental treatment condition (*n* = 54) were allowed to go back to the texts any time during the 20 min essay task.	- Allowing students to revisit texts during an essay task reduces ECL but does not affect ICL or essay performance.- No significant differences were found in perceived task complexity or learning task performance between conditions.- Restricting access to texts during the essay task may enhance the integration of information in students' essays.

Chen et al. (2019) [168]	- To demonstrate a molecular pathway for exercise-induced learning enhancement.- To show that chronic treadmill exercise activates the mTOR pathway in the mouse motor cortex.- To establish that mTOR activation is necessary for spinogenesis, neuronal activation, and axonal myelination, leading to improved motor learning.- To provide new insights into neural network adaptations through exercise and support interventions for cognitive deficits using exercise training.	- Male mice- C57BL/6J strain- Thy1-YFP transgenic strain- 4 weeks old	1. Treadmill exercise at 12 m/min for 1 h daily for 3 weeks.2. Rapamycin administration at 3 mg/kg body weight every 3 days during the exercise training (only for some participants).	- Chronic treadmill exercise activates the mTOR pathway in the mouse motor cortex.- Activation of the mTOR pathway is necessary for spinogenesis, neuronal activation, and axonal myelination, leading to improved motor learning.- The study provides in vivo evidence that exercise enhances motor skill learning via mTOR-dependent neural adaptations.

Chen et al. (2021) [169]	- Compare cognitive load between flipped teaching and traditional teaching.- Explore the practice of mixed teaching in a group communication behavior system.- Enhance group interaction and learning through mobile devices.- Determine significant differences in cognitive load between flipped and traditional teaching methods.	- University students- Senior undergraduate students- Majority female in flipped teaching (74%)- Majority male in traditional teaching (87%)- Located in Taiwan	1. Flipped teaching intervention for the experimental group: - Pre-class video teaching using TOLP (TronClass Online Learning Platform). - Group interactive games using Kahoot (v4.1) and Quizlet Live (v6.0) on mobile devices. - Mind mapping using XMind app (v1.1) on mobile devices. - Access to diversified visual learning materials (text, images, online videos) before class. - Interactive lectures, collaborative design and creation, peer-assisted learning, case participation, and solving homework problems in class. - Independent review of learning materials at home using TOLP’s mobile devices. - Frequency: Six hours of classes per week.	- Flipped teaching resulted in lower cognitive load and higher academic performance compared to traditional teaching.- Students in the flipped classroom model had an average grade of 89.40, higher than the 80.95 average grade in the traditional teaching model.- Significant differences were found in cognitive load factors between flipped and traditional teaching methods.

Chen et al. (2021) [170]	- To test hypotheses regarding the role of brain integration versus segregation underlying broad training effects.	- Older adults- With mild cognitive impairment (MCI)	Vision-based speed of processing (VSOP) training	- Learners in the vision-based speed of processing training group showed improvements in executive function and episodic memory.- Enhanced segregation in brain networks, indicated by greater global clustering coefficients, was observed in learners compared to controls.- Learners with more severe baseline neurodegeneration experienced greater improvements in brain network segregation after training.
Colom et al. (2018) [171]	- To enhance intelligence through individualized intervention programs.- To increase fluid reasoning ability and working memory capacity using a challenging working memory task.- To test whether a dual n-back task impacts structural brain features and cognitive abilities beyond spontaneous improvements.	- University undergraduates- Young adults (likely aged 18–25)- Includes female participants (56 women mentioned)	Adaptive dual n-back task: 24 sessions over twelve weeks, with two sessions per week (training group only).	- The training program improved visuospatial processing skills across cognitive domains.- No significant improvements were found in fluid reasoning ability and working memory capacity at the construct level.- The training program attenuated cortical thinning in individuals with lower baseline cognitive abilities.

Cook et al. (2014) [172]	- Compare the effects of gist reasoning (top-down) versus rote memory learning (bottom-up) on the ability to abstract meanings, recall facts, and utilize core executive functions in adolescents with chronic-stage TBI.- Explore whether either training is associated with generalized benefits to untrained domains, specifically frontally mediated measures of executive control.	- Adolescents aged 12–20- Sustained mild, moderate, or severe closed head TBI at least 6 months prior- Recruited from the Dallas/Fort Worth community- Exclusion of pre-existing neurological disorders, learning disabilities, severe psychiatric disorders, history of child abuse, penetrating gunshot wound to the brain, history of hypoxia/anoxia- Attention deficit disorder not an exclusionary factor	1. Gist reasoning training (SMART program): Eight 45 min sessions over 1 month.2. Rote memory learning: Eight 45 min sessions over 1 month.	- Gist reasoning training significantly improved the ability to abstract meanings and recall facts in adolescents with chronic-stage TBI.- The training also generalized untrained executive functions such as working memory and inhibition.- Rote memory training did not yield significant improvements in these cognitive domains.
Cruz et al. (2014) [173]	- Determine the treatment intensity of home-based cognitive training strategies.- Assess patient adherence to home-based cognitive training strategies.- Analyze aspects of the quality of cognitive training delivered, specifically adherence and continued use in subgroups of diseases.	- Patients aged 11–84 years- 35.6% female- Neurologic and psychiatric diseases (e.g., neurodegenerative diseases, memory complaints with depressive symptoms, static brain lesions)- Average education level of 7.8 years- Participants were outpatients at a memory clinic- Study conducted in Portugal	1. Web-based cognitive training using the COGWEB system: minimum of 7 sessions per week, each lasting at least 30 min (210 min per week minimum), with an average of 363.5 min per week.2. Weekly face-to-face sessions with a neuropsychologist (for 11 out of 45 participants): approximately 60 min per session.	- The study found high weekly training intensity and significant adherence to Web-based cognitive training, with an average of 363.5 min per week and 82.8% adherence at 6 months.- Patients with dementia and static brain lesions trained more intensively than other groups.- Face-to-face sessions increased training intensity, highlighting the benefit of combining traditional methods with technology.

Czibula et al. (2022) [174]	- Introduce and apply the IntelliDaM framework to improve data mining tasks and decision-making processes.- Conduct a longitudinal educational data mining study using IntelliDaM on real data from a Computer Science course.- Analyze students' performance using the IntelliDaM framework.- Confirm the usefulness of IntelliDaM in educational environments for improving decision-making processes such as course design, examination setup, plagiarism avoidance, and stress management support.	- Students enrolled in a Computer Science course at Babe-Bolyai University, Romania	Application of the IntelliDaM framework to educational data at Babe-Bolyai University for a Computer Science course to analyze students' performance and improve decision-making processes.	- IntelliDaM achieved a high F1 score of around 92% for a classification task in educational data mining.- The use of discriminative data feature selection led to statistically significant performance improvements.- IntelliDaM is confirmed to be useful in educational environments for enhancing decision-making processes.
Dekker et al. (2015) [175]	- Examine how well biology teachers are acquainted with the functional aspects of the brain and its involvement in learning.- Enhance teachers' knowledge of "Brain and Learning."- Teach students an incremental theory of intelligence (TOI).	- 32 biology teachers interested in "Brain and Learning"- 1241 students in grades 8–9- Average student age: 14.5 years- 46% of students are boys- Participants from high educational tracks- Schools distributed across the Netherlands	A teaching module titled "Brain and Learning" consisting of three 45 min lessons covering: (1) brain processes underlying learning, (2) neuropsychological development during adolescence, and (3) lifestyle factors that influence learning performance. This was implemented for the intervention group consisting of 18 teachers and 456 students.	- The teaching module significantly improved biology teachers' knowledge of brain functions and development.- The module increased the prevalence of incremental theories of intelligence among students.- The study demonstrated the feasibility of integrating the module into the high school biology curriculum.

Diliberto-Macaluso et al. (2016) [176]	- To examine the impact of mobile applications or apps on student learning in an introduction to psychology course.	- Students in an introduction to psychology course	Interactive 3D Brain app used for a learner-centered worksheet activity on the brain and central nervous system. Duration, frequency, and amount not specified.	- The app group showed significant improvement in performance from pretest to posttest across all measures, while the text group only improved significantly in labeling.- The app group outperformed the text group on multiple-choice and composite measures, but not on labeling.- There was no difference in self-reported enjoyment between using the app and the textbook.
Ekstrand et al. (2018) [177]	- To examine the impact of immersive virtual-reality neuroanatomy training and compare it to traditional paper-based methods.	- First- or second-year medical students- University of Saskatchewan	A 5 min tutorial on navigating the virtual-reality system, followed by a 12 min session using the virtual-reality environment to study spatial relations between neural structures. Participants controlled visualization and navigation within the virtual-reality environment.	- Immersive virtual-reality environments are effective tools for learning neuroanatomy, showing significant improvement in understanding spatial relations compared to traditional methods.- Virtual reality decreased neurophobia among medical students, enhancing their learning experience.- Both virtual-reality and paper-based methods improved neuroanatomy knowledge, but virtual reality showed greater accuracy in spatial understanding.

Faretta-Stutenberg et al. (2018) [178]	- To understand how individual differences in cognitive abilities contribute to second language development in different contexts.- To examine the role of cognitive abilities in changes in L2 behavioral performance and neurocognitive processing for learners in ' at-home' and 'study-abroad' settings.	- Learners studying Spanish as a second language- University students	A semester of study in a traditional university classroom context (Experiment 1) or a study-abroad context (Experiment 2) for L2 Spanish syntax acquisition.	- At-home learners showed behavioral improvements without a predictive role for cognitive abilities.- Study-abroad learners showed behavioral and processing improvements partially explained by procedural learning ability and working memory.- The study offers preliminary insights into the role of cognitive abilities in language learning across different contexts.
Fatima et al. (2016) [179]	- Link transient changes in functional brain networks to individual differences in behavioral and cognitive performance.- Obtain comprehensive features (behavioral, cognitive, and neurophysiological) that highlight individual differences in learning novel associations using data-driven methods.- Establish the link between whole-brain functional connectivity at different temporal scales and individual differences in performance measures and cognitive ability.- Identify holistic markers of individual differences in acquiring novel associations.	- Right-handed young adults- Aged 19–30 years (mean age: 22)- 8 females out of 14 participants- Normal to corrected vision- Exclusion of individuals with metal implants, neurological, psychiatric, and substance abuse-related problems	Associative learning task involving learning four scene-color associations through trial-and-error with feedback, conducted over 152 trials. Each scene is presented 38 times, with scenes shown for 500 ms followed by a delay and color pairs displayed for up to 1.2 s for participant response. Feedback is provided after each response.	- Fast learners showed early connectivity in the posterior network and later connectivity in the associative memory network, while slow learners showed the opposite pattern.- Time-dependent changes in connectivity were linked to visuospatial abilities, with fast learners performing better on visuospatial subtests.- Individual differences in learning rates are supported by differences in cognitive ability and time-sensitive connectivity in functional neural networks.

Flak et al. (2019) [180]	- To investigate if a 5-week computerized adaptive working memory training program (Cogmed®) is effective in improving working memory capacity and other neuropsychological functions compared to a non-adaptive working memory training program in adult patients with mild cognitive impairment (MCI).	- Individuals aged 43 to 88 years- 45 men and 23 women- Diagnosed with mild cognitive impairment (MCI)- Recruited from memory clinics in Norway- Socioeconomic status assessed using Hollingshead's index- Not severely or moderately depressed	Computerized adaptive working memory training program (Cogmed®) for 30–40 min per day, 5 days per week, for 5 weeks, with a total of 20 to 25 sessions.	- The adaptive working memory training did not show significantly greater improvement in working memory performance compared to non-adaptive training in MCI patients.- No significant differences were found between adaptive and non-adaptive training on secondary cognitive function outcomes.- The hypothesis that adaptive training would lead to greater improvements was not supported.
Flogie et al. (2015) [181]	- Evaluate the attitude of students and teachers towards educational changes.- Create and evaluate a new educational paradigm (transdisciplinary model) and innovative curriculums.- Evaluate the influence of the transdisciplinary approach on the attitudes of students and teachers towards school.- Focus on the effect of ICT on the attitude of students towards school and teachers towards recommended changes.	- Students in grades 7 to 9 (approximately aged 12–15)- Gender: 42% girls, 58% boys- National origin: Slovenia- School type: Suburban and urban lower secondary schools	Transdisciplinary cognitive neuro-education model used for at least 30% of lessons, incorporating ICT and innovative teaching approaches, over a period of two years in nine schools. Included individualized contents and e-materials as part of the TECH8 intelligent tutoring system.	- The transdisciplinary cognitive neuro-education model led to a positive shift in students' attitudes towards school, making them feel more comfortable and safer.- Students in the experimental group showed a greater affiliation with their school and an increased liking for mathematics when innovative teaching methods were used.- The study emphasized the importance of integrating ICT and innovative pedagogies to improve both students' and teachers' attitudes towards education.

Frank et al. (2018) [182]	- Test the immediate, short-term, and long-term effects of tRNS on skill acquisition involving multitasking.- Assess whether subjects receiving tRNS show higher performance in a dual-task in the first week.- Determine if there is a retention effect of tRNS after two weeks.- Investigate if tRNS-related improvements depend on baseline general mental ability.	- 40 subjects (24 female, 16 male)- Mean age: active group, 21.05 years; sham group, 23.58 years- Healthy individuals with normal or corrected-to-normal vision- No history of neurological or psychiatric illness- Recruited from the University of Oxford- Novices in the complex task used in the study	1 mA transcranial random noise stimulation (tRNS) applied to the dorsolateral PFC for 12 min, with 30 s ramp-up and 20 s ramp-down, during the skill acquisition phase.	- tRNS improved multitasking performance immediately and shortly after application, particularly in the secondary task.- Two weeks later, tRNS enhanced retention of the primary task, especially for individuals with lower general mental ability.- The effects suggest that tRNS may reduce cognitive load during skill acquisition, leading to better long-term retention.
Fredericks et al. (2021) [183]	- Assess the effect of participating in clinical simulation on subjective measures of anxiety and cognitive load (CL) among final-year undergraduate medical students.- Compare participants' anxiety ratings with their ICL, ECL, and self-perceived learning (SPL) ratings.	- Undergraduate medical students- 19 males and 22 females- Median age: 23 years (IQR: 22–24)- Fifth-year students in a five-year medical program- Conducted in a small medical school	Participation in high-fidelity clinical simulation teaching sessions, conducted over a period from January to April 2019, with each session lasting 90 min and comprising three segments: briefing (10 min), scenario (15 min), and debriefing (45 min).	- State-anxiety during simulation is associated with increased ECL but not with ICL or SPL.- High state anxiety is linked to higher ECL scores post-scenario compared to low state-anxiety.- Debriefing reduces state-anxiety levels that are elevated during simulation scenarios.

Gallen et al. (2016) [184]	- Investigate the relationship between baseline brain network modularity and training-related cognitive gains in older adults.- Test the hypothesis that higher baseline modularity predicts greater cognitive improvements.- Examine whether the predictive relationship between modularity and training gains is more pronounced in association cortex sub-networks compared to sensory-motor sub-networks.	- Cognitively normal older adults- Age range: 57–70 years- Mixed gender (9 females in each group)- High cognitive ability (mean IQ: 120.4 ±11.7 for control group, 122.1 ±8 for training group)	Strategic Memory and Reasoning Training (SMART) for 12 weeks, consisting of one hour of small group training per week and two one-hour sessions of home practice per week.	- Older adults with more modular brain networks at baseline showed greater improvements in cognitive training.- The relationship between modularity and cognitive gains was stronger in association cortex modules compared to sensory-motor modules.- Brain network assessments can potentially be used as biomarkers to guide cognitive interventions.
Guerra-Carrillo et al. (2017) [185]	- To understand the cognitive effects of education by testing the relationship between educational attainment and cognitive abilities at one timepoint.- To assess LE from one timepoint to another.- To examine performance on cognitive assessments of executive functioning and reasoning.- To detect differences in performance associated with educational attainment and age.- To evaluate the effect of educational attainment on changes in cognitive performance after participation in a cognitive training program.	- Ages 15–60- Mean age approximately 40 years-53.72% female in retrospective analysis-58.84% female in prospective analysis-Reside in the United States, Canada, or Australia- Considered demographic variables: gender, ethnicity, native language- Considered household income	Online cognitive training program for approximately 100 days, with participants engaging for an average of 166.23 h over this period.	- Higher educational attainment is associated with better cognitive performance, particularly in reasoning, but has a minimal effect on LE.- The age of peak cognitive performance aligns with typical graduation ages, indicating a cumulative effect of recent educational experiences.- Differences in cognitive performance are moderate to large between different educational levels, such as Bachelor’s vs. High School and Ph.D. vs. Some High School.

Hadie et al. (2021) [186]	- Explore the impact of CLT and CTML-based online lectures on health profession students' lecture comprehension, cognitive load, cognitive engagement, and intrinsic motivation.- Investigate whether CLT-based online lectures enhance comprehension of difficult health professional topics regardless of learning and lecture styles.- Determine if CLT-based applications are effective in an online setting.- Assess whether CLT-based online teaching provides an advantage in enhancing motivation and reducing cognitive loads compared to traditional lectures.	- First-year undergraduate students- Medical, dentistry, and nutrition programs- More female students than male (3:1 ratio)- Students from the University Sains Malaysia- Health science students older than medical and dental students	A CLT-based online lecture delivered once, 8 weeks after a typical face-to-face lecture, lasting 1 h, using Cisco WEBEX teleconferencing application (Cisco Systems, Inc., San Jose, CA, USA).	- CLT-based online lectures significantly improved students' comprehension of lecture content and self-perceived learning.- The lectures enhanced student engagement and motivation.- They effectively reduced intrinsic and extraneous cognitive loads, decreasing mental burden.

Henssen et al. (2019) [187]	- Investigate differences in test scores, cognitive load, and motivation after neuroanatomy learning using AR applications or cross-sections.- Determine the effectiveness of GreyMapp-AR compared to cross-sections in neuroanatomy learning.- Primary outcome: Difference in learning outcomes measured by pre and posttest scores.- Secondary outcomes: Participants' experienced cognitive load and motivation levels.	- Medical and biomedical students- 19 males (61.3%) and 12 females (38.7%)- Mean age 19.2 ±1.7 years- First-year students- Conducted in the Netherlands- Participants were volunteers	GreyMapp-AR application used during practical assignments to study subcortical structures of the brain. Duration and frequency not specified.	- Students using cross-sections showed greater improvement in test scores, especially on cross-sectional questions, compared to those using GreyMapp-AR (v5.6.3).- GreyMapp-AR users experienced less cognitive load, suggesting it may be beneficial for learning complex 3D structures.- No significant differences in motivation were found between the groups, indicating similar levels of engagement with both methods.
Hoorelbeke et al. (2016) [188]	- Examine the relationship between cognitive control and self-reported emotion regulation cross-sectionally.- Assess the effects of cognitive control training (CCT) on reappraisal ability in a lab context.- Evaluate the effects of CCT on the deployment and efficacy of positive appraisal and rumination in daily life.- Explore whether CCT holds potential in increasing resilience in a convenience sample.	- Undergraduate students- Mean age around 21 years- Majority female (CCT: 4 males, 25 females; sham: 5 males, 27 females)- Recruited from Ghent University- Generally healthy	CCT using a modified version of the Paced Auditory Serial Addition Task (PASAT), performed online in 10 sessions over 14 days, with a maximum of one session per day.	- CCT improved working memory functioning as shown by performance on the dual n-back task.- CCT reduced rumination in response to a low positive effect but did not enhance adaptive emotion regulation.- CCT did not increase resilience in an unselected student population.

Hung et al. (2020) [189]	- To forecast learners' performances using data generated in a blended learning environment.- To apply the generated predictive model to other classes.- To identify specific learning models from learner behavior and define learning groups based on certain variables.	- First-year university students- Located in northern Taiwan- Enrolled in general education courses	Blended learning approach for Python programming courses, including:1. Weekly online lectures available on the LMS.2. Instructional videos for asynchronous learning.3. Face-to-face courses for peer interaction.4. Online quizzes and tests.5. Facebook live classes held twice during the semester.	- The Random Forest model effectively predicts student performance with an F1-score of 0.83, outperforming other models.- The study identifies distinct learning patterns that can guide targeted interventions for different student groups.- A stable learning pace is crucial for better student performance in a blended learning environment.
Jeun et al. (2022) [190]	- Provide customized cognitive training and confirm its effect on neural efficiency by investigating PFC activity using fNIRS.- Collect PFC activity during cognitive tasks and establish an algorithm to predict performance levels based on PFC activity.- Investigate the effects of personalized cognitive training with the algorithm on neural efficiency in healthy adults.	- Adults over 20 years old- Healthy conditions without visual or auditory impairments- Intact global cognitive function- all in their twenties- Majority female (algorithm group: 77.7% female, training group: 92.3% female)- College students- Recruited from Asan-si, South Korea	Virtual reality (VR)-based spatial cognitive training conducted four times a week for 30 min per session over three weeks, with personalized difficulty levels based on PFC activity measured by fNIRS. A total of 12 sessions were conducted.	- Personalized cognitive training improved VR-based spatial cognitive performance and executive function.- There was a significant improvement in trail-making task performance, indicating enhanced executive function.- The training led to decreased PFC activity, suggesting increased neural efficiency.

Jones et al. (2019) [191]	- Investigate the effectiveness of Cogmed working memory training in typically developing children.- Examine near-transfer effects from working memory training compared to an adaptive control group.	- Typically developing children- Aged 9–14 years	1. Cogmed working memory training: Daily after-school sessions involving a battery of 11 short-term and working memory tasks with visuospatial and verbal stimuli.2. MetaCogmed training: Daily after-school sessions involving the standard Cogmed protocol combined with a metacognitive strategy workbook focusing on planning, monitoring, and evaluating.	- Working memory training improved working memory and mathematical reasoning compared to the control group.- Improvements in working memory were maintained for 3 months and were greater with metacognitive strategy training.- The training did not improve reading comprehension, and the improvement in mathematical reasoning was not sustained at 3 months.
Jurj et al. (2021) [192]	- Improve the safety of vehicles equipped with Adaptive Cruise Control (ACC) using a physics-guided reinforcement learning (PGRL) approach.- Demonstrate that PGRL is better at avoiding collisions compared to a pure RL approach.- Prove that incorporating physical knowledge into AI models enhances safety and efficiency in autonomous vehicles.- Show effectiveness of PGRL across different deceleration levels and fleet sizes, even with perturbed input data.	Not applicable (the study focuses on vehicle simulations rather than human participants)	PGRL approach for Adaptive Cruise Control (ACC) using a Soft Actor–Critic (SAC) algorithm incorporating jam-avoiding distance.	- The PGRL approach significantly reduces collisions and ensures more equidistant travel in Adaptive Cruise Control systems compared to traditional RL approaches.- Integrating physical knowledge into the RL model enhances its performance, making it more reliable and effective in various scenarios, including those with perturbed input data.- The PGRL approach shows better results in criticality metrics like TW and THW, indicating improved safety for autonomous vehicles.

Kaldo et al. (2021) [193]	- To evaluate how accurate ML algorithms can predict a single patient's final outcome and evaluate the opportunities for using them within an Adaptive Treatment Strategy.- To construct an individually tailored self-care intervention including a technical solution, acting as a proof of concept that self-guided digital interventions for mental health can be administered in a safe, effective, personalized, and cost-effective way.	- Patients receiving ICBT for major depression, panic disorder, or social anxiety disorder- Arabic-speaking patients suffering from an emotional disorder (subset)	Internet-delivered Cognitive Behavioral Therapy (ICBT) with scheduled weekly therapist guidance. The exact duration and dose are not specified.	- ML algorithms predicted treatment success or failure with a balanced accuracy between 56% and 77%, outperforming previous strategies.- Predictive power increased when treatment week data were added to baseline data.- The algorithms outperformed a previous predictive algorithm that included therapist input.
Kálózi-Szabó et al. (2022) [194]	- Report on a pilot study at the intersection of neurodiversity and educational robotics.- Promote the love for classic children's and young people's literature.- Develop cognitive and socioemotional abilities of students.- Assess measurable changes in targeted development areas through robotics.- Build a sustainable bridge between technology and education, ensuring Self-Regulated Learning and considering learners' neurodiversity.	- Sixth-grade students- Aged between 11.25 and 13.08 years (M = 12.16; SD = 0.65)- 9 females out of 22 participants- Study conducted in Budapest, Hungary	RIDE program sessions using ArTec robots, held once per week in school settings, with five modules completed due to COVID-19 lockdowns. The program aimed to develop cognitive skills such as computational thinking, spatial relations, visuo-constructive ability, attention, and reading ability.	- Participants showed significant improvements in visuo-constructive abilities, reading accuracy, and reading comprehension after the robotics program.- The study observed a general improvement in most cognitive measures, although not all were statistically significant.- The RIDE project's curriculum is considered innovative and inclusive, contributing to its effectiveness.

Ke et al. (2019) [195]	- Explore the effect of tDCS on the variation in performance during WM training in healthy young adults.- Analyze the variation of performance of the stable-load task during multisession load-adaptive WM training with anodal HD-tDCS.- Investigate whether anodal HD-tDCS facilitates the WM training procedure and boosts the training speed of the stable-load task.	- College students- Aged 20–25- 18 males out of 30 participants- Healthy (no self-reported history of mental or neurological illness and drug abuse)- Normal or corrected to normal vision	Active anodal high-definition transcranial direct current stimulation (HD-tDCS) targeting the left dorsolateral PFC, administered at 1.5 mA for 25 min per session, over 5 consecutive days.	- Active anodal HD-tDCS led to higher learning rates and greater performance improvements during WM training compared to sham stimulation.- The benefits of tDCS were transferable to similar untrained WM tasks.- Individuals with lower baseline performance showed greater training improvements with tDCS.
Keebler et al. (2014) [196]	- Examine the effects of a novel AR guitar learning system (Fretlight®) in relation to embodied music cognition theories.- Compare the Fretlight® system to standard instructional materials (diagrams) in terms of learning effects.- Experiment 1: Investigate short-term learning effects and performance differences using Fretlight® versus diagrams (Optek Music Systems, Inc., Reno, NV, USA).- Experiment 2: Examine long-term retention effects of learning with Fretlight® over a two-week interval.	- Undergraduate students- Adults aged 18 and above- Right-handed individuals- No prior formal or informal stringed instrument training- Experiment 1: 30 females, 25 males- Experiment 2: Mean age, 29.83 years; age range, 24–39 years; 2 females, 4 males	Fretlight® guitar with LED lights for finger placement guidance, used for 30 training trials in Experiment 1 and Experiment 2, with a follow-up test after 2 weeks in Experiment 2.	- The Fretlight® guitar system led to significantly better long-term retention and initial learning ease compared to traditional methods.- Participants using the Fretlight® system demonstrated improved performance in early training trials and shorter scale completion times.- Overall, the Fretlight® system provided a lower barrier of entry and enhanced LE for guitar playing.

Kerr et al. (2015) [197]	- Evaluate the efficacy of the Cogmed working memory program in children with epilepsy.	- Children- Have epilepsy	Cogmed computerized working memory program	Not mentioned (the abstract does not provide specific results or conclusions of the study)
Kesler et al. (2017) [198]	To determine if resting state fMRI acquired at pre-treatment baseline could accurately predict breast cancer-related cognitive impairment at long-term follow-up.	- Female- Aged 34–65- Diagnosed with primary breast cancer- Undergoing or had undergone chemotherapy- Includes a control group of healthy females	1. Doxorubicin, cyclophosphamide, and paclitaxel (16 participants).2. Cyclophosphamide, doxorubicin, and fluorouracil (2 participants).3. Cyclophosphamide and paclitaxel (9 participants).4. Doxorubicin, carboplatin, and paclitaxel (2 participants).5. Fluorouracil, epirubicin, and cyclophosphamide (2 participants).	- Cognitive impairment at 1 year post chemotherapy was observed in 55% of breast cancer patients.- Resting state fMRI combined with ML accurately predicted cognitive impairment with up to 100% accuracy.- The neuroimaging-based model was significantly more accurate than models using only patient-related and medical variables.
Kirchner et al. (2016) [199]	- Show that P300-related activity is naturally evoked when task messages are presented and recognized. - Investigate modulation of P300 by operator demands and task engagement.- Demonstrate that single-trial detection of P300-related activity can be used to adapt interaction based on task engagement. - Investigate if ISI adaptation can achieve balanced task involvement and optimized performance.	- Male- Aged 20–38 years (mean: 28.74, SD: 6.92)- Normal or corrected to normal vision	Participants received an intervention involving the use of a man–machine interface (MMI) for multi-robot control, which adapted to changes in task load and task engagement based on P300-related brain activity. The intervention included six runs, each with 30 tasks, where EEG was used to monitor brain activity and adjust the inter-stimulus interval (ISI) online in runs 5 and 6 based on P300 detectability.	- The developed MMI significantly improved runtime for interaction tasks by adapting to user needs.- Single-trial detectability of P300 was used to measure task load and engagement, allowing for individual MMI adaptation without increasing workload.- Online adaptation of ISI based on P300 detectability improved user performance by balancing task engagement and avoiding overload.

Kosch et al. (2022) [200]	- Demonstrate a placebo effect in adaptive interfaces.- Investigate how the belief in receiving AI support affects expectations and performance.- Integrate findings into technological acceptance theories.- Explore how system descriptions can alter subjective evaluations and task performance.- Investigate if sham treatments can influence subjective and objective metrics of effectiveness.- Evaluate the placebo effect in Human–AI interfaces.	- 166 female, 80 male, 4 identified with another gender, 1 preferred not to disclose gender- Native speakers from the US and the UK- Participants recruited through Prolific	Not applicable (the paper describes sham treatments as part of a placebo effect study, but no actual interventions were applied).	- Belief in receiving AI support increases participants' expectations about their own task performance, demonstrating a placebo effect on subjective performance ratings.- The placebo effect does not significantly impact objective performance measures, such as error rates, in task completion.- System descriptions can alter subjective evaluations and expectations without affecting objective task performance.
Lackmann et al. (2021) [201]	- Compare lecture capture and infographic video formats to identify which engages students more emotionally and cognitively over time.- Determine which video format provides better learning outcomes.- Examine the relationship between engagement and learning outcomes.	- 26 participants- 16 males and 10 females- Average age: 26.20 years- Participants were young students- No prior university-level psychology education- Excluded individuals with psychological diagnoses such as epilepsy	1. Infographic video: continuous flow of images, graphics, and text synchronized with an audio track for approximately 14 min.2. Lecture capture: video recording of a class lecture without additional enrichment for approximately 14 min.	- Infographic videos maintain higher emotional and cognitive engagement over longer periods compared to lecture capture videos.- Infographic videos lead to significantly improved performance on difficult questions.- There is a positive relationship between engagement and performance, with a quadratic relationship observed for cognitive engagement.

Lagoa et al. (2014) [202]	- Introduce adaptive intensive interventions.- Illustrate new methods from control engineering for designing adaptive intensive interventions.- Achieve an approximately 30 percent improvement over mean smoking urge without treatment.	Not mentioned (the paper uses simulated data for methodological illustration and does not provide real-world demographic characteristics)	Adaptive intensive intervention using a smartphone application for smoking cessation, involving self-report data collection three times per day for 50 days. The application includes motivational messages, coping skills improvement, positive reinforcement, and reminders for quitting smoking. Treatment is provided probabilistically (50% chance) at each data collection point.	- Adaptive intensive interventions designed using control engineering methods improve outcomes with less frequent treatment.- These interventions effectively reduce participant burden while maintaining or enhancing effectiveness.- The adaptive intervention achieved a lower smoking urge, negative affect, and higher self-efficacy compared to full treatment.
Lee et al. (2018) [203]	- Use individualized physical maneuvers to create controlled lower and higher pain states in chronic low back pain patients.- Develop multivariate machine learning models using brain imaging and autonomic activity data to predict within-patient and between-patient clinical pain intensity states.- Introduce a model with potential biomarkers for clinical pain, applicable in noncommunicative patients and for identifying objective pain endophenotypes.	- Patients with chronic low back pain (cLBP)- Age range: 18–60 years old- Mean age: 37.37 years- 33 females out of 53 patients- Fluent in English- Able to exacerbate back pain through physical maneuvers- Excluded if they had specific causes of back pain, radicular pain below the knee, complicated back problems, major systemic or neuropsychiatric diseases, substance abuse disorder in the past two years, contraindications to MRI scanning, or high use of prescription opioids/steroids	Individualized physical maneuvers to exacerbate clinical pain, including toe touches, back arches, and facet joint loading twists, performed to increase pain ratings by at least 30%.	- The study developed a machine-learning model that accurately classifies within-patient clinical pain states using combined multimodal neuroimaging and autonomic metrics.- The model successfully predicts between-patient clinical pain ratings, demonstrating potential for clinical applications in noncommunicative patients.- Combining S1 connectivity, regional cerebral blood flow, and high-frequency heart rate variability enhances the model’s predictive accuracy.

Lee et al. (2018) [204]	- To assess the impact of cognitive styles and learning modules using mobile e-learning on knowledge gain, competence gain, and satisfaction for emergent ORL-HNS disorders.	- Undergraduate medical students- Age range: 22–26 years, median age 23 years- Gender: 36 males, 24 females- Novices in ORL-HNS (no previous training in this field)- Participants were in a medical clerkship	Novel interactive multimedia (IM) module on a 7-inch tablet for 100 min, involving interactive elements such as operating a character, interacting with nonplayer characters, and engaging in game-based quizzes.	- Mobile e-learning effectively improves knowledge of emergent ORL-HNS disorders in millennial undergraduate medical students.- Different cognitive styles necessitate the development of various learning modules to optimize educational outcomes.- Students preferred the interactive multimedia module over the PowerPoint show module due to its efficiency and enjoyment.
Leung et al. (2015) [205]	- Examine the behavioral effects of a systematic thirteen-week cognitive training program on attention and working memory in older adults at risk of cognitive decline.- Evaluate the specific cognitive effects of planned experience delivered in a cognitive training program.- Assess the effects of a brain plasticity-based training program on enhancing attention and working memory in older Chinese adults at risk of cognitive decline.	- Community-dwelling older Chinese adults- At risk of cognitive decline (MoCA scores 19–26)- Aged 60 years or above-literate- Normal or corrected-to-normal vision and/or hearing-Right-hand dominant-Normal intelligence (as per TONI-III)- No history of neurological or psychological disorders-No history of substance abuse or alcoholism-Not on antidementia medication- No thyroid dysfunction or vitamin B12 deficiency- Not scoring in the moderate or severe range on HADS depression or anxiety subscales	Cognitive training program modeled after the Brain Fitness Program, consisting of three one-hour sessions per week for thirteen weeks. Participants practiced four out of six cognitive exercises (approximately 15 min each) per session, focusing on attention and working memory.	- Cognitive training improved auditory and visual-spatial attention and working memory in older adults at risk of cognitive decline.- The training effects were specific to the domains targeted by the program, with no significant changes in verbal and visual-spatial memory.- Initial cognitive status did not limit the benefits of training, indicating preserved neural plasticity in older age.

Lin et al. (2017) [206]	- Examine the prospective relationship between an adaptive parasympathetic nervous system response to cognitive stimuli and VSOP training-induced plasticity.- Investigate the role of the parasympathetic nervous system in cognitive and neural improvements resulting from VSOP training in older adults with amnestic mild cognitive impairment.	- Participants with amnestic mild cognitive impairment (aMCI)- Aged 60 years or older- English-speaking- Community-dwelling- 10 participants in the VSOP group (5 male)- 11 participants in the MLA group (6 male)- Recruited from university-affiliated memory clinics- Excluded if actively participating in another cognitive intervention study or on antidepressants/anxiolytics	Vision-based speed of processing (VSOP) training, consisting of five computerized attention tasks (Eye for Detail, Peripheral Challenge, Visual Sweeps, Double Decision, and Target Tracker) for 6 weeks. The tasks automatically adjust in difficulty and speed based on participant performance.	- VSOP training resulted in a significant U-shaped HF-HRV response pattern and decreased striatum–prefrontal connectivity, linked to cognitive improvements.- The study provides evidence of PNS adaptation being associated with cognitive and neural improvements following VSOP training.- Significant group differences were observed in HF-HRV and striatum-prefrontal connectivity, correlating with training-induced cognitive changes.
Liu et al. (2016) [207]	- Use neuroimaging to understand the processes underlying the testing effect.- Provide a theoretical explanation for inconsistent patterns in previous studies on the testing effect.- Explore how the allocation of effort to the re-encoding process during retrieval is influenced by ease of retrieval without feedback.- Manipulate the degree of overlearning/ease of retrieval using multiple tests.- Explore contributions of retrieval and re-encoding processes during tests and restudy processes on subsequent learning.	- Young adults aged approximately 20 years- Nine females out of twenty participants- Students at Carnegie Mellon University- Normal or corrected-to-normal vision	1. STT-T condition: Two tests after initial encoding before a final test on the second day.2. SST-T condition: One restudy opportunity followed by one test before a final test on the second day.3. SSS-T condition: Study opportunities on Day 1 and a final test on the second day.	- The study identifies two distinct processes underlying the testing effect: retrieval and re-encoding.- Left PFC activation predicts success after the first correct test but predicts failure after multiple correct recalls, indicating diminishing returns with repeated testing.- Right hemisphere activation consistently predicts successful recall, highlighting its role in retrieval processes.

Lucia et al. (2021) [208]	- Test the effects of cognitive-motor training on athletes' sport performance and cognitive functions.- Verify whether CM-DT training improves sport performance in basketball players compared to physical training only.- Examine the effects of CM-DT training on behavioral performance during a cognitive DRT and on anticipatory processes associated with pre-stimulus BP and pN components.	- Young male adolescents (mean age 16.6 years)- Semi-professional basketball players- Part of an Under-18 team- from Stella Azzurra Basketball Rome (likely Italian)- Absence of neurological and psychiatric disorders- Not on medication during the study- Right-handed- At least 6 years of formal basketball training	Cognitive-motor dual-task (CM-DT) training using the Witty-SEM system, performed twice a week for 30 min per session, involving six exercises divided into three phases (Activation, Central Phase, and Free Choice), with each exercise lasting 1 or 3 min and repeated twice.	- The experimental group showed significant improvements in sport-specific tests and cognitive test accuracy compared to the control group.- Cognitive-motor training enhanced anticipatory cognitive processes in the PFC, improving proactive inhibition and attention.- The training specifically augmented the pN component, indicating enhanced proactive cognitive control.
Mahncke et al. (2021) [209]	To evaluate the effects of a self-administered computerized cognitive training program on cognitive function in people with a history of mild traumatic brain injury (TBI) and cognitive impairment, compared to active control (computer games).	- People with a history of mild TBI- People with cognitive impairment	Self-administered computerized cognitive training program	- A self-administered computerized cognitive training program significantly improved cognitive function in individuals with mild TBI and cognitive impairment.- The improvements were enduring and superior to those achieved by an active control group using computer games.

Maimon et al. (2022) [210]	- Explore the neural mechanism underlying surgery simulation training.- Test the relationship between cognitive load, skill acquisition, and brain oscillation activity levels.- Track cognitive load neuro-markers using an EEG device during surgical simulator tasks.- Test medical students and interns with no prior experience in surgery simulators or real-life patients.- Compare "online gains" and "offline gains" in skill acquisition.	- Predominantly female (68% in Experiment 1, 63% in Experiment 3)- Mean age around 25–28 years (range 25–36 years)- Healthy- Medical interns or students- Completed 6 years of medical studies (Experiment 1) or in their first to sixth years of study (Experiment 3)	1. Surgery simulator task using Simbionix LAP MENTOR™ (Simbionix USA Corp., Cleveland, OH, USA) involving grasping and clamping blood vessels with laparoscopic arms, conducted over three trials with a 5 min break between trials.2. Brain activity monitoring using a single-channel EEG device (Aurora by Neurosteer® (Neurosteer Inc., New York, NY, USA)) with a three-electrode patch attached to the forehead during the simulator tasks.	- Participants' behavioral performance improved with trial repetition, indicating enhanced laparoscopic skills.- Delta and VC9 biomarker activity decreased with trial repetition and better performance, suggesting reduced cognitive load.- VC9 biomarker showed strong correlation with performance, validating its use as a measure of cognitive load during surgical tasks.
Martín-Perea et al. (2020) [211]	- To establish whether ML analysis can be used to quantitatively identify discrete fossiliferous levels in paleontological and archeological sites based on spatial distribution.- To apply and test the method in Batallones-3 and Batallones-10 to determine if deposits are homogeneous or heterogeneous with discrete fossiliferous levels.	- Fossilized remains from the Late Miocene era (ca. 9.1 Ma)- Batallones-3: Predominantly carnivoran fossils- Batallones-10: Predominantly herbivore fossils	ML algorithms for pattern recognition, including: 1. Unsupervised learning using DBSCAN for density-based clustering.2. Expert-in-the-loop collaborative intelligence for refining clusters.3. Supervised learning using Support Vector Machines (SVM) and Random Forest (RF) for final model tuning.	- ML algorithms were successfully used to identify three discrete fossiliferous levels in both Batallones-3 and Batallones-10.- The study demonstrates the effectiveness of a hybrid intelligence system in quantitatively identifying fossiliferous levels based on spatial data.

Metzler-Baddeley et al. (2017) [212]	- Explore the neural substrates underpinning adaptive training-induced white matter plasticity on the local level within parietofrontal white matter of the superior longitudinal fasciculus (SLF).- Use non-DT-MRI microstructural indices to investigate the underpinnings of white matter plasticity.	- Healthy adults- Aged 19–40 years- Both males and females	Adaptive working memory training using Cogmed, consisting of computerized exercises of verbal and spatial span tasks, practiced five times per week for 8 weeks (40 sessions, approximately 30 h in total), with task difficulty adjusted based on performance.	- Adaptive working memory training improves working memory capacity and induces microstructural changes in parietofrontal and parahippocampal white matter.- These changes include increases in R1, restricted volume fraction, fractional anisotropy, and reductions in radial diffusivity, particularly in the right dorsolateral superior longitudinal fasciculus and left parahippocampal cingulum.- No significant effects were observed on other cognitive domains beyond working memory capacity improvements.

Mo et al. (2022) [213]	- Explore the internal mechanism of learning under the online mode using CLT.- Assist students in using AL at a personalized video playback speed.- Determine what speed students should choose for their online courses.- Investigate if the learning effect differs by playback speeds and if learning ability influences this effect.- Examine if learners' cognitive load differs by playback speed.- Explore the correlation between students' learning effect and cognitive load.- Promote personalized AL under the online learning environment.	- 76 undergraduates- University A in Zhejiang Province- Likely young adults (typical undergraduate age range)	Participants watched instructional videos at one of four different playback speeds (1.0×, 1.25×, 1.5×, or 2×) in a single session.	- Video playback speed significantly influences learning outcomes, with optimal effects at 1.25× and 1.5× speeds.- The best playback speed varies by learning ability: high-level learners perform best at 1.5×, while low-level learners perform best at 1.25×.- Science and engineering students perform better than liberal arts students at 1.5× speed due to differences in cognitive load.
Monlezun et al. (2018) [214]	- Determine if hands-on cooking and nutrition education versus traditional education can improve student competencies and attitudes about providing patients with nutrition education.- Assess if the program can improve students' own diets.- Evaluate if the program could be scalable.	- Medical trainees- Mean age: 25.71 years (SD 2.91)- 61.43% female- 22.65% had nutrition education prior to medical school- 23.21% adhered to a special diet- 30.27% in clinical years- 25.22% intended to enter a primary care specialty	Hands-on cooking and nutrition education program consisting of 28 h of instruction over 8 classes, with each class including a 0.5 h pre-class lecture video, 1.5 h of hands-on cooking, and a 0.75 h post-class Problem-Based Learning session.	- Hands-on cooking and nutrition education significantly improved medical students' competencies in nutrition counseling compared to traditional curriculum.- The intervention increased students' adherence to the Mediterranean Diet.- The program reduced the odds of daily soft drink consumption among trainees.

Montani et al. (2014) [215]	- Develop a novel adaptive videogame to support rehabilitation of attention and executive function impairments in TBI patients.- Focus on design features making the game suitable for brain-damaged patients.- Validate the game with unimpaired participants to ensure activation of desired cognitive functions and assess short training effects.	- Undergraduate students- Aged 19–25 years- Normal or corrected-to-normal vision- Healthy young adults	Playing the adaptive videogame “Labyrinth” for 40 min daily for 14 days (totaling less than 10 h) by healthy young adults.	- The adaptive video game successfully engaged and enhanced attentional control in healthy participants.- Participants showed improved performance in multitasking and task switching, indicating enhanced cognitive flexibility.- The game effectively increased task difficulty over time, demonstrating its potential as a training tool for cognitive skills.
Moore et al. (2017) [216]	- Examine the effect of experimental manipulations of both memory load and pain on tasks sensitive to pain interference.- Investigate the effect of cognitive load on pain-related attentional interference.	- Healthy adult men and women- Recruited from the University of Bath staff and student population- Not currently in pain or with chronic pain conditions- Not taking analgesic medication- Mean age around late 20s to early 30s	Experimental thermal pain induction using a Medoc PATHWAY-Advanced Thermal Stimulator (ATS), with a thermode attached to the right ankle. Temperature starts at 32 °C, increases at 8 °C/second to 1 °C above the pain threshold (maximum 48 °C), oscillates +/−1 °C around the threshold at 8 °C/second for 10 oscillations, and repeats throughout the cognitive tasks.	- Pain-related interference with attention was observed only under high cognitive load conditions for the attention span task.- Cognitive load influences the interruptive effect of pain on attention selectively, affecting some tasks but not others.- The study’s findings were unexpected, as pain did not affect attentional switching or divided attention tasks under high load conditions.

Pat et al. (2022) [217]	- Develop brain-based predictive models for cognitive abilities that are developmentally stable over years during adolescence.- Account for the relationships between cognitive abilities and socio-demographic, psychological, and genetic factors.	- Children aged 9–10 years at baseline and 11–12 years at follow-up- Both male and female participants- Recruited from 21 sites across the United States- Focus on children of European ancestry for genetic analyses- Consideration of socio-demographic factors such as neighborhood safety and school environment	Not applicable (the paper is observational and does not discuss an intervention)	- Brain-based predictive models for cognitive abilities were stable over two years and generalizable across different sites, predicting around 20% of the variance in childhood cognition.- The models accounted for significant variance in childhood cognition due to socio-demographic, psychological, and genetic factors, with mediation proportions of approximately 18.65% and 15.6%, respectively.- The stacked model integrating multiple MRI modalities improved predictive performance over single modalities, demonstrating construct validity according to the RDoC framework.

Perdikis et al. (2018) [218]	- Corroborate the importance and efficacy of mutual learning in motor imagery (MI) brain–computer interface (BCI).- Train two end-users with severe motor impairments using a mutual learning approach to control the Brain Runners BCI application and participate in the Cybathlon BCI race.	- Two male participants- Aged 48 and 30- Tetraplegic with chronic spinal cord injury (ASIA A)- Wheelchair-bound- No control over lower limbs, limited control over upper limbs- No pacemakers or other implants- Do not suffer from epilepsy or cyber-sickness- Do not require respiratory assistance- Use advanced assistive technology in daily life- P1 has previous MI BCI study experience; P2 is BCI naive	1. Mutual learning approach for BCI control: - Offline open-loop BCI training: approximately twice a week, 40 runs for P1, 15 runs for P2. - Online closed-loop BCI feedback training: approximately twice a week, 12 runs for P1, 19 runs for P2. - Race training: approximately twice a week, 182 runs for P1, 57 runs for P2. - Duration: April-October 2016 for P1 (35 sessions), July–October 2016 for P2 (16 sessions).	- Mutual learning in motor imagery BCI is effective, as demonstrated by strong learning effects at machine, subject, and application levels.- The study provides quantitative evidence of operant subject learning in noninvasive MI BCI training.- The Cybathlon competition results highlight the practical success of the mutual learning approach, with one participant setting a competition record.
Peruyero et al. (2017) [219]	To analyze the effect of three physical education sessions of different intensities (no exercise, predominantly light intensity, and predominantly vigorous intensity) on the inhibition response in adolescents.	- Adolescents aged approximately 16 years- 23 boys and 21 girls- From a large city in Spain- Middle socioeconomic class	1. 5 min warm-up, 20 min of light-to-moderate intensity Zumba dance, and 5 min cool-down.2. 5 min warm-up, 20 min of moderate-to-vigorous intensity Zumba dance, and 5 min cool-down.	- Vigorous intensity exercise significantly improves cognitive inhibitory control in adolescents compared to light or no exercise.- Moderate-to-vigorous intensity sessions result in higher accuracy in cognitive tasks than light-to-moderate or no exercise sessions.- Exercise intensity is crucial for enhancing cognitive function when session time is maintained within recommended values.

Piette et al. (2016) [220]	- Demonstrate that AI-CBT has pain-related outcomes equivalent to standard telephone CBT.- Document that AI-CBT achieves these outcomes with more efficient use of clinician resources.- Demonstrate the intervention’s impact on proximal outcomes associated with treatment response, including program engagement, pain management skill acquisition, and patients’ likelihood of dropout.	- Veterans- Patients with chronic low back pain	AI-CBT intervention: 1. Weekly hour-long telephone counseling sessions initially for all patients.2. For responders in the AI-CBT group: - 15 min contact with a therapist. - CBT clinician feedback via interactive voice response calls (IVR). - Personalization based on daily feedback including pedometer step count and CBT skill practice.	Not mentioned (the study is in the start-up phase and no results or conclusions are provided in the abstract).
Pozuelos et al. (2018) [221]	- To test the combined effect of metacognitive scaffolding and computer-based training of executive attention in typically developing preschoolers at the cognitive and brain levels.	- Typically developing preschoolers	Metacognitive scaffolding and computer-based training of executive attention for typically developing preschoolers. Specific details on frequency, duration, or amount are not mentioned.	- Children in the metacognitive group showed larger gains in intelligence compared to regular training and control groups.- Significant increases in an electrophysiological index associated with conflict processing were observed in the metacognitive group.- Changes in conflict-related brain activity predicted intelligence gains in the metacognitive scaffolding group.

Priya et al. (2021) [222]	- To propose ML-Quest, a game that incrementally presents a conceptual overview of three ML concepts: Supervised Learning, Gradient Descent, and K-Nearest Neighbor (KNN) Classification.- To help K-12 students boost their understanding of ML at an early age by applying these concepts in a simulated game world.- To introduce the definition and working of these ML concepts to higher-secondary school students without overwhelming them with complex details.	- Upper-secondary school students	ML-Quest game introduced Supervised Learning, Gradient Descent, and K-Nearest Neighbor (KNN) Classification to 41 upper-secondary school students. Duration and frequency not specified.	- Students who played ML-Quest performed better in tests than those who did not, with 5% scoring full marks.- 77% of participants agreed that ML-Quest made learning interactive and helpful for understanding ML concepts.- The game was perceived as easy to use, useful, and correctly aligned with ML concepts, with high satisfaction scores from participants.
Rafique et al. (2021) [223]	- Develop a system to predict students' performance and help teachers introduce corrective interventions.- Explore the potential of collaborative learning as an intervention to improve student performance.	Students	Collaborative learning (specific details on frequency, duration, and implementation not provided)	- A system was developed to predict student performance and enable timely interventions to improve low-performing students' outcomes.- Collaborative learning methods significantly enhance students' learning capabilities.- Students who actively participated in class activities and completed tasks performed better than others.

Rahman et al. (2022) [224]	- To determine if adding neural measures to a behaviorally adaptive training system improves human performance on a transfer task.- To measure the effectiveness of adding neural measures within a closed-loop BCI into adaptive training.	- Healthy adults- Screened for normal or corrected-to-normal vision- Excluded if they had a tendency for motion sickness or brain-related diseases- Participants included both males and females- Mean age around 29–33 years	1. Behaviorally Adaptive Training (BAT): Task difficulty varied based on behavioral performance, involving 600 trials over 20 blocks, with each trial lasting 1.5 s and inter-trial intervals of 1.0–2.0 s.2. Combined Adaptive Training (CAT): Task difficulty varied based on both behavioral performance and EEG measures, involving 600 trials over 20 blocks, with each trial lasting 1.5 s and inter-trial intervals of 1.0–2.0 s.	- The Combined Adaptive Training (CAT) system, which integrates neural and behavioral measures, significantly improves transfer task performance compared to Single Item Fixed Difficulty (SIFD) and Behaviorally Adaptive Training (BAT) systems.- CAT showed a 6% improvement over SIFD and a 9% improvement over BAT in transfer task performance.- The integration of neural measures into adaptive training systems enhances learning outcomes beyond what is achieved with behavioral measures alone.
Renn et al. (2021) [225]	- Assess the feasibility of an intelligent tutoring system (ITS) as a classroom adjunct.- Assess the acceptability of an ITS as a classroom adjunct.- Assess the effectiveness of an ITS as a classroom adjunct to improve training BSW students in client engagement strategies.	- Undergraduate students in a Bachelor of Social Work program	Intelligent Tutoring System (ITS) as a classroom adjunct for training in client engagement strategies for BSW students enrolled in a class on telephone-based cognitive behavioral therapy (tCBT). Frequency, duration, and amount not specified.	- The intelligent tutoring system (ITS) was effective, with 81.8% of students in Wave 1 and all students in Wave 2 passing the clinical skills role-play.- Students who progressed more quickly through the ITS had better competency ratings in tCBT.- The ITS has the potential to streamline and scale training in evidence-based practices.

Rennie et al. (2019) [226]	- Use unsupervised ML techniques to identify differential trajectories of change in children undergoing working memory training.- Provide an alternative approach to analyzing cognitive training data beyond individual task changes.- Establish a method for identifying data-driven subgroups with distinct cognitive profiles.- Demonstrate a proof of principle for exploring multivariate profiles of change.	- Children aged 5.16–17.91 years- Mean age around 9 years- Typically developing- Attending mainstream schools in the UK- Includes both boys and girls (45 girls mentioned in one sample)	Intensive working memory (WM) training using tasks from the Automated Working Memory Assessment (AWMA), including Forward Digit Recall and Backward Digit Recall tasks. Specific frequency, duration, and amount of training are not mentioned.	- Unsupervised ML techniques revealed differential trajectories of change in children undergoing working memory training.- Fluid intelligence scores were predictive of children’s improvement trajectories, indicating individual differences in response to training.- Task relationships changed following training, suggesting that cognitive processes involved in tasks may become more task-specific rather than domain-general.

Risti et al. (2023) [227]	- To determine if the adaptive e-learning model provides a higher degree of knowledge and positively influences knowledge duration compared to a standard non-adaptive e-learning system.- To assess if the adaptive e-learning model increases students' learning motivation compared to a standard non-adaptive e-learning system.- To explore the relationship between learning styles and achievement scores on A1, A2, S1, and S2 tests.- To investigate if there is a statistically significant difference between gender, learning motivation, achievement scores on tests, and satisfaction with the adaptive e-learning system.	- 228 students- Third-year undergraduate students- Likely aged around 20–22 years- Studying at the Faculty of Management in Serbia	Adaptive e-learning system based on the VAK learning style model, implemented in Moodle, used for six chapters during the second half of a semester for 228 students.	- Adaptive e-learning systems significantly improve learning effectiveness, satisfaction, and motivation compared to standard e-learning systems.- Students achieve better test results after using adaptive e-learning modules, indicating enhanced academic performance.- There is a significant relationship between adaptive e-learning systems and increased student motivation, which is not observed with standard systems.

Roberts et al. (2016) [228]	- To test whether a computerized adaptive working memory intervention program improves long-term academic outcomes of children 6 to 7 years of age with low working memory compared with usual classroom teaching.- To determine the efficacy of Cogmed on reading, spelling, and mathematics at 12 and 24 months.- To evaluate the costs and benefits of the intervention.	- Children aged 6 to 7 years- From Melbourne, Australia- Attending government, Catholic, and independent schools- Majority have parents with tertiary education- Likely English-speaking families	Cogmed working memory training, comprising 20 to 25 training sessions of 45 min' duration at school over 5 to 7 weeks. Each session involved children using computers and noise-canceling headphones to complete adaptive tasks, with a new task introduced every 5 to 6 days.	- The Cogmed intervention provided a temporary benefit to visuospatial short-term memory but did not improve long-term academic outcomes in reading, spelling, or mathematics.- The intervention was not cost-effective due to high costs and loss of classroom time without lasting benefits.- The study does not recommend the population-based delivery of Cogmed within a screening paradigm due to the lack of sustained academic improvement.
Roelle et al. (2015) [229]	- Test the active <constructive learning hypothesis.- Test different types of prompts to induce interactive learning activities.- Test the constructive <interactive learning hypothesis.	- Eighth-grade students aged 13–15- Eleventh-grade students aged 16–19- Participants from a German high-track secondary school (Gymnasium)- Gender distribution: Experiment 1—47 females, 36 males; Experiment 2—28 females, 12 males	1. Complete explanations with engaging prompts (active condition) for 12 concepts.2. Reduced explanations with inference prompts (constructive condition) for 12 concepts.3. Reduced explanations with inference prompts and adapted remedial explanations with engaging prompts (interactive/engaging prompts condition) for 12 concepts.4. Reduced explanations with inference prompts and adapted remedial explanations with revision prompts (interactive/revision prompts condition) for 12 concepts.	- Inference prompts were more effective than engaging prompts in enhancing conceptual knowledge, supporting the active <constructive learning hypothesis.- Revision prompts were more effective than engaging prompts in eliciting interactive learning activities during remedial explanations.- Learners in the interactive/revision prompts condition acquired more conceptual knowledge than those in the constructive condition, supporting the constructive <interactive learning hypothesis.

Ruiz et al. (2019) [230]	- Investigate the relationship between instruction, individual differences in cognitive abilities (working memory and declarative memory), and second language vocabulary acquisition in a web-based ICALL context.- Examine whether individual differences in working memory and declarative memory predict L2 lexical acquisition.- Explore how these cognitive abilities interact with different instructional conditions (meaning-focused vs. form-focused).- Focus on the lexical learning of English phrasal verbs.- Determine if an ICALL system can be used for large-scale experimental research on these topics.	- Adult learners of English- Mean age: 24.3 years- Predominantly female (91 women)- Majority native German speakers (78%)- Advanced-level English proficiency (61% advanced learners)	1. Form-focused instruction: Reading news texts and completing automatically generated multiple-choice gaps where phrasal verbs appeared, for about two weeks.2. Meaning-focused instruction: Reading news texts without completing any gaps, for about two weeks.	- Working memory is a significant predictor of vocabulary acquisition in form-focused instructional conditions, indicating an aptitude-treatment interaction.- Declarative memory, particularly nonverbal, is associated with vocabulary learning, but its effect is not moderated by instructional condition.- The study underscores the role of individual cognitive differences in second language vocabulary acquisition within ICALL environments.

Sánchez-Pérez et al. (2018) [231]	- Examine the efficacy of a school computer-based training program composed of working memory and mathematics tasks.- Evaluate the effects of the training on children’s cognitive skills, including executive functions (EF) and IQ.- Assess the impact of the training on children’s academic achievement in math and language.	- Primary school children	Computer-based training program consisting of:1. Working memory tasks with varying difficulty levels (1-, 2-, 3-back) and presentation times (500 ms or 1000 ms).2. Mathematics tasks requiring solving mathematical operations, numerical sequences, and problems within a time limit of two minutes.	- The study found significant improvements in cognitive skills, such as non-verbal IQ and inhibition, and better school performance in math and reading among children who participated in the training.- Most of the improvements were attributed to training on working memory tasks.- The computer-based training program combining working memory and mathematics activities was confirmed to be effective in enhancing children’s academic competences and cognitive skills.

Sánchez-Pérez et al. (2019) [232]	- Investigate the effectiveness of computer-based cognitive training on improving cognitive and academic-related skills in primary school-aged children.- Examine brain functional connectivity effects induced by WM-based training, specifically in the MFG area of the attentional networks and the frontoparietal network.- Investigate the relationship between improvements in inhibition-related abilities and changes in brain functional connectivity.	- Primary school-aged children- Mean age approximately 9 years- Training group: 19 boys, 14 girls; control group: 15 boys, 8 girls- Significant differences in socioeconomic status (SES) between groups- Likely Spanish or residing in Spain	Computer-based cognitive training program focused on working memory tasks, integrated into school routine, supervised by trained teachers, with personalized difficulty levels. Duration and frequency not specified.	- A computer-based cognitive training program improved cognitive and academic skills, including inhibition skills, non-verbal IQ, mathematics, and reading skills, in primary school-aged children.- The training led to increased functional connectivity in the right middle frontal gyrus (MFG), associated with improvements in inhibitory control.- Connectivity between the r-MFG and homolateral parietal and superior temporal areas was more strongly related to inhibitory control improvement in trained children compared to the control group.
Scharnowski et al. (2014) [233]	- Assess changes in effective brain connectivity associated with neurofeedback training of visual cortex activity.- Investigate the neural underpinnings of successful self-regulation using dynamic causal modeling (DCM).- Characterize effective connectivity changes between the trained visual ROI and the cSPL.	- 16 human volunteers- Ages between 18 and 37 years- 6 male participants- All right-handed- Normal or corrected-to-normal vision	Neurofeedback training using real-time fMRI, conducted over at least three sessions with each session including an average of two training runs lasting 8.3 min each. Each training run consisted of seven 38 s baseline blocks interleaved with up-regulation blocks of the same duration. Feedback was provided via a thermometer display indicating signal change.	- Neurofeedback training increased effective connectivity between the visual cortex and the superior parietal lobe.- Successful training was characterized by enhanced top-down control from the superior parietal lobe to the visual cortex and reduced bottom-up processing.- The connectivity changes were associated with the use of visual-spatial attention and imagery as cognitive strategies.

Schlatter et al. (2022) [234]	- To evaluate the effectiveness of two types of adaptive instruction (macro-adaptive and micro-adaptive) in teaching scientific reasoning to children.- To compare these adaptive methods against a non-adaptive control condition in terms of learning outcomes.	- Children	1. Macro-adaptive instruction based on standardized test scores (*n* = 58).2. Micro-adaptive instruction based on performance in the previous lesson (*n* = 46).	- All three instructional conditions (macro-adaptive, micro-adaptive, and non-adaptive) led to comparable improvements in pre- and post-test scores.- Children’s task performance improved during the lessons, with this improvement interacting with the instructional condition.- More specific information and frequent adaptations might lead to better learning outcomes, suggesting potential for future research in hybrid solutions.
Shangguan et al. (2020) [235]	- Examine the impacts of visual and behavioral emotional design on emotional, motivational, and cognitive outcomes of middle school students.- Investigate the multi-leveled effects of emotional design (visual and behavioral) on multimedia learning.- Explore the effects of emotional design on positive emotions, cognitive load, motivation, and learning outcomes with a new learning topic.	- Middle school students- Ages 13–16- Gender distribution: Experiment 1—29 males, 21 females; Experiment 2—79 males, 94 females- Normal or corrected-to-normal vision	1. Visual positive emotional design: colorful and anthropomorphic elements in learning materials.2. Behavioral positive emotional design: self-control of learning progress by fast-forwarding, rewinding, or repeating the learning video.	- Both visual and behavioral emotional designs positively affect learners’ emotions, enhancing the emotional experience during learning.- Visual positive emotional design increases mental effort and perceived task difficulty, indicating a complex interaction with cognitive processes.- Combining visual and behavioral emotional designs improves learning performance, particularly in terms of transfer scores.

Singh et al. (2022) [236]	- Predict participants' daily adherence to cognitive training programs based on previous adherence patterns.- Understand long-term adherence barriers and develop algorithms to predict and prevent adherence failures.- Use multivariate time series data to determine if participants will meet minimum adherence criteria.	- Older adults with a mean age of 72.6 years- 66% female, 32% male, 2% unspecified gender- Mean age for females: 71.5 years- Mean age for males: 75.0 years- Participants had varying levels of technology proficiency (average MDPQ score: 27.10)	Gamified cognitive training tasks using the Mind Frontier software (Aptima, Inc., Woburn, MA, USA) for 45 min per day, 5 days a week, for 12 weeks.	- Deep learning models, including CNN, LSTM, and CNN-LSTM, effectively predicted older adults' adherence to cognitive training programs with high F-scores.- Data augmentation techniques significantly improved the generalization performance of the predictive models.
Stiller et al. (2019) [237]	- Investigate the effects of game play and expertise in gaming and English on motivation, cognitive load, and performance.- Compare the effects of an educational game with a traditional text-based hypertext instruction on motivation, cognitive load, and performance.	- German university students- Mixed gender (majority female: 30 out of 39)- Recruited from Regensburg University and East Bavarian Technical University of Regensburg- Less experienced in e-learning environments and educational games- Little prior knowledge about cell biology	Playing the educational game "CellCraft" for 1 h.	- Educational games increased motivation but did not lead to superior performance compared to hypertext learning.- Cognitive load patterns differed between groups, but overall levels were similar.- The hypertext group showed greater knowledge gains than the gaming group.
Sun et al. (2022) [238]	- Design and test a brain–machine interface (BMI) that combines automated pain detection with treatment in freely behaving rats.- Accurately detect and treat acute evoked pain and chronic pain using the BMI.	- rats	Optogenetic activation or electrical deep brain stimulation (DBS) of the PFC in freely behaving rats, as part of a closed-loop brain–machine interface for on-demand pain relief. Frequency, duration, and dose are not specified.	- A multi-region brain–machine interface accurately detected and treated acute and chronic pain in rats.- The analgesic effects of the brain–machine interface were stable over time.- The study suggests that brain–machine interface approaches might be effective for treating chronic pain of different etiologies.

Tacchino et al. (2015) [239]	- Describe the design of Cognitive Training Kit (COGNI-TRAcK), an app for mobile devices for at-home cognitive rehabilitation.- Test the disposability-to-use (usability, motivation to use, compliance to treatment) of COGNI-TRAcK on cognitive-impaired patients with multiple sclerosis.	- Patients with multiple sclerosis (MS)- Mean age: 49.06 years (range 33–67)- Gender: 3 men and 13 women- Recruited from the AISM Rehabilitation Center, Genoa, Italy- Forms of MS: 9 relapsing-remitting, 7 progressive- Mean education: 11.75 years- Mean EDSS score: 3.75- Mean disease duration: 161.69 months- Familiar with electronic devices	8-week at-home intervention using the COGNI-TRAcK app, consisting of 5 daily scheduled 30 min sessions per week, each including three types of working memory exercises (Vs-WM, Op-NB, and D-NB) for about 10 min each.	- The COGNI-TRAcK app demonstrated high adherence (84%) among patients with multiple sclerosis, indicating consistent use.- The app was well-received, with most patients finding it easy to use, interesting, and useful for cognitive rehabilitation.- Patients reported high motivation and low stress levels during the use of the app, suggesting it is a viable tool for at-home cognitive training.
Taxipulati et al. (2021) [240]	- To determine if different types of feedback affect problem-solving performance in the test stage.- To assess the impact of feedback types on subjective cognitive load and objective eye-tracking trajectory.- To evaluate the effect of feedback types on learner motivation.- To explore if cognitive load and motivation mediate the effect of feedback on problem-solving performance.	- Undergraduate and graduate students- Aged 17–26- 38 men and 119 women- From Northeast Normal University	1. Knowledge of Correct Response (KCR) feedback: question stem + correct answer.2. Elaborated Feedback (EF): question stem + correct answer + correct answer resolution.3. Adaptive Feedback (AF): if the answer is correct, provide KCR feedback; if the answer is wrong, provide EF.4. Immediate feedback: provided after each problem.5. Delayed feedback: provided after all problems are completed.	- Immediate feedback results in higher academic performance compared to delayed feedback.- Adaptive feedback improves academic performance more than elaborated and knowledge of correct response feedback.- Germane Cognitive Load (GCL) partially mediates the effect of adaptive feedback on academic performance.

Tee et al. (2023) [241]	- To evaluate the efficacy of an Artificial Intelligence-driven tutoring system in providing risk-free training and objective assessment to improve surgical technical skills.- To compare the teaching efficacy of the AI-driven system with human instructor training.	- Medical students	1. Real-time intelligent instruction: Tutoring by an AI system with error clips and expert-level demonstrations after each repetition.2. Real-time human instruction: Tutoring by human instructors with critiques and demonstrated correction techniques after each repetition.	- The AI-driven tutoring system led to significant performance improvements in surgical skills training, with higher scores than human instruction by the fifth repetition.- The AI system resulted in higher extrinsic cognitive load compared to human instruction, indicating more efficient learning.- No significant differences were found between the groups for intrinsic and GCL.
Tremblay et al. (2022) [242]	- Determine the impact of modulating task and environment complexity on novices' performance in simulation.- Determine the impact of modulating task and environment complexity on novices' cognitive load in simulation.- Determine the impact of modulating task and environment complexity on novices' knowledge in simulation.	- Second-year undergraduate pharmacy students- Mostly female (72%)- Mean age of 22 years (SD = 2.5)- College degree prior to PharmD program (78%)- Limited clinical experience (3 to 4 weeks of internship)- 27% had prior real-life experience with similar cases	Students participated in a simulation-based education intervention where they acted as pharmacists in one of four conditions: simple task in simple environment, complex task in simple environment, simple task in complex environment, or complex task in complex environment. Each student participated in one session comprising three different learning tasks, playing the pharmacist role once. The intervention was designed to vary task complexity (number of information elements and interactions) and environment complexity (orderliness and visual load).	- Task and environment complexity interact to affect novices' performance, with simple task performance decreasing in complex environments.- Task complexity significantly impacts ICL, but environmental complexity does not.- Increasing complexity does not necessarily lead to cognitive overload or reduced performance in simulation-based education.

Tuti et al. (2019) [243]	- Determine the effectiveness of offering adaptive versus standard feedback on the learning gains of clinicians using a smartphone-based game.- Examine the effects of learner characteristics and learning spacing on individualized normalized learning gain.	- Clinicians providing bedside neonatal care- Participants from low-income countries- Healthcare providers in training or actively practicing- Excludes retired clinicians and those from high-income settings- Varied socioeconomic status, with some facing financial constraints	Adaptive differentiated immediate feedback provided through a smartphone-based serious gaming app, tailored to individual performance during learning tasks. Only participants in the experimental group received this intervention. The frequency and duration are not specified as they depend on user interaction with the app.	- Adaptive feedback had a small and statistically insignificant effect on learning gains at the group level.- When controlling for individual learner characteristics, adaptive feedback significantly increased learning gains with immediate repetition.- Spaced learning of a week or more significantly reduced learning gains.
Tzachrista et al. (2023) [244]	- To provide an in-depth review of the neurocognitive aspects of creativity and its association with academic achievement in children.- To examine and provide answers to the following research questions: - What are the cognitive processes associated with creative thinking? - How does creativity affect academic performance? - What are the differences in the neurocognitive profiles of creative and noncreative students? - How can creativity be fostered in the classroom? - How does creativity interact with other cognitive processes to affect academic performance?	- Students aged 5 to 16- Normal, typical development (no diagnosed developmental disorders)- Attending public schools	1. 20 min Hatha yoga sessions.2. Cooperative high-intensity interval training.	- There is a significant positive relationship between creativity and academic performance, particularly in reading, comprehension, and writing tasks.- Neurocognitive processes like associative thinking, divergent thinking, executive functions, and predictive representations are crucial in shaping creativity.- The study advocates for fostering creativity in educational settings through cultural resources and aligning teachers' attitudes with creativity promotion.

Varga et al. (2019) [245]	- Identify the cognitive factors contributing to individual differences in self-derivation and retention of knowledge through memory integration in adults.- Test whether a similar profile of cognitive correlates is observed in 8-to 10-year-old children.- Examine whether self-derivation through memory integration is associated with concurrent and longitudinal academic success.	- Adults aged 18–24- Majority female (63 out of 117)- Racial composition: 9% African American, 25% Asian, 59% Caucasian, 4% mixed racial descent- 8% Hispanic ethnicity- Undergraduate students at a private institution- Children aged 8–10 (third grade)- Racial composition: 45% African American, 40% Caucasian non-Hispanic, 11% Caucasian Hispanic- Attending a rural public school in the southeastern United States- Approximately 87% qualify for federally funded school lunch assistance	Participants read 60 sentences (30 pairs of stem facts) over two sessions spaced one week apart and were tested for self-derivation of 30 possible integration facts. They also completed standardized cognitive assessments in short-term memory, relational reasoning, working memory, long-term memory retrieval, reading comprehension, and verbal knowledge.	- Verbal knowledge and skills are significant predictors of self-derivation performance in both adults and children.- Working memory predicts self-derivation performance in adults but not in children.- Self-derivation through memory integration is associated with concurrent and longitudinal academic success.
Veen et al. (2016) [246]	- To test whether recall of an aversive autobiographical memory loads working memory (WM) compared to no recall.- To test whether recall with eye movements (EM) reduces the vividness, emotionality, and cognitive load of recalling the memory more than only recall or cognitive effort (i.e., recall of an irrelevant memory with EM).	- Undergraduates	Recall relevant memory with eye movements (EM) for 8 ×24 s and 16 ×24 s.	- Recalling an aversive memory with eye movements reduces its vividness and emotionality more than recalling without eye movements or an irrelevant memory with eye movements.- The cognitive load of recalling the memory decreases with eye movements, but not consistently more than in control conditions.- Recalling an aversive autobiographical memory is a cognitively demanding task.

Vekety et al. (2022) [247]	- Examine the effects of mindfulness training supplemented with EEG feedback on objective measures of executive functions and brain activity correlates in elementary school children.- Explore the potential effects of a mindfulness program with EEG feedback to empower children’s attention regulation, measured through neurocognitive tests and brain activity.	- Children aged 9–10 years- Recruited from a local primary school in Budapest, Hungary- From families of middle and high socioeconomic status- Gender distribution: 51% girls, 49% boys- Generally healthy (children with psychological disorders were excluded)	Mindfulness training with EEG feedback using a Muse brain-sensing headband was conducted over eight sessions in 4 weeks. Session durations were: 1 min for the first two sessions, 2 min for the third and fourth sessions, 3 min for the fifth and sixth sessions, and 4 min for the seventh and eighth sessions. The intervention included mindful breathing exercises with auditory feedback.	- Mindfulness training with EEG feedback significantly improved children’s inhibition and information processing compared to a control group.- The intervention maintained alpha and theta brain activity levels, which decreased in the control group, indicating a stabilizing effect on brain function.- These findings suggest potential benefits for children’s Self-Regulated Learning and academic achievements.
Venkat et al. (2020) [248]	- Assist teachers in the health professions in improving their learners’ experiences using tenets of CLT.- Assess the efficacy of the workshop.- Understand how teachers would envision CLT as applying to their workplace teaching settings.- Consider challenges and barriers they might face as they attempt to implement those changes.- Assess whether educators can independently craft plans for improving their teaching practices based on CLT.	- Health professions educators- Majority female (78%)- Primarily from medicine, nursing, education, and dentistry	A 2 h workshop on CLT for health professions’ workplace educators, including large-group didactics, small-group discussions, and individual reflective activities. The workshop was structured as follows: 0–30 min for a large-group overview of CLT, 30–50 min for a small-group activity using a worked example, 50–60 min for a group discussion, 60–80 min for an individual activity to apply CLT principles, and 80–120 min for sharing results and debriefing.	- The workshop increased participants’ self-assessed familiarity with CLT from a mean of 36 to 59.- Participants demonstrated retention of CLT concepts with an average score of 85% on content knowledge questions.- Approximately half of the participants planned or implemented changes in their teaching practices based on CLT principles.

Vidanaralage et al. (2022) [249]	- Explore schema congruent and incongruent participants' behavior in video-based learning within a flipped learning environment.- Examine the emotional valency of participants during the study and test phases using AI-based emotion analysis.	- Healthy young adults- Aged 20–34 years- Mean age 27.31 years- 9 males (56.25%)- 7 females (43.75%)	Participants watched an educational learning video on a given topic.	- Retrieval accuracy was better for the schema incongruent group compared to the schema congruent group.- Response time was quicker for the schema congruent group than for the schema incongruent group.- Both groups showed more negative emotions during the study and more positive emotions during the test phase.
Wiest et al. (2022) [250]	- Examine the effectiveness of cognitive training for students diagnosed with ADHD and SLD.- Examine the underlying structure among the included cognitive abilities.	- Children and adolescents aged 6–17 (mean age 11.7)- 22 males and 21 females- Diagnosed with ADHD- Diagnosed with specific learning disorders (26 with reading SLD, 6 with writing SLD, 4 with math SLD)- Received psychoeducational evaluations due to educational concerns	Cognitive training via the Captain's Log program, consisting of 20 sessions, each lasting 60 min, conducted over 4–8 weeks in a clinical setting with supervision by a psychometrician or staff member.	- Cognitive training significantly improved attention, working memory, and inhibition in children with ADHD and SLD.- The study demonstrated structural changes in cognitive abilities following 20 h of computer-based intervention.

Winn et al. (2019) [251]	- Develop an interactive workshop to teach five cognitive learning strategies to pediatric educators.- Provide a platform for educators to understand, apply, and incorporate these strategies into their teaching.- Evaluate the workshop’s effectiveness in promoting behavioral changes in teaching practices.	- Pediatric residents- Chief residents- Fellows- Junior attending faculty members- Senior attending faculty members- Residency program directors- Fellowship program directors- Associate residency program directors- Associate fellowship program directors	A 90 min interactive workshop teaching five cognitive learning strategies: spaced retrieval practice, interleaving, elaboration, generation, and reflection. Each strategy was taught in a 10 min session, including a review, interactive activities, and a brainstorming session.	- The workshop led to behavioral changes in teaching practices, with 82% of participants implementing changes based on the workshop.- Participants initially committed to using interleaving and reflection but eventually applied all five cognitive learning strategies.- The commitment-to-change evaluation strategy confirmed that participants gained and applied knowledge and skills from the workshop.
Yilmaz et al. (2023) [252]	To compare learning efficacy by a real-time intelligent instruction system with in-person human instructor-mediated training.	- Medical students	1. Real-time intelligent instruction by an AI system during five virtually simulated brain tumor resections.2. In-person human instruction during five virtually simulated brain tumor resections.	- Both AI-based and human instruction significantly improved surgical skills compared to baseline.- AI-based instruction led to higher performance scores than human instruction by the final task.- AI systems can enhance LE with objective, real-time feedback.
Yilmaz et al. (2023) [253]	To compare a real-time intelligent tutoring system in technical skills learning with human expert instructor-mediated training.	- Medical students	1. Real-time intelligent instruction during simulated surgical tasks (Group 2).2. In-person human instruction during simulated surgical tasks (Group 3).	- Both AI and human instruction significantly improved surgical skills from baseline.- The AI-instructed group outperformed the human-instructed group by the fifth repetition.- AI systems may offer equally or more efficient learning compared to human instruction.

Yin et al. (2020) [254]	- Investigate the impact of a chatbot-based micro-learning system on students' learning motivation.- Investigate the impact of a chatbot-based micro-learning system on students' performance.	- First-year students	Chatbot-based micro-learning system (applied to the chatbot-based micro-learning group)	- Students in both chatbot-based and traditional learning environments achieved comparable performance, indicating effective independent learning in the chatbot environment.- Chatbot-based learning significantly increased students' intrinsic motivation compared to traditional learning, with perceived choice and value as key factors.- Students with high initial perceived choice benefit more from chatbot-based learning, while those with low initial perceived choice benefit more from traditional learning.
Yoon et al. (2022) [255]	- Examine the effects of segmentation and self-explanation designs on ICL.- Examine the effects of segmentation and self-explanation designs on ECL.- Examine the effects of segmentation and self-explanation designs on GCL.- Explore students' perspectives on segmentation and self-explanation designs in instructional videos.	- Undergraduate students- 32 males and 89 females- From a large public university in the southeastern United States- Includes both education and non-education majors- Includes freshmen, sophomores, juniors, seniors, and fifth-year students	1. Segmentation: Video divided into six segments, allowing control of pacing, applied once during a 7 min and 45 s video session.2. Self-explanation: Seven open-ended prompts provided to guide self-explanation, applied once during a 7 min and 45 s video session.3. Combination: Both segmentation and self-explanation prompts applied once during a 7 min and 45 s video session.	- Segmentation in instructional videos resulted in significantly less GCL compared to non-segmenting designs.- Self-explanation did not significantly outperform the control in GCL but was better than segmentation.- Combining segmentation and self-explanation did not enhance GCL compared to using them separately or the control.

Yu et al. (2015) [256]	Explore the effect of visual stimuli degradation on cognitive workload.	Not mentioned (no information on population characteristics is included in the abstract)	Degradation of visual stimuli.	- Degradation of visual stimuli increases cognitive workload, confirmed by subjective assessments and P300 amplitude attenuation.- A single-trial EEG/ERP detection method achieved 85% accuracy in identifying four workload levels.- Frontal EEG signals carry information useful for differentiating workload levels.

Table 3

Comparison of CLT, SRL, and PBL in AI-driven learning environments.

Learning Theory	Strengths	Weaknesses	AI Integration Potential	Empirical Evidence
Cognitive Load Theory (CLT)	Optimizes cognitive efficiency by reducing extraneous load; improves retention through structured instructional design.	Overemphasis on reducing cognitive load may limit engagement with complex tasks; assumes one-size-fits-all instructional pacing.	AI-driven cognitive load monitoring and adaptive feedback can dynamically adjust content complexity in real time.	Two studies found: AI-enhanced CLT-based instruction improved comprehension and retention (e.g., video playback speed optimization).
Self-Regulated Learning (SRL)	Encourages learner autonomy, metacognitive awareness, and self-directed skill development.	Highly dependent on learner motivation and self-discipline; may require structured guidance to be effective.	AI-enhanced learning analytics can track learner engagement and provide personalized feedback to optimize self-regulation.	One study found: AI-driven robotics-based SRL programs improved reading accuracy and cognitive abilities.

Problem-Based Learning (PBL)	Fosters real-world problem-solving, critical thinking, and application-based learning.	High cognitive load can overwhelm learners without adequate scaffolding; effectiveness depends on problem authenticity and learner readiness.	AI-based simulations, intelligent tutors, and problem-solving recommendation engines can adjust PBL task complexity dynamically based on real-time learner performance, bridging cognitive gaps effectively.	Four studies found: AI-driven PBL was applied in various fields, including medical training, law education, and STEM; AI-enhanced scaffolding improved learner decision-making speed by 18% and conceptual application by 22%.

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DETAILS

Subject:	Neurobiology; Problem solving; Pedagogy; Students; Neuroimaging; Artificial intelligence; Functional magnetic resonance imaging; Memory; Brain research; Instructional design; Neurosciences; EKG; Cognitive load; Medical imaging; Neuroplasticity; Deep learning; Cognition &reasoning; Efficiency; Galvanic skin response; Data processing; Educational objectives; EEG; Infrared spectroscopy; Educational materials; Ethics; Retention; Metacognition; Problem based learning; Education; Adaptive learning; Neural networks

Business indexing term:	Subject: Artificial intelligence Retention
Identifier / keyword:	cognitive load theory; educational neuros cience; artificial intelligence; machine learning; personalized learning; adaptive learning; K-12 education; learning efficacy
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Examining the Role of AI in Changing the Role of Nurses in Patient Care: Systematic Review

Inas Al Khatib ; Ndiaye, Malick . Inas Al Khatib; Ndiaye, Malick.

ABSTRACT (ENGLISH)

Background:This review investigates the relationship between artificial intelligence (AI) use and the role of nurses in patient care. AI exists in health care for clinical decision support, disease management, patient engagement, and operational improvement and will continue to grow in popularity, especially in the nursing field.
Objective:We aim to examine whether AI integration into nursing practice may have led to a change in the role of nurses in patient care.
Methods:To compile pertinent data on AI and nursing and their relationship, we conducted a thorough systematic review literature analysis using secondary data sources, including academic literature from the Scopus database, industry reports, and government publications. A total of 401 resources were reviewed, and 53 sources were ultimately included in the paper, comprising 50 peer-reviewed journal articles, 1 conference proceeding, and 2 reports. To categorize and find patterns in the data, we used thematic analysis to categorize the systematic literature review findings into 3 primary themes and 9 secondary themes. To demonstrate whether a role change existed or was forecasted to exist, case studies of AI applications and examples were also relied on.
Results:The research shows that all health care practitioners will be impacted by the revolutionary technology known as AI. Nurses should be at the forefront of this technology and be empowered throughout the implementation process of any of its tools that may accelerate innovation, improve decision-making, automate and speed up processes, and save overall costs in nursing practice.
Conclusions:This study adds to the existing body of knowledge about the applications of AI in nursing and its consequences in changing the role of nurses in patient care. To further investigate the connection between AI and the role of nurses in patient care, future studies can use quantitative techniques based on recruiting nurses who have been involved in AI tool deployment—whether from a design aspect or operational use—and gathering empirical data for that purpose.

FULL TEXT

The science and engineering field of artificial intelligence (AI) is concerned with the theory and application of creating systems that display the traits we identify with intelligence in human behavior [1]. The years 2000 to 2015 saw an upward trend in the growth of AI. With dramatic revolutions influenced by both ideas and methodologies, the progress of AI has promoted the development of human civilization in our day and age. However, due to its interdisciplinary nature and rapid expansion, AI is a discipline that is challenging to fully comprehend and is getting more and more flexible from the standpoint of reference behavior [2].

The previous decade was defined by AI, and the upcoming one will most likely also be defined by it. Systems that exhibit intelligent behavior by analyzing their surroundings and acting with some autonomy to accomplish predetermined goals are referred to as AI systems. Greater accuracy is needed to have relevant and fruitful discussions on AI because it encompasses so many different methodologies and circumstances. Arguments regarding straightforward "expert systems" that serve advising functions, for instance, must be separated from those about sophisticated data-driven algorithms that make conclusions about specific persons automatically. Similarly, it is crucial to distinguish between arguments regarding hypothetical future advancements that may never materialize and those regarding actual AI that already has an impact on society today including the nursing practice [3].

Numerous ideas, including computing, developing software, and transmitting data, are built on AI. Machine learning (ML), deep learning, natural language processing (NLP), voice recognition, robots, and biometric identification are examples of technologies that use AI. AI is used in a wide range of industries, including the health care, industrial, and automotive sectors as well as corporate organizations. AI also provides several benefits that help it become increasingly popular across numerous industries. AI-powered machines are accurate and efficient, can do many tasks at once, and their work costs less than a human's. However, there are other issues with AI that make it difficult to use. Technology, security, and data issues are common with AI, and if users do not comprehend the system, mishaps may occur. The expanded use of AI has changed several industries by improving organizational effectiveness and enabling data security [4].

AI in nursing is revolutionizing the field by enhancing patient care, improving efficiency, and reducing the workload on nurses. AI-powered tools and applications enable real-time monitoring of patient's vital signs, predicting potential health deteriorations, and providing alerts for immediate intervention. AI algorithms can analyze large volumes of patient data to assist in accurate diagnosis and personalized care plans [5]. Moreover, AI chatbots and virtual assistants support administrative tasks, such as scheduling and documentation, allowing nurses to focus more on direct patient care [6]. By automating routine tasks and providing decision support, AI empowers nurses to deliver higher quality care with greater precision and efficiency [7].

Research Rationale and Aim

The rationale behind this research is to investigate how the increasing use of AI in health care affects the role of nurses in patient care. As AI technologies become more integrated into health care systems, understanding their impact on nursing practice is crucial. AI's applications, ranging from clinical decision support to operational improvements, promise to transform various aspects of health care, including nursing. By examining whether AI has led to changes in the nursing role or is likely to do so, this research aims to provide insights into how these technologies influence nursing responsibilities and practices. The aim of this review is to explore the evolution of AI as a technology through its various developmental phases. In this systematic literature review, we examine the different applications and deployments of AI in the nursing field. The primary research question addressed is "How will AI transform the role of nurses in patient care?"

Research Significance

The review offers important perspectives on how AI is transforming the roles and duties of nurses in patient care. This understanding is essential for adapting nursing education, training, and practice to align with evolving technological advancements. By identifying how AI impacts nursing roles, the research can guide the effective implementation of AI tools in health care settings. It highlights the importance of involving nurses in the development and deployment of AI technologies to ensure that these tools enhance rather than disrupt nursing practice. The findings can inform health care policies and training programs by emphasizing the need for ongoing professional development and support for nurses as they integrate AI into their workflows. This ensures that nurses are prepared to leverage AI effectively while maintaining high standards of patient care. The study contributes to the existing body of knowledge on AI in health care and sets the stage for future research. It opens avenues for quantitative studies and empirical data collection to further explore the relationship between AI and nursing roles, providing a foundation for evidence-based practice and decision-making. Overall, this research is important for its potential to enhance the understanding of AI's impact on nursing practice, guide effective technology integration, and shape the future of nursing education and policy.

Methods

Overview

A well-defined review protocol (Textbox 1) was established at the outset of the research to guarantee that the review process is transparent, reproducible, methodical, and provides a clear roadmap for conducting and reporting the review.

Textbox 1.Systematic literature review protocol.

DETAILS

Subject:	Evidence-based nursing; Nursing education; Literature reviews; Bibliometrics; Algorithms; Artificial intelligence; Visualization; Systematic review; Nurses; Technology; Decision making
Business indexing term:	Subject: Artificial intelligence
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Exploring Older Adults' Perspectives and Acceptance of AI-Driven Health Technologies: Qualitative Study

Publication info: Arkers Kwan Ching Wong; Jessica Hiu Toon Lee; Zhao, Yue; Lu, Qi; Yang, Shulan; et al.

ABSTRACT (ENGLISH)

Background: Artificial intelligence (AI) is increasingly being applied in various health care services due to its enhanced efficiency and accuracy. As the population ages, AI-based health technologies could be a potent tool in older adults' health care to address growing, complex, and challenging health needs. This study aimed to investigate perspectives on and acceptability of the use of AI-led health technologies among older adults and the potential challenges that they face in adopting them. The findings from this inquiry could inform the designing of more acceptable and user-friendly AI-based health technologies.

Objective: The objectives of the study were (1) to investigate the attitudes and perceptions of older adults toward the use of AI-based health technologies; (2) to identify potential facilitators, barriers, and challenges influencing older adults' preferences toward AI-based health technologies; and (3) to inform strategies that can promote and facilitate the use of AI-based health technologies among older adults.
Methods: This study adopted a qualitative descriptive design. A total of 27 community-dwelling older adults were recruited from a local community center. Three sessions of semistructured interviews were conducted, each lasting 1 hour. The sessions covered five key areas: (1) general impressions of AI-based health technologies; (2) previous experiences with AI-based health technologies; (3) perceptions and attitudes toward AI-based health technologies; (4) anticipated difficulties in using AI-based health technologies and underlying reasons; and (5) willingness, preferences, and motivations for accepting AI-based health technologies. Thematic analysis was applied for data analysis. The Theoretical Domains Framework and the Capability, Opportunity, Motivation, and Behavior (COM-B) model behavior change wheel were integrated into the analysis. Identified theoretical domains were mapped directly to the COM-B model to determine corresponding strategies for enhancing the acceptability of AI-based health technologies among older adults.
Results: The analysis identified 9 of the 14 Theoretical Domains Framework domains—knowledge, skills, social influences, environmental context and resources, beliefs about capabilities, beliefs about consequences, intentions, goals, and emotion. These domains were mapped to 6 components of the COM-B model. While most participants acknowledged the potential benefits of AI-based health technologies, they emphasized the irreplaceable role of human expertise and interaction. Participants expressed concerns about the usability of AI technologies, highlighting the need for user-friendly and tailored AI solutions. Privacy concerns and the importance of robust security measures were also emphasized as critical factors affecting their willingness to adopt AI-based health technologies.
Conclusions: Integrating AI as a supportive tool alongside health care providers, rather than regarding it as a replacement, was highlighted as a key strategy for promoting acceptance. Government support and clear guidelines are needed to promote ethical AI implementation in health care. These measures can improve health outcomes in the older adult population by encouraging the adoption of AI-driven health technologies.

FULL TEXT

Introduction

Background

Artificial intelligence (AI) refers to a computerized system that is capable of executing a wide range of tasks that typically involve human intelligence—ranging from physical tasks, cognitive functions, and problem-solving to decision-making—and can be performed without explicit instructions from humans [1]. AI can be classified into 4 main subsets—machine learning, natural language processing (NLP), physical robots, and robotic process automation. The field of AI is rapidly advancing, and AI technologies have been widely applied in different aspects of health care services, including diagnostic assistance, health screening, and imaging interpretations [2]. It has been described as a "second set of eyes" for medical practitioners [3]. Furthermore, over the past decade, the application of AI systems has increasingly centered on empowering patients to actively manage their health and boost their participation in the shared decision-making process, giving rise to diverse AI-driven products such as robots, smart assistants, virtual or augmented reality, wearable devices, and mobile apps [4]. Particularly notable is the emergence of AI-powered chatbot services, which permit patients to seek medical advice and receive triage for their conditions in a prompt and cost-effective manner [5]. With the debut of ChatGPT by OpenAI in November 2022 and the popularity it has gained, it is envisioned that AI-based conversational large language models with NLP abilities could conceivably revolutionize health care practice and education, contributing to substantial transformative shifts [6,7].

The world is currently encountering a significant expansion in the aging population, with the number of people aged 60 years or above anticipated to rise to 1.4 billion by 2030 and 2.1 billion by 2050 [8]. Conventional older adult health care has relied heavily on in-person monitoring; however, the further intensification of the shortage of health care workers could in the long run present a global challenge to the sustainability of delivering quality medical care [9]. In recent years, digital technologies, such as smart older adult health care products, which involve the deep integration of AI, have been used in older adult health care sectors [10]. Evidence has shown that AI-based technologies can play a constructive role in improving the physical and psychological well-being, quality of life, and independent living of older adults [11]. However, there is a great digital divide between the older and younger generations, with the former being the age group that is the least likely to have access to computers and the internet, due to physical obstacles such as physical disabilities and to psychological factors such as a lack confidence in using technology as well as ethical concerns [12,13].

While AI-based health technologies have rapidly evolved, and some studies have comprehensively discussed the advantages of applying them in the field of geriatrics, insufficient academic attention has been paid to acquiring a clear understanding of the attitudes, perceptions, and experiences of seniors toward these technologies [10]. This gap may implicitly influence the acceptance of, and motivation to use, these technologies in the future. In addition, while studies have primarily focused on the perceptions of medical practitioners and patients regarding AI health technologies, the perspectives of older adults—a key user group—have received limited attention [14-16]. For instance, although some research has explored older adults' views on general AI-powered technologies, their relevance to AI health technologies remains uncertain [17]. Concerns about accuracy, reliability, and trust in AI tools compared with in-person medical advice further underscore the need for targeted investigation. This study addresses this gap by exploring older adults' perceptions of and acceptability toward AI-based health technologies, with a specific focus on practical strategies to enhance adoption. By identifying barriers, facilitators, and preferences, the findings have clear clinical implications, offering actionable insights for health care providers, policy makers, and AI developers. These insights can inform the design of tailored, user-friendly AI tools and guide their ethical implementation in health care, ultimately improving older adults' health outcomes.

Theoretical Framework

The interview guide for this study was developed using the Theoretical Domains Framework (TDF) and the Capability, Opportunity, Motivation, and Behavior (COM-B) model behavior change wheel to comprehensively explore factors influencing the acceptability of AI-based health technologies among older adults. The TDF consists of 14 domains that integrate behavioral determinants derived from over 30 psychological theories [18]. To ensure comprehensive coverage of these domains, the interview guide focused on five key areas: (1) general impressions of AI, (2) previous experiences with AI-based technologies, (3) perceptions and attitudes toward AI-based health technologies, (4) expected difficulties and underlying reasons, and (5) willingness. These focus areas were aligned with the study objectives and systematically mapped to the relevant TDF domains, as summarized in Table 1. This approach ensured that all 14 domains were addressed, either directly or indirectly, during the interviews.

Table 1.The interview questions guided by the Theoretical Domains Framework (TDF).

Focus area	Aligned TDF domains	Example question
General impressions of AI[a]	Knowledge, emotion, and optimism	"What comes to mind when you think about artificial intelligence and its role in health technologies?"
Previous experiences with AI-based technologies	Memory, attention, and decision processes; knowledge; and skills	"Have you used any AI-based technologies before? Can you describe your experience?"
Perceptions and attitudes toward AI-based health technologies	Social or professional role and identity; beliefs about capabilities; beliefs about consequences; emotion; and optimism	"What are your thoughts about using AI-based technologies for managing your health?"

Expected difficulties and underlying reasons	Environmental context and resources; skills; social influences; behavioral regulation; and memory, attention, and decision processes	"What challenges do you think you might face when using AI-based health technologies? Why do you think these occur?"
Willingness	Intentions; goals; beliefs about capabilities; and reinforcement	"Would you be willing to use AI-based health technologies? Why or why not?"

[a]AI: artificial intelligence.

To further enhance the applicability of findings, the identified TDF domains were mapped to the COM-B behavior change wheel (Table 2). The COM-B model summarizes 6 sources of behavior—social or physical opportunity, automatic or reflective motivation, and physical or psychological capability. This model provided a practical framework for identifying specific behavior change factors and strategies to improve the acceptance and adoption of AI-based health technologies among older adults [19].

Table 2.Capability, Opportunity, Motivation, and Behavior (COM-B) model components and its relation to Theoretical Domains Framework (TDF) domains.

COM-B components		TDF domains
Capability		
	Psychological capability	Knowledge Skills Memory, attention, and decision processes
	Physical capability	Behavioral regulation Skills
Opportunity		
	Social opportunity	Social influences
	Physical opportunity	Environmental context and resources
Motivation		
	Reflective motivation	Social or professional role and identity Beliefs about capabilities Optimism Beliefs about consequences Intentions Goals
	Automatic motivation	Social or professional role and identity Optimism Reinforcement Emotion

The interview guide included open-ended questions designed to elicit rich, detailed responses.

This structured mapping ensured that the interview guide covered all 14 TDF domains comprehensively, while tailoring the questions to elicit insights into factors influencing the acceptability of AI-based health technologies among older adults. While alternative models, such as the technology acceptance model and the unified theory of acceptance and use of technology are commonly used in technology adoption studies, these models primarily focus on individual perceptions, such as perceived usefulness and ease of use (technology acceptance model) or performance expectancy and effort expectancy (unified theory of acceptance and use of technology). These constructs, while valuable, may not fully capture the complex interplay of factors influencing older adults’ adoption of AI technologies.

The systematic alignment between the interview guide and the TDF framework facilitated the identification of theoretical mediators and behavioral determinants. This mapping subsequently informed the integration of the findings with the COM-B behavior change wheel, allowing for the development of tailored strategies to promote the use of AI-based health technologies in this population.

Objectives

The objectives of the study were (1) to investigate the attitudes and perceptions of older adults toward the use of AI-based health technologies; (2) to identify potential facilitators, barriers, and challenges influencing older adults’ preferences toward AI-based health technologies; and (3) to inform strategies that can promote and facilitate the use of AI-based health technologies among older adults.

Methods

Study Design

A qualitative descriptive design was adopted for this study [20]. This approach helps in the effort to uncover and understand the experiences, attitudes, and perceptions of people, making it appropriate for this study. The findings from a qualitative descriptive study are able to inform strategies that promote and facilitate the use of AI-based health technologies, which makes it particularly useful for this research. To explore perceptions on and acceptability of the use of AI-based technologies in health maintenance among older adults, and to provide insights into their subjective views, in-depth semistructured interviews guided by an interview guide were conducted.

Participants and Recruitment

Community-dwelling older adults aged 60 years or above were recruited from a local community center using a convenience sampling method. Eligible participants included those with or without previous exposure to AI tools who were willing to participate and share their experiences. Exclusion criteria included underlying physical, psychological, or neurodevelopmental problems that impaired interaction, mental instability, cognitive impairments such as traumatic brain injury, substance abuse, dementia, severe psychiatric disorders, intellectual disability, or being bedridden.

Sampling and Sample Size

Convenience sampling approach was employed, guided by the principle of data saturation. The target sample size was 25 participants, which is commonly regarded as sufficient for qualitative descriptive studies to achieve thematic depth and richness [21]. Ultimately, 27 older adults were recruited, providing adequate data to explore the study’s focus areas.

Data Collection

Data collection involved 3 sessions of semistructured interviews with each participant, each lasting 1 hour. To minimize ambiguity, AI was classified into 4 categories: machine learning, NLP, physical robots, and robotic process automation. Interviews covered five focus areas: (1) general impressions of AI; (2) previous experiences with AI-based technologies; (3) perceptions and attitudes toward AI-based health technologies; (4) anticipated difficulties in using AI-based health technologies and their underlying reasons; and (5) willingness, preferences, and motivations in accepting AI-based health technologies.

In the first focus area, examples of AI tools were not initially provided to elicit spontaneous responses. However, recognizing that participants might not be fully aware of everyday interactions with AI, the second focus area included real-life examples to clarify potential misconceptions. Examples of machine learning technologies included fitness tracking devices, such as Google Fitbit and Apple Watch, which monitor physical activity and provide insights into health trends. For NLP, the interviewer referenced virtual assistants like Siri (Apple Inc) and Alexa (Amazon Inc), as well as health care chatbots that answer patient inquiries. Computer vision was illustrated with examples of AI systems that analyze medical images, such as detecting abnormalities in x-rays or CT scans. This approach enabled a nuanced exploration of participants’ experiences with general AI technologies versus their attitudes toward AI for health purposes. The data were securely stored in Cloud storage, accessible only to the research team.

Data Analysis

Thematic analysis was used in this study [22]. The interview recordings were first translated into English, transcribed, read, and reread to gain a sense of the participants' experiences. Initial ideas were noted down. Next, the data were coded to extract key insights from the transcript. The codes were reviewed in a weekly discussion with the supervisor to obtain agreement on the interpretations. The underlying subthemes that emerged from the codes were identified and the subthemes were further clustered into themes. The themes, subthemes, and representative quotes were used to present the findings. Data were mapped to TDF to identify underlying theoretical mediators that influenced the perceptions and acceptability to the older adults of the use of AI-based health technologies. Once these theoretical domains were identified, they were mapped to components of the COM-B behavior change wheel that matched theoretical mediators with corresponding key strategies.

Ethical Considerations

The study protocol and procedures were approved by the Ethical Committee of the Hong Kong Polytechnic University (approval HSEARS20230810006) on August 29, 2023, and adhered to the ethical standards of the Declaration of Helsinki. Before starting the study, all participants provided informed consent during a face-to-face interview with the researcher. All the participants were fully informed about the nature and purpose of the study. They were guaranteed the right to withdraw from the study at any time without adverse consequences. The collected data were encrypted and stored in a password-protected database. Although the researchers did not foresee any significant risks associated with the proposed study, the researchers recognized that older adults might experience discomfort or fatigue from sitting through the interviews. To address this, the researchers ensured that participants were given scheduled breaks throughout the interview. In addition, participants were encouraged to request breaks as needed to ensure that they were comfortable during the entire interview process. Participants who completed the interviews received an HK $100 (US $12.80) supermarket gift voucher to compensate for transportation costs.

Results

Participant Characteristics

The study included 27 participants, with 18 females (66.7%) and 9 males (33.3%). The mean age was 69.44 (SD 6.7) years. Most participants were married (19/27, 70.4%) and had a high school education (14/27, 51.9%). A majority lived with family (19/27, 70.4%) and rated their health as good (14/27, 58.3%). In addition, 66.7% (18/27) reported having chronic diseases. Regarding technology, 51.9% (14/27) felt somewhat comfortable using smartphones or tablets, and 59.3% (16/27) were somewhat familiar with tech products. Over 80% (23/27, 85.2%) of participants had heard of AI health technology, though their familiarity was limited. AI product usage varied, with approximately half of the participants reporting they used AI products often or occasionally, while the other half reported they used them seldom or were unfamiliar with them. Most participants (21/27, 77.8%) believed AI was to some extent helpful in health management, and 66.7% (18/27) had a positive overall impression of AI. Further details about the characteristics of the participants are provided in Table 3.

Table 3.Participant characteristics.

Characteristic		Total (N=27)
Gender, n (%)		
	Men	9 (33.3)
	Women	18 (66.7)
Age (y)		

	Mean (SD)	69.44 (6.17)
	Median (IQR)	70 (66-74)
Marital status, n (%)		
	Single	1 (3.7)
	Married	19 (70.4)
	Divorced	1 (3.7)
	Widowed	6 (22.2)
Education level, n (%)		
	Primary school and below	4 (14.8)
	Junior high school	7 (25.9)
	High school	14 (51.9)
	College or university	2 (7.4)
	Postgraduate degree	0 (0)
Living status, n (%)		
	Live with family	19 (70.4)
	Live alone	7 (25.9)
	Did not complete	1 (3.7)
Self-rated health status, n (%)		
	Poor	1 (3.7)
	Fair	12 (44.4)
	Good	14 (58.3)
Any chronic diseases, n (%)		
	Yes	18 (66.7)

	No	9 (33.3)
Comfort level with using smartphone or tablet, n (%)		
	Very comfortable	10 (37.0)
	Somewhat comfortable	14 (51.9)
	Not very comfortable	2 (7.4)
	Completely uncomfortable	0 (0)
	Did not complete	1 (3.7)
Familiarity with technology products, n (%)		
	Very familiar	0 (0)
	Somewhat familiar	16 (59.3)
	Not very familiar	8 (29.6)
	Completely unfamiliar	2 (7.4)
	Did not complete	1 (3.7)
Have heard of AI[a] health technology, n (%)		
	Yes, very familiar	0 (0)
	Yes, somewhat familiar	11 (40.7)
	Yes, not very familiar	12 (44.4)
	No, completely unfamiliar	3 (11.1)
	Did not complete	1 (3.7)
Frequency of AI product usage, n (%)		
	Often used	6 (22.2)
	Occasionally used	6 (22.2)
	Seldom used	5 (18.5)

	Never used	7 (25.9)
	Did not complete	3 (11.1)
Attitude toward AI's helpfulness in health management, n (%)		
	Very helpful	2 (7.4)
	To some extent helpful	21 (77.8)
	Not helpful	0 (0)
	Uncertain	2 (7.4)
	Did not complete	2 (7.4)
Overall impression about AI technology, n (%)		
	Positive	18 (66.7)
	Neutral	6 (22.2)
	Negative	0 (0)
	Uncertain	1 (3.7)
	Did not complete	2 (7.4)

[a]AI: artificial intelligence.

Objective 1: Investigate Older Adults' Attitudes and Perceptions Related to the Use of AI-Based Health Technologies

General Impressions of AI-Based Health Technologies

Most participants had positive views of AI-based health technologies, recognizing their potential to improve health outcomes by enhancing health monitoring, providing personalized recommendations, and assisting in decision-making. However, there was also limited awareness and understanding of specific AI-based health technologies, with some participants confusing them with general technologies such as smartphones. In addition, concerns were raised about fraud and scams associated with AI-based health technologies.

Attitudes and Perceptions Toward AI-Based Health Technologies

Privacy and data security were recurring themes in participants' discussions of AI-based health technologies. Many participants expressed concerns about the potential misuse of personal data and highlighted the importance of robust security measures. These concerns were particularly pronounced among participants with limited experience using technology or those influenced by media reports of data breaches. However, a subset of participants viewed privacy as a societal issue rather than a specific risk associated with AI-based technologies. For instance, one participant remarked:

Yes, it's acceptable….Uh, what privacy do you have? There is no privacy in the whole world. Everyone's mobile phone is being monitored.[Participant 3]

Another noted:

Not to mention privacy nowadays, from where we sit now there is completely no privacy…even if you listen to this *song now, then this song will automatically appear (on your phone). When you are viewing clothes, then you will see the clothes later on (on your phone).*[Participant 5]

These contrasting perspectives highlight the varying levels of concern about privacy among older adults and underscore the need for transparent communication about data security in the development and deployment of AI-based health technologies.

Trustworthiness and Accuracy

Trust in AI-based health technologies varied among participants, influenced by previous experiences, information sources, and perceptions of accuracy. While some acknowledged the utility of AI in self-monitoring, others expressed reservations about its accuracy and trustworthiness, stressing the irreplaceable value of human judgment and expertise in health care.

Objective 2: Identify Potential Facilitators, Barriers, and Challenges That Influence Older Adults' Preferences Toward AI-Based Health Technologies

Technological Barriers

Participants identified multiple technological challenges that hindered their ability to use AI-based health technologies effectively. These challenges included operational difficulties, limited digital literacy, and lack of access to required resources, such as hardware or stable internet connectivity. These barriers were particularly evident among participants with physical or cognitive impairments due to age-related degeneration.

For instance, 1 participant described how physical limitations affected their interaction with technology:

I have degeneration, too. I could remember a lot of things before. But now I can't. My body movements are slow now, so it's difficult for me to use AI-based health technologies.[Participant 3]

Another significant barrier was self-perceived incompetence in using digital tools, often leading to frustration or feelings of inadequacy:

"*I feel like I am stupid after learning something....*" [Participant 7]

In addition, resource-related challenges, such as a lack of access to necessary hardware (eg, smartphones) and stable internet connections, were raised, further limiting participants' ability to engage with AI technologies.

Emotional and Psychological Barriers

Emotional and psychological factors emerged as significant barriers to the adoption of AI-based health technologies. These included fear of technology, skepticism regarding its reliability, and concerns about losing human connection in health care interactions. The prevalence of scams and fraudulent activities in the digital age further compounded participants' fears, making them hesitant to trust digital tools.

For example, 1 participant expressed a deep apprehension about interacting with technology:

I don't feel comfortable with these technologies because they seem complicated, and I worry about making mistakes.[Participant 6]

Concerns about scams were also prevalent, with another participant noting:

Nowadays, you hear so much about fraud. It makes me scared to trust anything online, even if it looks helpful. [Participant 4]

These findings illustrate that emotional and psychological barriers are not only about individual fears but also reflect broader societal concerns regarding trust and safety in the digital world.

Perceived Usefulness and Relevance

Participants perceived AI-based health technologies as useful, particularly those that addressed specific health needs such as the monitoring of blood pressure, blood sugar, and cholesterol. They also appreciated technologies that could assist with health monitoring, reminders, and personalized care.

I hope that these three things could be more mature, help to reduce blood pressure, blood sugar, or blood cholesterol, whatever. At least I know whether my blood sugar is good or not; if it is not good, I will eat something and exercise to increase my physical capacity.[Participant 3] *Yeah, like an alarm. As a reminder to alert you. Well, high blood pressure, high blood sugar, high cholesterol level, those we get when are older. If AI can help with these three things, it is definitely good.*[Participant 2]

Acknowledgment by Authorities

The endorsement of AI-based health technologies by official authorities or regulatory bodies significantly facilitated their acceptance and adoption. Participants felt more confident and trusting when these technologies were validated by reputable sources, such as health care agencies or government bodies.

If it is something organized by the Hospital Authority or the government, it will be more trustworthy. Because sometimes, if it is made by pharmaceutical companies, it may not necessarily be that clear.[Participant 2] *Well, if you talk about it being official, like the doctors and government, I will assume that this AI is reliable, you will basically feel at ease.*[Participant 1] *I have to see if the AI comes from a large or a small company. For example, Hong Kong Polytechnic University, Baptist University —they are more reliable then.*[Participant 4]

Objective 3: Inform Strategies That Promote and Facilitate the Use of AI-Based Health Technologies Among Older Adults

Integration of Human Expertise

While recognizing the potential benefits of AI, participants emphasized the need for AI technologies to complement rather than replace human expertise in health care. They suggested that AI could be useful as an auxiliary tool for making preliminary medical suggestions, but that the final decision-making should involve consultations with a human being.

I just ask the AI, but I can ignore its answers or I will think about it again. It is just a reference and I won't believe it completely. Well, when you see a doctor, you won't just see one doctor, you will see many many right?...AI is just the first contact point.[Participant 2]

User-Friendly Design

To enhance the acceptability of AI-based health technologies, it is crucial to develop solutions that are user-friendly and tailored to the specific needs of older adults. A user-friendly design should include simplified and intuitive interfaces that minimize cognitive load, with features such as large, high-contrast text and icons for better visibility and ease of use. Voice command functionality can further improve accessibility for users with limited dexterity or vision impairments. In addition, providing step-by-step tutorials, user manuals in multiple formats (eg, videos and print), and accessible customer support can address challenges related to digital literacy. These features collectively ensure that the technology is not only easy to use but also aligns with the physical and cognitive capabilities of older adults, thereby fostering greater adoption and satisfaction.

Addressing Privacy and Security Concerns

Given the concerns around privacy and data security, the development of AI-based health technologies should include robust security measures to protect the personal information of users. Addressing these concerns is essential to building trust and encouraging adoption among older adults.

Government and Regulatory Support

Participants highlighted the importance of government and regulatory support in promoting the ethical implementation of AI in health care. Clear guidelines and endorsements from authoritative bodies can foster trust and enhance the acceptability of AI-based health technologies among older adults.

Table 4 provides a detailed description of how the identified barriers and facilitators toward the use of AI-based health technologies were mapped to the TDF domains and corresponding COM-B components. These mappings were derived from participants' responses during the interviews. The barriers and facilitators were categorized based on their alignment with the TDF domains and subsequently mapped to the COM-B components to identify actionable strategies for behavior change.

Table 4. Identified Theoretical Domains Framework (TDF) domains and Capability, Opportunity, Motivation, and Behavior (COM-B) components related to the adoption of artificial intelligence (AI)–based health technologies.

Barrier or facilitator	COM-B components	TDF domains	Illustrative participant quote
Barrier: limited technological skills	Capability	Knowledge and skills	"I find it difficult to use these technologies because my body movements are slow, and I don't know how to start." [P3]
Facilitator: perceived usefulness and relevance	Motivation	Beliefs about consequences, intentions, and goals	"If AI can help monitor my blood pressure or remind me, it would be very helpful." [P2]
Barrier: lack of official recognition or endorsement	Opportunity	Social influences	"If it's recognized by the government or hospitals, I would trust it more." [P1]
Facilitator: confidence in trustworthiness and accuracy	Motivation	Beliefs about capabilities	"If the results are accurate, I can rely on it for some guidance." [P4]
Barrier: privacy and data security concerns	Motivation	Emotion	"I worry about my personal information being stolen if I use this technology." [P5]
Facilitator: AI as an auxiliary tool for initial suggestions	Motivation	Beliefs about consequences and intentions	"I can use AI for some advice, but I still prefer to consult a doctor for the final decision." [P2]

Discussion

Principal Findings

The aim of the study was to provide insights into the perceptions and acceptability of AI-based health technologies among older adults, using the TDF and the COM-B behavior change wheel as theoretical frameworks. These frameworks were instrumental in identifying key behavioral determinants and mapping them to actionable strategies for enhancing AI adoption. In total, 9 of the 14 TDF domains (knowledge, skills, social influences, environmental context and resources, beliefs about capabilities, beliefs about consequences, intentions, goals, and emotion) were identified and mapped to 6 COM-B components (psychological capability, physical capability, social opportunity, physical opportunity, reflective motivation, and automatic motivation). By applying these frameworks, the study provided a structured approach to understanding the factors influencing older adults' behavior toward AI adoption.

The responses of the participants shed light on various aspects of the adoption and utilization of AI-based health technologies among older adults. First, the participants expressed a range of attitudes and perceptions toward AI-based health technologies, including curiosity, skepticism, and enthusiasm toward the use of AI in the management and maintenance of health. These perceptions align with the TDF domains of knowledge and beliefs about consequences, which underscore the need to enhance understanding of AI and clearly communicate its benefits to older adults. The interviews provided a deeper understanding of the factors influencing these attitudes and the potential benefits and concerns associated with AI adoption in the context of the participants' health. They shared their perceptions of AI technologies, addressing aspects such as reliability, trustworthiness, and their perception of the impacts on health care outcomes. These insights informed the reflective motivation component of the COM-B framework, highlighting the importance of fostering trust and reliability in AI-based technologies to enhance adoption.

In addition, the study revealed an interesting finding regarding older adults' preferences for using AI in asking for advice and self-health maintenance. Contrary to expectations, participants expressed a higher level of trust and reliability in real persons, particularly physicians, when making decisions about pharmacological interventions such as changing drug dosages. Participants believed that AI could play a valuable role in providing information and acting as a reference tool for self-health maintenance. However, they expressed reservations about relying solely on AI for decisions related to medication management. This finding is linked to the TDF domain of social influences and the social opportunity component of the COM-B framework, as participants emphasized the irreplaceable role of human expertise and interpersonal trust in health care decision-making. They viewed AI as a useful source of information but considered the expertise and experience of physicians and other health care professionals to be more reliable and crucial in making decisions regarding medical interventions and treatment. The emotion domain of TDF also played a role, as participants' skepticism and emotional barriers highlighted the importance of addressing concerns through education and reassurance. The findings were also in line with a mixed methods study indicating that the lack of empathy and a professional human approach made AI chatbots less acceptable to some users [15]. This insight has significant implications for the development of AI-based health technologies. It might indicate that older adults desire a collaborative approach that combines the benefits of AI with the guidance and expertise of real-person health care providers [23-25]. Developers could focus on creating AI systems that could provide accurate and evidence-based information, acting as a reference tool to support older adults' self-health maintenance efforts. In this context, AI could assist older adults in accessing reliable and up-to-date information about medications, potential side effects, and alternative treatment options. AI-based systems could also offer personalized recommendations for lifestyle modifications, nonpharmacological interventions, and self-care strategies that align with the preferences and needs of older adults.

While privacy and confidentiality are often considered to be potential concerns when using AI in health care, surprisingly, many expressed a relaxed and relatively pessimistic attitude toward privacy. One of the reasons for this was that the perceived benefits outweighed the concerns. Most expressed the view that the potential benefits of AI-based health technologies have overshadowed any concerns about privacy or confidentiality. They may have viewed the potential improvement in their health outcomes or access to personalized care as more significant than the potential risks to their privacy. Another underlying reason may be that the participants may have had other concerns that they considered more important than privacy and confidentiality in the context of AI-based health technologies. For example, they may have been more focused on the usability, effectiveness, or reliability of the technology. Regardless, the absence of expressed concerns does not necessarily indicate the lack of importance of privacy and confidentiality. Rather, it highlights the need for researchers and developers to proactively address these concerns and ensure that robust privacy and security measures are in place when designing and implementing AI-based health technologies. It is crucial for future research and development efforts to emphasize the importance of privacy and confidentiality in AI-based health technologies, which involves implementing strong data protection measures, obtaining informed consent from users, and transparently communicating how their data will be used and safeguarded.

To enhance older adults' acceptance of AI-based health technologies, strategies should focus on improving technological skills through tailored training programs, securing official recognition and endorsement from health care authorities, addressing concerns over privacy and data security with robust protocols, emphasizing the trustworthiness and accuracy of AI tools, positioning AI as auxiliary aids for medical suggestions, highlighting the usefulness and relevance of AI applications, and providing emotional support to mitigate psychological barriers. These strategies are directly informed by the COM-B framework, targeting capability, opportunity, and motivation as the key drivers of behavior change. By implementing these targeted strategies, older adults might be encouraged to embrace AI technologies, leading to improved health care outcomes and increased engagement with innovative health care solutions. Meanwhile, government endorsements could also contribute to the establishment of guidelines, standards, and regulations that ensure the ethical use of AI in health care, addressing concerns related to privacy, data security, and quality assurance.

Limitations

The limitations of this study were the sample size and representativeness of participants. While we recognize that this sample size may not fully capture the diversity of the population, the study aimed to offer initial, in-depth insights into older adults' perceptions of AI-based health technologies. Future studies could address subgroup comparisons by incorporating stratified sampling to examine variations across different demographic or socioeconomic groups. In addition, while quantitative comparisons were not a focus of this study, future research could include mixed method approaches to statistically assess participant perceptions and examine their relationships with demographic and contextual factors by using validated survey tools. Last but not the least, many participants had limited before knowledge or experience with AI-driven health technologies. Some participants conflated AI technologies with general digital tools, such as mobile apps, due to a lack of familiarity with the distinction. To address this, the interviewer provided concise explanations and real-life examples of AI subsets, including machine learning, NLP, computer vision, and expert systems. While this approach helped participants better understand the discussion, their responses were still shaped by their interpretations and familiarity with technology. Consequently, the findings reflect older adults' perceptions and acceptance of health technologies they associate with AI, rather than definitive perspectives on AI-driven health technologies.

Conclusion

While the majority of participants recognized the potential advantages of AI-based health technologies, they underscored the indispensable role of human expertise and interaction. Vital strategies for improving acceptability include crafting user-friendly and customized AI solutions, addressing privacy concerns, ensuring robust security measures, and integrating AI as a complementary tool alongside health care providers. Government backing and guidelines can play a pivotal role in advancing ethical AI integration in health care, fostering trust, and enhancing personalized care for older adults, ultimately leading to improved health outcomes in this population.

Conflicts of Interest

None declared.

Abbreviations

AI: artificial intelligence
COM-B: Capability, Opportunity, Motivation, and Behavior
NLP: natural language processing
TDF: Theoretical Domains Framework

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DETAILS

Bridging the Gap in the Adoption of Trustworthy AI in Indian Healthcare: Challenges and Opportunities

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ABSTRACT (ENGLISH)

The healthcare sector in India has experienced significant transformations owing to the advancement in technology and infrastructure. Despite these transformations, there are major challenges to address critical issues like insufficient healthcare infrastructure for the country’s huge population, limited accessibility, shortage of skilled professionals, and high-quality care. Artificial intelligence (AI)-driven solutions have the potential to lessen the stress on India’s healthcare system; however, integrating trustworthy AI in the sector remains challenging due to ethical and regulatory constraints. This study aims to critically review the current status of the development of AI systems in Indian healthcare and how well it satisfies the ethical and legal aspects of AI, as well as to identify the challenges and opportunities in adoption of trustworthy AI in the Indian healthcare sector. This study reviewed 15 articles selected from a total of 1136 articles gathered from two electronic databases, PubMed and Google Scholar, as well as project websites. This study makes use of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR). It finds that the existing studies mostly used conventional machine learning (ML) algorithms and artificial neural networks (ANNs) for a variety of tasks, such as drug discovery, disease surveillance systems, early disease detection and diagnostic accuracy, and management of healthcare resources in India. This study identifies a gap in the adoption of trustworthy AI in Indian healthcare and various challenges associated with it. It explores opportunities for developing trustworthy AI in Indian healthcare settings, prioritizing patient safety, data privacy, and compliance with ethical and legal standards.

FULL TEXT

1. Introduction

Artificial intelligence systems refer to computational models that use machine learning techniques to operate autonomously or with human assistance. These systems take data as input, interpret human-defined goals, and then use statistical and mathematical techniques to make decisions, recommendations, or predictions that influence digital or real-world circumstances [1]. Trustworthy artificial intelligence (AI) [2] refers to AI systems that are built and run with reliability, ethics, and human values in mind. According to the Independent High-Level Expert Group on Artificial Intelligence study [3,4] from the European Union, this means ethics, legality, and robustness that respect human autonomy, rights, and dignity without compromising or unfairly affecting people’s privacy [5].

Trustworthy AI is a framework of principles and practices that aims to ensure the safety, fairness, transparency, and social usefulness of AI technologies as shown in Figure 1. There are numerous applications for AI in healthcare; however, if AI tools and technologies are adopted in this field without taking into account issues such as explainability, transparency, data privacy, and equity or treating all users equally, there may be significant consequences.

1.1. Background

The adoption and implementation of AI technologies has been expanding the significance of healthcare systems for a few years now as they improve different aspects of diagnosis, clinical trials, and patient care, including healthcare robotics, thus improving the whole process involved in healthcare for doctors, healthcare workers, and patients. One such sphere is medical imaging, where AI algorithms support specialists in trying to identify cancers early [6,7], which is often not achievable through early diagnostics alone. In addition, AI-based models are developed to predict disease outbreaks [8,9] and develop risk stratification models for patients.

In general, there are adoptions of AI technology in improving treatment planning and decision making in congenital heart disease [10], telemedicine [11] for remote consultations, health monitoring [12], and management of chronic diseases such as diabetes [13] or hypertension in real time [14]. This is especially useful in rural areas and in developing nations with a shortage of healthcare professionals. In addition to patient care, the use of AI is a game changer in the field of drug discovery [15], reducing the time to provide advanced therapeutics to patients by predicting the outcome of new medications and their interactions in a cost-effective manner. In addition, it improves the management of hospital resources by improving administrative procedures, staff and bed allocation, and supply chain management [16].

Just as many other developing nations, India is committed to the innovation and adoption of artificial intelligence in healthcare. As illustrated in Figure 2, there is an increasing trend in the applications of AI in healthcare [17]. The artificial intelligence (AI) market in India was estimated to be worth USD 374.7 million in 2023. The value is predicted to increase significantly to approximately USD 6.9 billion in 2032. This trend indicates the growing interest in research and innovations in AI-based applications in the Indian healthcare sector.

India has an estimated population of 1.428 billion people and is the sixth largest country in the world with an area of 3,287,263 square kilometers. The Indian government does not own the entire healthcare system. In reality, there are private organizations working in partnership with the public sector to meet the challenging demands of a diverse population for high-quality healthcare facilities. Some of the key challenges faced by the Indian healthcare sector, highlighted by the WHO, include inadequacy of qualified healthcare professionals and infrastructure, non-uniform accessibility to healthcare services throughout the country, the inaffordability of healthcare facilities primarily for people living in rural areas, and the lack of awareness among the masses about essential healthcare services, preventive care, and treatment options. The application of artificial intelligence (AI), along with machine learning (ML), robotics, sensor technologies, and the Internet of Medical Things (IoMT), has a great potential to make a greater impact in the Indian healthcare sector, and there is much evidence to prove it. AI-enabled technological solutions have led to better-informed decision-making and personalized diagnosis [18] and treatment taking into account genetic, environmental, and lifestyle factors. In particular, there has been growing evidence of the benefits of technological innovation, and particularly artificial intelligence, within healthcare systems in developed and low- and middle-income countries [19].

During the COVID-19 pandemic [20], the Indian government used artificial intelligence technologies to contain the spread of the disease and the distribution of vaccines. NITI Aayog, India’s policy think tank, had taken an initiative to detect tuberculosis by analyzing X-rays using AI technology, especially in those parts of the country where there is limited access to TB diagnostic tools. Wipro GE healthcare [21] had launched an AI-enabled cath lab in India to improve the affordability and quality of cardiac care for patients with cardiovascular disease. Similarly, Apollo Hospitals, in collaboration with Microsoft, developed AI tools for cardiovascular disease management. Healthcube, an

Indian healthcare technology company, has developed and deployed portable diagnostic tool that allow real-time health monitoring such as glucose levels, blood pressure, and so on. The eSanjeevani platform, an initiative of the India’s Ministry of Health and Family Welfare, applies AI and IoT-based technologies for remote consultations and telemedicine services. The platform, with the support of the Common Service Centres, was instrumental during the COVID-19 pandemic and was widely used throughout India to bridge the healthcare gaps between the rural and urban population.

Artificial intelligence has the potential to make a positive impact in the Indian healthcare sector; however, there is the need for trustworthy AI that complies with ethical and legal considerations ensuring accuracy, reliability, transparency, accountability, and fairness to build trust and acceptance among stakeholders of the healthcare sector. Transparency in healthcare helps clarify the way decisions are made. Ethical AI [22] ensures impartial treatment that is easily accessible to everyone regardless of their diverse demographic background, respects patient autonomy by ensuring that patients have the right to make their own informed decisions about their own healthcare, and prevents misuse of sensitive data by AI systems, mitigating the risk of data breaches, especially in a diverse country such as India. Without these principles, AI could exacerbate the issue of protecting patient privacy and data security, limit accountability of the treatment process, and compromise patient safety. Baldassarre et al. [23] emphasize the importance of key legal and ethical considerations, underscoring the need for AI systems to be explicable, equitable, and accountable. Despite the growing discourse on trustworthy AI globally, the practical application in the Indian healthcare context remains underexplored. Challenges such as limited access or availability of unbiased datasets that can be used to train and validate AI-based models, lack of robust regulatory frameworks, and insufficient awareness in the general public persist. These issues underscore the need to understand the current state of AI development in the Indian healthcare sector, with a focus on how these AI systems meet ethical and legal standards. Moreover, identifying the challenges and opportunities for adopting trustworthy AI in the healthcare sector can provide actionable insights for stakeholders, including policymakers, healthcare professionals, and technologists, to create a legal and ethical AI ecosystem in the Indian healthcare sector.

1.2. Ethical and Legal Considerations in AI for Healthcare

The key ethical considerations [22] about AI applications in healthcare are as follows:

- (a). Patient Privacy and Data Security: Vast amounts of sensitive data which may be personal are used in AI systems; therefore, it is crucial to ensure patient privacy. Furthermore, the possibility of a data breach cannot be denied, making it essential to have a proper mechanism for secure data storage and data transfer, preventing unauthorized data access.

- (b). Informed Consent and Transparency: Patients should be informed and consent must be obtained before using their data for any diagnosis or treatment by AI systems. At the same time, AI systems should not be viewed as “black boxes”, which specifies that there should be transparency in the operation mechanism of AI systems and the risks involved in them.

- (c). Unbiased and Fair: AI models should be trained without bias in training data, and impartial treatment should be easily accessible to everyone regardless of their diverse demographic background.

- (d). Liability and Accountability: In the treatment process with AI systems, accountability is required to determine who is responsible for any incorrect treatments or recommendations: developer, healthcare provider, or organization. Adequate legal and regulatory frameworks must be in place to establish liability and proper compensation to affected patients for those decisions.

- (e). Explainability and Interpretability: Ensuring explainability and transparency in AI systems builds trust and improves cooperation among stakeholders in the healthcare system. Transparent decision-making processes that are interpretable for both patients and medical professionals make it easy to understand the requirement for a certain diagnosis or a recommended treatment plan, particularly in critical medical conditions.

The key legal considerations [23] about AI applications in healthcare can be stated as:

- (a). Data Privacy and Protection Laws: Healthcare data, such as patient medical records, treatment histories, and other information, may contain personal information and are generally sensitive in nature. These data are likely to be exploited by AI systems, making them susceptible to misuse and data breaches. To alleviate any exploitation, such a system is to be governed by data protection laws such as the General Data Protection Regulation (GDPR) of Europe [24], the Health Insurance Portability and Accountability Act (HIPAA) of the United States [25], and the Digital Personal Data Protection Act (DPDP) [26] of 2023 of India.
- (b). Regulatory Approval and Compliance: Before deploying an AI healthcare system in clinical settings, it must be approved by regulatory bodies. Even a small modification in the algorithms of AI systems may require approval from regulatory bodies. For example, the European Medical Device Regulation (MDR) requires that medical devices, including AI-powered systems, have CE markings. Likewise, in the United States, the Food and Drug Administration (FDA) is responsible for regulating AI/ML-based products [27].
- (c). Intellectual Property Rights: Developers can seek legal protection, copyrights, and licensing for their original work or innovations made in the AI healthcare system.
- (d). Cross-Border Regulations: AI healthcare systems which are deployed for any purpose in different nations must adhere to the laws and regulations prevalent in the multiple jurisdictions of different nations [28]. For example, an organization deploying an AI healthcare system in the US and Europe must adhere to both the HIPAA and GDPR regulations present in the US and Europe, respectively.
- (e). Patient Consent: Patients are entitled to see their medical records, ask for updates, and decide with whom their information is shared [29]. Before using patient data for an AI system to diagnose or treat them, they should be informed and their consent must be obtained.

1.3. Research Objectives

The advancement of AI-enabled technological solutions has led to a paradigm shift in the healthcare sector of India. The country is faced with numerous issues and challenges in an attempt to provide quality healthcare facilities to its diverse population, which the country can overcome using AI-driven solutions. However, not much is known about the advances made in the application of trustworthy AI in the healthcare sector of India. This scoping review intends to investigate the current state of trustworthy AI application, the challenges to be addressed, and future opportunities in the Indian healthcare sector.

1.4. Contributions

In this study, the following contributions are made to the discourse on legal and ethical aspects of AI in the context of Indian healthcare:

- (a). Scoping Review of Trustworthy AI in Indian Healthcare Sector: This study conducts a critical evaluation of the current state of the development of the AI system in Indian healthcare, assessing its adherence to ethical and legal standards.
- (b). Identification of Key Challenges and Opportunities: This study attempts to identify the challenges and opportunities associated with the adoption of trustworthy AI in the healthcare sector of India and offers future prospects and actionable recommendations.
- (c). Emphasis on Policy Frameworks: The study explores the potential of AI in healthcare sectors and emphasizes the need for robust legal and regulatory frameworks designed for India's healthcare ecosystem in accordance with international standards on AI ethics and governance.

2. Methodology

2.1. Study Design and Setting

The developments and applications of trustworthy AI in Indian healthcare are the primary focus of this scoping review article. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) [30,31] are used throughout this scoping review process. PRISMA-ScR is a framework used in the review process for a systematic and structured approach to present the findings of research studies. The study protocol was registered in the Open Science Framework [32].

2.2. Search Criteria and Selection Method

The search aimed to look for the current state of the development of AI systems in the Indian healthcare sector and to see how well they satisfy key ethical and legal considerations of AI, as well as to identify the challenges and opportunities in the adoption of trustworthy AI in the Indian healthcare sector. Keywords such as healthcare sector, trustworthy artificial intelligence, privacy, and India were used to conduct the search in the electronic databases and project websites in India. There were no restrictions on the type of publications published from 2015 to March 2024, although only articles written in English were considered for review. The scoping review study was initiated by searching two electronic databases and project websites. The initial search was performed manually on 16 May 2023, utilizing two databases, PubMed/Medline and Google Scholar. Subsequently, on 29 March 2024, another manual search was performed in these databases to identify any additional literature published since the initial search. We investigated databases and websites (see Appendix A, Table A1) related to trustworthy AI initiatives in the healthcare sector of India.

Articles that were found using our search criteria were initially imported into the Sysrev Web application [33]. The software is publicly available and is used mainly for systematic review and evidence-based research (SER), involving humans and machines collaborating to evaluate digital documents. In general, there are four phases involved in Sysrev, namely, creating data sources, defining labels, user review, and data export. Using the tool, after importing the searched articles, duplicates were first eliminated and then the articles were screened. Two reviewers had independently reviewed the title and abstract of the articles, and each reviewer categorized the article as 'Yes' if the article was to be included or 'No' if it was to be rejected. However, if there was a tie, then it was reviewed by the third reviewer independently to resolve the uncertainty. The review results were then exported to an Excel file for data charting and further analysis. Secondly, both the reviewers independently reviewed the full text of the articles to make final decisions about inclusion. This time, the third reviewer was not involved in reaching the consensus.

3. Results

3.1. Characteristics of the Studies Included in the Review

The PRISMA-Scoping Review diagram in Figure 3 illustrates that of the 1136 articles that were retrieved from the two electronic databases and the project websites, 15 articles satisfied the inclusion requirements for the scoping review.

This study explores various applications of AI in the Indian healthcare sector. Ten articles are peer-reviewed, as shown in Table 1, while five articles are additional articles (informal literature) discussed in Section 3.2 identified from other sources such as project reports and institutional websites. The selected articles are evaluated against key ethical and legal considerations in AI healthcare applications, using a defined scale of "Full", "Partial", and "Not Found" (see Table 2 and Table 3). The scale "Full" indicates complete alignment of the system with the relevant key considerations for trustworthy AI. "Partial" signifies the system addresses some of the key considerations relevant to trustworthy AI, and "Not Found" means there is no mention of the relevant key considerations for trustworthy AI.

A machine-learning-based tool is developed by Kaur et al. [34] to predict the presence of dengue infection and risk levels, based on symptomatic and clinical investigations. The system performs a real-time diagnosis and alerts patients to possible internal hemorrhage. The model has a high accuracy of more than 90% and high sensitivity and specificity values, with experimental evaluation indicating its performance efficiency and utilization. In this work, some aspects of trustworthy AI can be indirectly inferred. For example, the high accuracy of the model implies constant performance, which is a crucial component of trustworthy AI, and the real-time diagnosis represents equitable healthcare delivery. The study uses patient data but does not explicitly mention patient privacy, and data security. Shaik and Kakulapati [35] developed software using artificial intelligence algorithms to predict tolerance to heart disease. The mobile app uses the heartbeat to identify heart problems, enabling doctors to make an accurate diagnosis of heart conditions. The AI algorithms perform comparative learning from end-to-end graphical demonstrations. The key aspects of trustworthy AI in healthcare satisfied by the proposed work include heart disease prediction accuracy and the end-to-end graphical demonstrations of outcomes, indicating transparency. The proposed system may be helpful for doctors to visualize the results and understand the logic behind the predictions as a step toward explainability and interpretability and the social usefulness aspects of trustworthy AI.

Healthcare in India faces challenges in rural areas due to lack of expert advice and timely treatment. Computer science and telecommunication can help address this issue by developing telehealth and artificial doctors, which are addressed by Kadian and Chaturvedi [36]. Telehealth uses telecommunication resources to connect remote villages to city hospitals, while artificial doctors use artificial neural networks to provide the best treatment options for unknown diseases. These technologies harness human intelligence and improve healthcare in rural areas, inherently promoting accessibility, one of the key ethical considerations for the applications of AI in healthcare. The concept of central data storage partially addresses patient data privacy but does not discuss the compliance to specific data privacy laws.

Kalita et al. [37] proposed an approach to improve maternal healthcare by combining blockchain and predictive data analytics using an ensemble machine learning algorithm. The blockchain-based pregnancy complications prediction system uses a publicly accessible dataset to securely store maternal health data and predict the risk levels of pregnancy complications. The effectiveness of the system has been evaluated, addressing issues such as data security, reliability, transparency, informed decisions, and accountability in healthcare services. The use of blockchain technology ensures secure and reliable maternal data collection with informed consent; however, in the work, explicit mechanisms of patient consent and interpretability of the system are not discussed.

Deka et al. [38] presented a method to represent individual samples in an image, regardless of dimension, using a convolutional neural network (CNN) for classification. To preserve data privacy, images are randomly rotated for classification. Comparison of these approaches with related techniques shows promising results. However, the author does not discuss other key aspects of trustworthy AI, such as informed consent and transparency, unbiasness and fairness, data privacy and protection laws, and patient consent.

Geetha et al. proposed a technique [39] to solve the issue of security and privacy for health-related applications, where sensitive medical image data must be transmitted in an open medium without compromising the individual’s privacy. An encryption technique was proposed which can be applied to the medical domain with an optimal secret key generation process. In their work, a new method named Pigeon-Inspired Optimization with Encryption-Based Secure Medical Image Management (PIOE-SMIM) has been proposed achieving a promising result of MSE, RMSE, and Peak Signal-to-Noise Ratio (PSNR). Again, the proposed techniques do not address most of the key legal and ethical considerations for trustworthy AI.

Kumar et al. proposed a hybrid technique [40] to preserve the privacy of the Electronic Health Record (EHR). The author has demonstrated the utility of data by applying ML techniques, namely the Support Vector Machine (SVM) and k Nearest Neighbors (k-NN) classification algorithms. The proposed privacy models achieve protection against attribute disclosure, thus managing to protect privacy of individuals fully satisfying patient privacy and data security consideration for trustworthy AI; however, other key considerations are not found in the work.

Shanmuga Sundari et al. [41] used conventional machine learning algorithms and the AdaBoost ensemble technique to develop a model to predict Cerebellar Ataxia (CA) disease with high accuracy. The model helps to detect neurological disorders early through symptoms by analyzing gait (AoG) to automatically classify abnormalities in individuals according to their walking patterns. The authors do not explicitly mention any key considerations for trustworthy AI; however, the focus on comparative analysis of several ML models indicates a transparent evaluation process and the selection of the most reliable model for early detection of neurological disorders. The use of AdaBoost indicates to some extent the interpretability aspect of AI.

Kruthika et al. [42] proposed a machine learning model integrated with blockchain technology to manage patient data and categorize whether a newly admitted patient is covered by critical illness insurance. The blockchain-based smart contract with machine learning application provides a viable alternative to minimize fraudulent claims made to insurance companies by insurers. The system manages to build trust and transparency through the use of smart contracts among stakeholders. However, informed consent is not mentioned when using patient or claimant data. The use of blockchain technology also ensures data security and unauthorized access but does not explicitly address patient privacy. Other key considerations are not found in the article.

The alarming rise in breast cancer cases in India—roughly 180,000 instances were recorded in 2020; was the subject of Malik et al.' s study [43]. The authors improved on two aspects of their proposal: drug responsiveness during breast cancer treatment and prediction of patient survival. With an accuracy of 94%, they presented a framework that examines diverse omics data, including proteomics and genomes, to accurately predict the progression of breast cancer. The proposed neural network-based regression model is highly beneficial for precision oncology. The high accuracy of the model implies constant performance, which is a crucial component of trustworthy AI. The integration of multi-omics data involves the use of sensitive patient data; however, most of the key legal and ethical considerations for trustworthy AI are not found in the article.

3.2. Gray Literature (Table 4)

Apollo Hospitals has developed a Clinical Intelligence Engine (CIE) [44,45], which is essentially a decision support tool developed by leveraging an advanced AI-powered chatbot. The clinical decision support that can be used in the Apollo24|7 platform tool assists in primary care of patients and helps analyze patient health data and provide personalized, actionable insights to both patients and doctors. In another work, HealthPlix Technologies designed a system to streamline the process of treatment of patients, particularly for those with chronic diseases. Their AI-powered electronic medical records (EMRs) [46] which can be used both online and offline, help healthcare professionals manage patient health records with ease of access and provide personalized care. The Wadhwani AI [47], a nonprofit organization-led TRACE-TB project, funded by the United States Agency for International Development (USAID), aims to develop and implement cutting-edge artificial intelligence (AI) solutions in order to tackle COVID-19, eliminate the spread of tuberculosis by 2025 in India, and other infectious diseases in India. In the same line, Wadhwani AI [48], partnering with the National Centre for Disease Control (NCDC) under the Union Health Ministry, Government of India, developed tools to automate the existing process of the disease surveillance system in India using AI. It primarily helps to collect, collate, compile, analyze, and distribute real-time health data.

An Indian startup, JiviAI [49], has claimed to develop a large language model, Jivi Medx, that can be applied to the healthcare industry to improve the precision and effectiveness of communication between patients and healthcare professionals. The model facilitates an exhaustive examination of patient health records, enabling an early and accurate diagnosis of the disease based on symptoms. The Jivi MedX system can also be used to support medical research and examination while streamlining administrative processes.

Table 4

Recent developments in AI-powered healthcare innovations in India.

Study	Purpose

PR Newswire, 2023 [44,45]	Developing an AI-powered chatbot by Apollo Hospitals that provides personalized, real-time health insights to improve diagnosis accuracy, doctor productivity, and patient satisfaction in Indian healthcare.
T. S. Kushwah, 2023 [46]	To manage Electronic Health Records (EHRs) of patients and streamline the treatment process using an AI-powered EMR platform.
Wadhwani AI, 2022 [47]	To apply advanced AI solutions to tackle infectious diseases in India: USAID-supported TRACE-TB project, led by Wadhwani AI.
J. Agarwal, Wadhwani AI, 2023 [48]	To automate the disease surveillance system in India using AI.
I. Negi, JiviAI, 2024 [49]	To develop India's healthcare language model.

The informal literature showcasing recent advances made by AI in India's healthcare industry (see Table 4) references to privacy policies on their respective websites but lacks important ethical and legal aspects of AI, such as accountability, transparency, fairness, and compliance with laws such as GDPR or HIPAA. Their primary focus is on obtaining personally identifiable information from patients and using it with an emphasis on protecting personal data from data breaches. Patients must agree to the platform's usage of their personal data in order to improve services, as stated in their privacy policies. It refers to data security measures to stop unauthorized access, but it skips over ethical and legal concerns specific to AI. Although it does not go into exhaustive detail about most of the ethical or legal issues unique to AI, it discusses data security procedures to prevent unauthorized access, which is in line with data privacy regulations. This study does not encompass understanding the exact procedure followed in doctor consultations, treatment procedures, and follow-ups, as it falls outside the scope of this review.

4. Discussion

4.1. Policy and Practice Implications

The World Health Organization (WHO) has released a set of guidelines [50] on ethics, governance, and applications of artificial intelligence (AI) in healthcare to its member states. In the same line, the National Health Policy (NHP) 2017 has been established in India with the objective of providing universal access to quality healthcare to all Indians regardless of their socioeconomic status. The policy focuses on various digital initiatives to deliver efficient healthcare services and has played an important role in bridging the gaps in the healthcare sector through its initiatives. It also promotes the creation of the National Digital Health Authority (NDHA) that would oversee the development, implementation, regulation, and utilization of digital health solutions. In 2018, NITI Aayog formulated a National Strategy on Artificial Intelligence (AI) titled "#AIforAll" with the aim of increasing human ability to address various economic and social challenges in five different sectors [51] viz. healthcare, agriculture, education, smart cities and infrastructure and smart mobility and transportation. To further build the national strategy on AI, NITI Aayog released its first part of the strategy titled "Towards Responsible AI for All" in the year 2021 [52], with an objective to establish broad ethics principles for the design, development, and deployment of AI in India—drawing on similar global initiatives but grounded in the Indian legal and regulatory context. The Srikrishna Committee was established in 2017 [53] with the objective of creating a framework for data protection in India, recognizing data privacy as a fundamental right of its citizens. Based on the recommendations made by the committee, the Personal Data Protection Bill (PDPB), aligned with the European Union's GDPR, was proposed in 2019. The Information Technology Act, 2000 (IT Act) was introduced as one of India's foundational legislations for cybersecurity, digital transactions, and data protection. Key government bodies involved in data protection, along with trustworthy AI in healthcare in India, include the Ministry of Electronics and Information Technology (MeITY), the Unique Identification Authority of India (UIDAI), and NITI Aayog among others.

India's regulatory landscape for artificial intelligence (AI) in healthcare is fragmented, sometimes with conflicting policies. A collaborative international research and development process for AI systems may get hampered by the Personal Data Protection Bill, 2019, for instance, which places a strong emphasis on user consent and data localization for user privacy. Policies must bridge the gap between ethical AI principles and their application, upholding ethical standards, and fostering innovation. Clear guidelines are necessary to ensure that the last mile benefits of AI are achieved while incorporating AI into public health initiatives like the Ayushman Bharat initiative [54] of India. In order to facilitate interoperability and link national regulatory frameworks with international standards, policies should promote collaborations with global organizations like the WHO and the United Nations Educational, Scientific and Cultural Organization (UNESCO) [55].

4.2. Challenges Hindering the Application of Trustworthy AI in Healthcare in India

In this scoping review, we have also explored the challenges faced in the widespread adoption of trustworthy AI in the healthcare sector as reported by publications in the literature. Some of the challenges include limited access to or availability of unbiased datasets [56] that can be used to train and validate AI-based models. Other challenges include a lack of awareness in the general public about data privacy and lack of legal and ethical standards [57] to be followed in the application of AI in healthcare. In addition to these, the authors have reported the lack of proper policies and strategies and insufficient human, infrastructure, and financial resources to implement trustworthy AI in healthcare.

There are various applications of ethical AI across the sectors [58] in India, such as primary healthcare, medical research and drug development, hospital administration, public health surveillance, and mental health, to name a few. In order to comply with legal and ethical considerations, certain initiatives must be undertaken, such as developing inclusive datasets that reflect India's diverse demographics, creating robust encryption protocols, assigning responsibility for errors made due to AI-driven systems, granting patients the right to make informed decisions, and continuous monitoring and updating of AI models. By ensuring fairness, accountability, transparency, and privacy in AI models, these sectors can adopt AI technologies that promote the well-being of the diverse population of India.

A scoping review was carried out to assess the current status of trustworthy AI in India. The review aims to understand how AI-based models are being adopted in Indian healthcare, with an emphasis on the requirement that these models comply with the legal and ethical standards for AI. To our knowledge and understanding, this kind of review is unique because it focuses on the adoption of trustworthy AI-based models in the healthcare sector of India. The number of relevant publications found is currently limited and modest, indicating that research in this area is still in a nascent stage, given the fact that there are multiple factors behind this. However, in recent years, the Indian healthcare industry has adopted AI technology, indicating a growing interest in adopting and integrating AI to improve healthcare outcomes. One can see a positive trend in the adoption of AI in the healthcare sector in India, but significant progress is still needed to ensure that AI technologies comply with guidelines regarding ethics, governance, and best practices in their applications in Indian healthcare settings. Addressing the associated challenges in aligning AI adoption in the Indian healthcare sector to comply with the transparency and explainability of AI solutions according to WHO guidelines remains a critical step in the journey.

4.3. Future Prospects and Recommendations

Adoption of AI and associated technologies has a great potential in the Indian healthcare sector. However, from the current findings, it is clear that there is a significant gap in addressing the legal and ethical considerations in the adoption of AI-based applications in the Indian healthcare sector. It shows that there is an urgent need to explore and work in this direction to design and develop trustworthy AI applications ensuring that they are used responsibly in Indian healthcare settings. To work in this direction, India must develop a robust data regulatory framework with legal support that complies with the WHO guidelines on the ethics and governance of AI for healthcare systems. Establishing guidelines for data anonymization and other measures to protect patient sensitive information should be the primary focus of data privacy and security. Simultaneously, the availability of quality healthcare data must be in place by creating a digital health infrastructure for data storage and seamless dissemination without compromising ethical and legal issues. Establishing a robust infrastructure to support the development and deployment of trustworthy AI algorithms in healthcare is essential. It is also essential that those involved in the healthcare industry are aware of and trained in the use of AI so that they can make informed treatment decisions. Collaborations between the corporate and public sectors should be promoted in order to advance research and innovation on the applicability of trustworthy AI in healthcare and its practices. Given that decisions can have a substantial impact on people’s lives, healthcare AI algorithms must be designed with interpretability in mind. Furthermore, given the socioeconomic diversity of India’s population, it must be impartial and fair.

4.4. Strengths and Limitations

This review article provides a broad assessment of the applications of AI-based technologies in the healthcare sector in India, emphasizing the legal and ethical standards currently in place. We believe that this review can play a key role in strengthening the research capacity in the area of trustworthy AI-driven healthcare service delivery and the development of future AI-based innovations that comply with ethical and legal standards. In this review, research is conducted mainly to assess research and publications in the applications of trustworthy AI and machine learning in the healthcare sector, specifically in India. The assessment covers relevant publications from the year 2015 onward, sourced from widely used electronic databases, namely Google Scholar and PubMed. In addition, an honest attempt has also been made to review the gray literature, assessing ongoing innovations and adoption of AI-based technologies by research organizations and hospitals aimed at improving healthcare facilities in India.

In this research, the study was mainly conducted on the applications of trustworthy AI-based models in the Indian healthcare sector, whereas we left out the research and publications made on the applications of trustworthy AI-based technologies in other sectors. We also acknowledge that we might have missed studies that did not use titles, abstracts, or words that were equivalent to the ones in our search query. Furthermore, we have limited our study to publications in the English language.

Ethical Considerations:

There were no unpublished secondary data or human participants in this study, and ethical approval for human research was not needed.

5. Conclusions

A scoping review of 15 studies related to AI applications in the health sector in India and the market size of AI in Indian healthcare reveals a clear trend of growing interest in research and innovations in AI-based healthcare solutions. These technology-driven solutions are supported by the Indian government and private organizations in order to enhance healthcare outcomes nationwide. However, the study identifies significant gaps and challenges associated with the adoption of trustworthy AI-based applications in the Indian healthcare setting. The challenges include limited access or unavailability of unbiased datasets to train and validate AI-based models, lack of awareness among the general public about data privacy, lack of patient consent, and the absence of proper legal and ethical standards as per international standards. This study stresses further exploration and work to address several key legal and ethical considerations in the adoption of trustworthy AI in the healthcare sector of India, including the development of regulatory frameworks with suitable policies and strategies, the provision of proper education and training to bridge the skill gap, and investing in adequate infrastructural and financial resources. This study also emphasizes the collaborative effort that stakeholders must undertake to create a patient-centered, privacy-aware, and ethical AI ecosystem in the Indian healthcare sector.

Author Contributions

Conceptualization, S.K.C., R.K.D. and M.J.S.; methodology, S.K.C. and R.K.D.; software, S.K.C. and R.K.D.; validation, S.K.C. and M.J.S.; formal analysis, S.K.C.; investigation, S.K.C. and M.J.S.; resources, R.K.D. and M.J.S.; data curation, S.K.C.; writing—original draft preparation, S.K.C. and R.K.D.; writing—review and editing, M.J.S.; visualization, S.K.C.; supervision, M.J.S.; project administration, S.K.C. and M.J.S.; funding acquisition, M.J.S. All authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

All data were presented in the main text.

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Conflicts of Interest

The authors declare no conflicts of interest.

Footnotes

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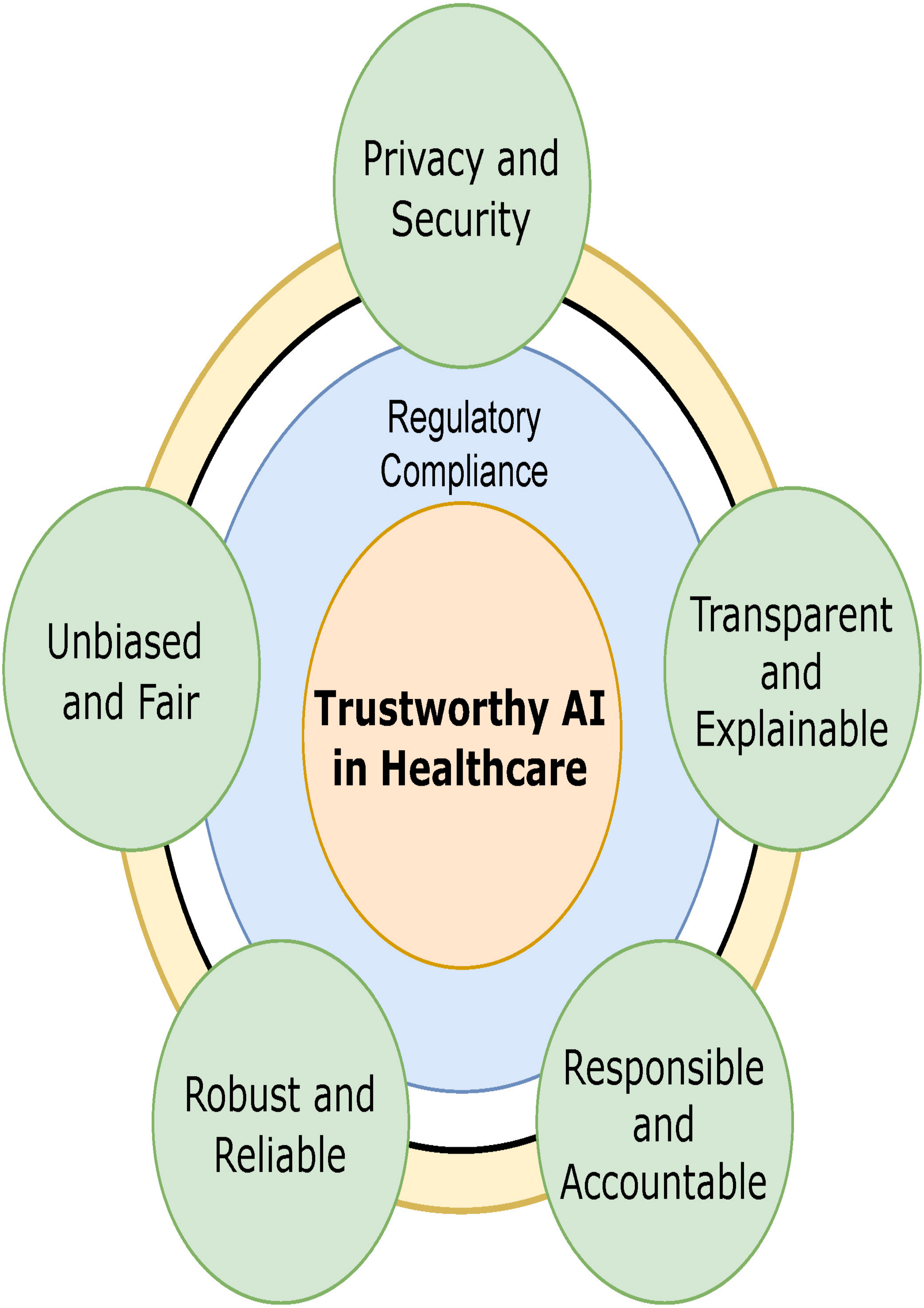
Figures and Tables



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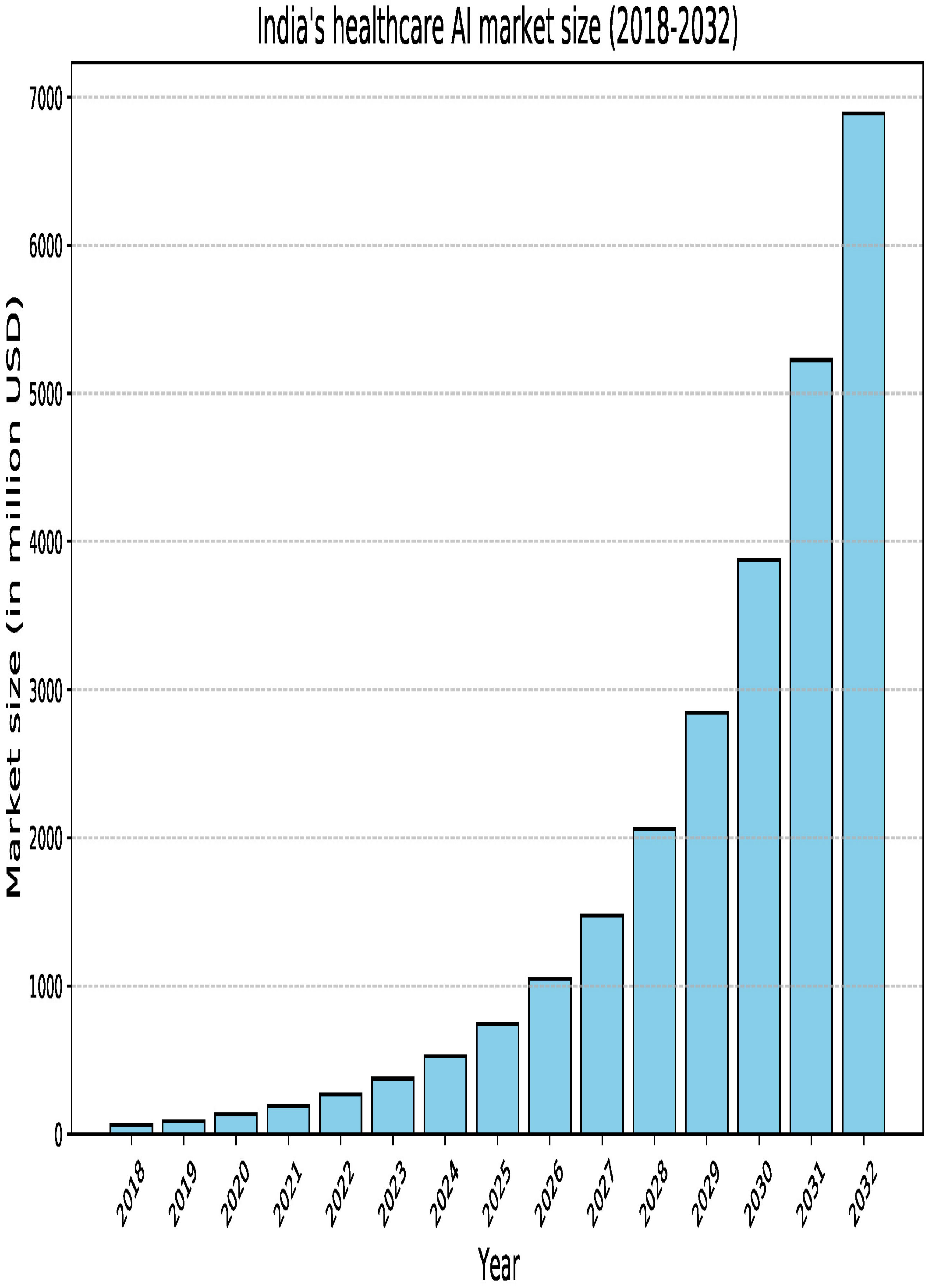

India's healthcare AI market size (2018-2032)
Market size (in million USD)
0
1000
2000
3000
4000
5000
6000
7000
2018
2019
2020
2021
2022
2023
2024
2025
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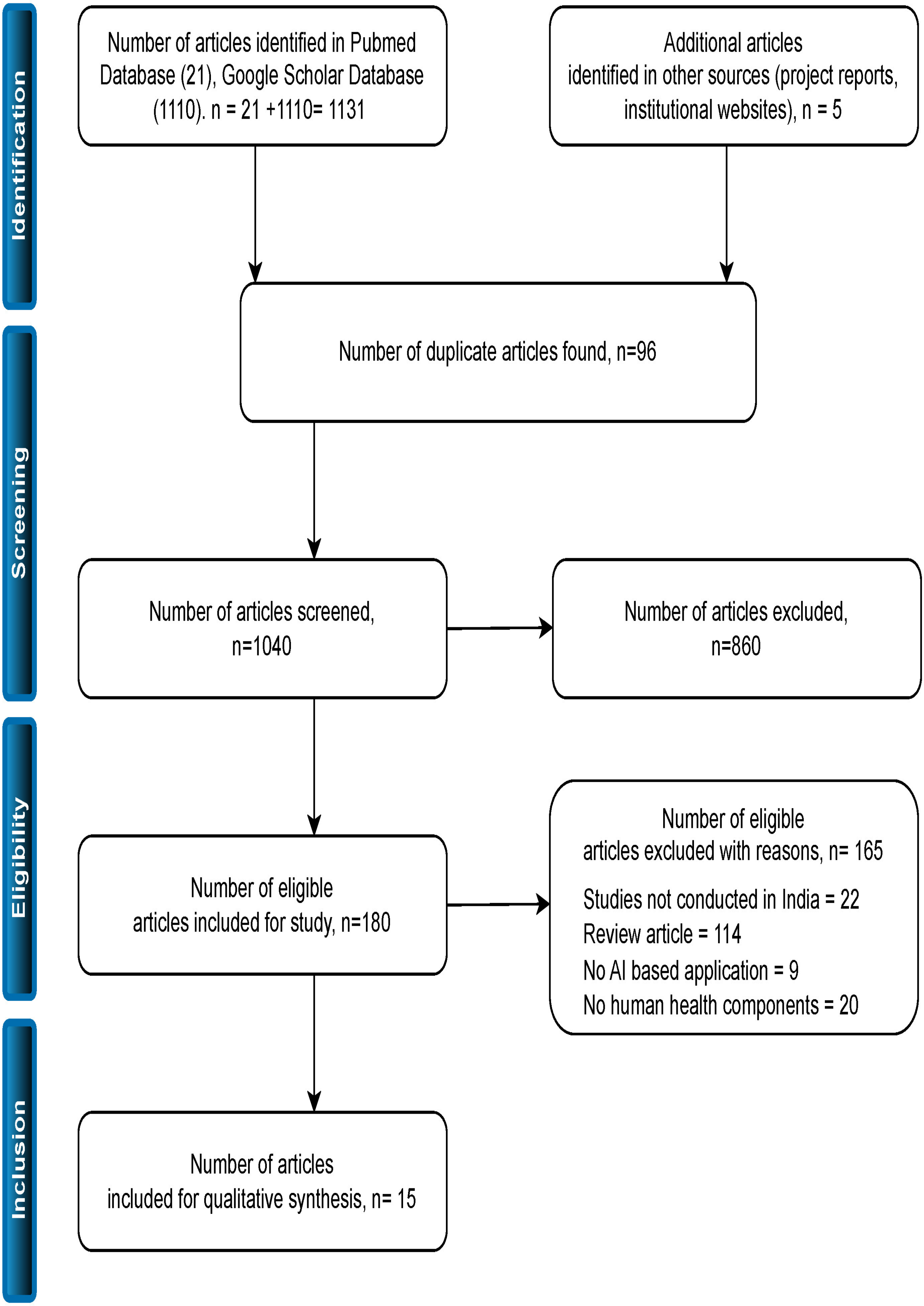

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Table 1

Characteristics of publications on AI-driven healthcare innovations in India.

Study	Aim (Purpose)	Algorithm(s) Used
S Kaur et al., 2022 [34]	To develop a tool for data collection and analysis for prediction of dengue infection and risk estimation.	RF
S Shaik et al., 2023 [35]	To predict heart illness tolerance using machine learning algorithms. This concept enables the mobile app to identify the heart problem based on the patient's heartbeat.	NB, DT, RF, SRP
S Kadian et al., 2017 [36]	To use two technological tools, telehealth and artificial doctor. Telehealth served as a communication medium between rural people and hospitals. Artificial doctor provides alternative treatment for unknown diseases.	ANN
KP Kalita et al., 2023 [37]	To combine the concept of blockchain and ensemble machine learning algorithms for data collection and storage, analyzing maternal data securely and reliably. Also, to predict risk levels of pregnancy complications.	RF
RK Deka et al., 2023 [38]	To develop a method to transform numerical data points into images for classification while keeping medical data private.	CNN
Geetha et al., 2022 [39]	To develop a technique for secure transmission of sensitive medical images in an open medium, preserving health data privacy.	PIOE-SMIM
Kumar, Anil et al., 2019 [40]	To develop a model to anonymize electronic health records (EHRs) with minimal loss of information and increased medical data privacy.	SVM, k-NN
Shanmuga Sundari et al., 2023 [41]	To use machine learning methods to forecast neuro-clinical data. The developed models predict the psychiatric disorders known as impulse control disorders (ICDs) in patients.	AB, SVM, NB, LR
Alnavar, Kruthika et al., 2021 [42]	To develop blockchain-based machine learning models to manage medical records and mitigate fraudulent health insurance claims.	RF, SVM

Malik, V et al., 2021 [43]	To develop models to predict the chance of survival of patients and response to medication for breast cancer.	ANN, KM

Abbreviations: RF = Random Forest, NB = Naive Bayes, DT = Decision Tree, SRP = Sparse Random Projection, ANN = Artificial Neural Network, CNN = Convolutional Neural Network, PIOE-SMIM = Pigeon-Inspired Optimization with Encryption-Based Secure Medical Image Management, SVM = Support Vector Machine, k-NN = k-Nearest Neighbors, AB = AdaBoost, LR = Logistic Regression, KM = K-Means Clustering.

Table 2

Evaluation of the selected articles against key ethical considerations for trustworthy AI in the healthcare sector.

Study	Patient Privacy and Data Security	Informed Consent and Transparency	Unbiasness and Fairness	Liability and Accountability	Explainability and Interpretability
S Kaur et al., 2022 [34]	Partial	Not Found	Partial	Not Found	Partial
S Shaik et al., 2023 [35]	Partial	Not Found	Partial	Not Found	Partial
S Kadian et al., 2017 [36]	Partial	Not Found	Partial	Not Found	Not Found
KP Kalita et al., 2023 [37]	Full	Partial	Not Found	Partial	Partial
RK Deka et al., 2023 [38]	Full	Partial	Partial	Not Found	Partial
Geetha et al., 2022 [39]	Full	Not Found	Partial	Not Found	Not Found
Kumar, Anil et al., 2019 [40]	Full	Not Found	Not Found	Not Found	Not Found
Shanmuga Sundari et al., 2023 [41]	Not Found	Partial	Not Found	Not Found	Partial
Alnavar, Kruthika et al., 2021 [42]	Partial	Partial	Not Found	Not Found	Not Found
Malik, V et al., 2021 [43]	Partial	Not Found	Not Found	Not Found	Not Found

Table 3

Evaluation of the selected articles against key legal considerations for trustworthy AI in the healthcare sector.

Study	Data Privacy and Protection Laws	Regulatory Approval and Compliance	Intellectual Property Rights	Cross-Border Regulations	Patient Consent
S Kaur et al., 2022 [34]	Partial	Not Found	Not Found	Not Found	Not Found
S Shaik et al., 2023 [35]	Not Found	Not Found	Not Found	Not Found	Not Found
S Kadian et al., 2017 [36]	Partial	Not Found	Not Found	Not Found	Not Found
KP Kalita et al., 2023 [37]	Full	Partial	Not Found	Not Found	Partial
RK Deka et al., 2023 [38]	Partial	Not Found	Not Found	Not Found	Not Found
Geetha et al., 2022 [39]	Partial	Not Found	Not Found	Not Found	Not Found
Kumar, Anil et al., 2019 [40]	Partial	Not Found	Not Found	Not Found	Not Found
Shanmuga Sundari et al., 2023 [41]	Not Found	Not Found	Not Found	Not Found	Not Found
Alnavar, Kruthika et al., 2021 [42]	Partial	Not Found	Not Found	Not Found	Not Found
Malik, V et al., 2021 [43]	Not Found	Not Found	Not Found	Not Found	Not Found

Appendix A

Search queries (performed from 2015 to May 2023 and then updated and rerun between February 2024 and March 2024).

Table A1

The databases and websites pertaining to trustworthy AI in healthcare in India.

Database/Source	Search Query	No. of Articles Returned
PubMed	((“india”[MeSH Terms] OR “india”[All Fields] OR “india s”[All Fields] OR “indias”[All Fields]) AND ((“health”[MeSH Terms] OR “health”[All Fields] OR “health s”[All Fields] OR “healthful”[All Fields] OR “healthfulness”[All Fields] OR “healths”[All Fields]) AND ((“privacies”[All Fields] OR “privacy”[MeSH Terms] OR “privacy”[All Fields]) AND ((“artificial intelligence”[MeSH Terms] OR (“artificial”[All Fields] AND “intelligence”[All Fields]) OR “artificial intelligence”[All Fields] OR (“antagonists and inhibitors”[MeSH Subheading] OR (“antagonists”[All Fields] AND “inhibitors”[All Fields]) OR “antagonists and inhibitors”[All Fields] OR “ai”[All Fields])) AND (“2013/05/12 00:00”:“3000/01/01 05:00”[Date—Publication] AND “review”[Publication Type] AND “loattrfull text”[Filter])) AND (“2013/05/12 00:00”:“3000/01/01 05:00”[Date—Publication] AND “review”[Publication Type] AND “loattrfull text”[Filter])) AND (“2013/05/12 00:00”:“3000/01/01 05:00”[Date—Publication] AND “review”[Publication Type] AND “loattrfull text”[Filter]))) AND ((y_10[Filter]) AND (review[Filter]) AND (fft[Filter]))	21
Google Scholar	’health sector’ OR ’healthcare sector’ AND ’trustworthy’ AND ’artificial intelligence’ AND ’privacy’ AND ’INDIA’	1110
Institution/Project Websites(accessed on 21 September 2024)	https://www.prnewswire.com/, https://www.ciengine.com/, https://cxotoday.com/, www.wadhwaniai.org/, https://techstory.in/	5

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Large language models could change the future of behavioral healthcare: a proposal for responsible development and evaluation

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ABSTRACT (ENGLISH)

Large language models (LLMs) such as Open AI’s GPT-4 (which power ChatGPT) and Google’s Gemini, built on artificial intelligence, hold immense potential to support, augment, or even eventually automate psychotherapy. Enthusiasm about such applications is mounting in the field as well as industry. These developments promise to address insufficient mental healthcare system capacity and scale individual access to personalized treatments. However, clinical psychology is an uncommonly high stakes application domain for AI systems, as responsible and evidence-based therapy requires nuanced expertise. This paper provides a roadmap for the ambitious yet responsible application of clinical LLMs in psychotherapy. First, a technical overview of clinical LLMs is presented. Second, the stages of integration of LLMs into psychotherapy are discussed while highlighting parallels to the development of autonomous vehicle technology. Third, potential applications of LLMs in clinical care, training, and research are discussed, highlighting areas of risk given the complex nature of psychotherapy. Fourth, recommendations for the responsible development and evaluation of clinical LLMs are provided, which include centering clinical science, involving robust interdisciplinary collaboration, and attending to issues like assessment, risk detection, transparency, and bias. Lastly, a vision is outlined for how LLMs might enable a new generation of studies of evidence-based interventions at scale, and how these studies may challenge assumptions about psychotherapy.

FULL TEXT

Introduction

Large language models (LLMs), built on artificial intelligence (AI) – such as Open AI’s GPT-4 (which power ChatGPT) and Google’s Gemini – are breakthrough technologies that can read, summarize, and generate text. LLMs have a wide range of abilities, including serving as conversational agents (chatbots), generating essays and stories, translating between languages, writing code, and diagnosing illness[1]. With these capacities, LLMs are influencing many fields, including education, media, software engineering, art, and medicine. They have started to be applied in the realm of behavioral healthcare, and consumers are already attempting to use LLMs for quasi-therapeutic purposes[2].

Applications incorporating older forms of AI, including natural language processing (NLP) technology, have existed for decades[3]. For example, machine learning and NLP have been used to detect suicide risk[4], identify the assignment of homework in psychotherapy sessions[5], and identify patient emotions within psychotherapy[6]. Current applications of LLMs in the behavioral health field are far more nascent – they include tailoring an LLM to help peer counselors increase their expressions of empathy, which has been deployed with clients both in academic and commercial settings[2,7]. As another example, LLM applications have been used to identify therapists' and clients' behaviors in a motivational interviewing framework[8,9].

Similarly, while algorithmic intelligence with NLP has been deployed in patient-facing behavioral health contexts, LLMs have not yet been heavily employed in these domains. For example, mental health chatbots Woebot and Tessa, which target depression and eating pathology respectively[10,11], are rule-based and do not use LLMs (i.e., the application's content is human-generated, and the chatbot's responds based on predefined rules or decision trees[12]). However, these and other existing chatbots frequently struggle to understand and respond to unanticipated user responses[10,13], which likely contributes to their low engagement and high dropout rates[14,15]. LLMs may hold promise to fill some of these gaps, given their ability to flexibly generate human-like and context-dependent responses. A small number of patient-facing applications incorporating LLMs have been tested, including a research-based application to generate dialog for therapeutic counseling[16,17], and an industry-based mental-health chatbot, Youper, which uses a mix of rule-based and generative AI[18].

These early applications demonstrate the potential of LLMs in psychotherapy – as their use becomes more widespread, they will change many aspects of psychotherapy care delivery. However, despite the promise they may hold for this purpose, caution is warranted given the complex nature of psychopathology and psychotherapy. Psychotherapy delivery is an unusually complex, high-stakes domain vis-à-vis other LLM use cases. For example, in the productivity realm, with a "LLM co-pilot" summarizing meeting notes, the stakes are failing to maximize efficiency or helpfulness; in behavioral healthcare, the stakes may include improperly handling the risk of suicide or homicide.

While there are other applications of artificial intelligence that may involve high-stakes or life-or death decisions (e.g., self-driving cars), prediction and mitigation of risk in the case of psychotherapy is very nuanced, involving complex case conceptualization, the consideration of social and cultural contexts, and addressing unpredictable human behavior. Poor outcomes or ethical transgressions from clinical LLMs could run the risk of harming individuals, which may also be disproportionately publicized (as has occurred with other AI failures[19]), which may damage public trust in the field of behavioral healthcare.

Therefore, developers of clinical LLMs need to act with special caution to prevent such consequences. Developing responsible clinical LLMs will be a challenging coordination problem, primarily because the technological developers who are typically responsible for product design and development lack clinical sensitivity and experience. Thus, behavioral health experts will need to play a critical role in guiding development and speaking to the potential limitations, ethical considerations, and risks of these applications.

Presented below is a discussion on the future of LLMs in behavioral healthcare from the perspective of both behavioral health providers and technologists. A brief overview of the technology underlying clinical LLMs is provided for the purposes of both educating clinical providers and to set the stage for further discussion regarding recommendations for development. The discussion then outlines various applications of LLMs to psychotherapy and provides a proposal for the cautious, phased development and evaluation of LLM-based applications for psychotherapy.

Overview of clinical LLMs

Clinical LLMs could take a wide variety of forms, spanning everything from brief interventions or circumscribed tools to augment therapy, to chatbots designed to provide psychotherapy in an autonomous manner. These applications could be patient-facing (e.g., providing psychoeducation to the patient), therapist-facing (e.g., offering options for interventions from which the therapist could select), trainee-facing (e.g., offering feedback on qualities of the trainee's performance), or supervisor/consultant facing (e.g., summarizing supervisees' therapy sessions in a high-level manner).

How language models work

Language models, or computational models of the probability of sequences of words, have existed for quite some time. The mathematical formulations date back to[20] and original use cases focused on compressing communication[21] and speech recognition[22–24]. Language modeling became a mainstay for choosing among candidate phrases in speech recognition and automatic translation systems but until recently, using such models for *generating* natural language found little success beyond abstract poetry[24].

Large language models

The advent of *large* language models, enabled by a combination of the deep learning technique transformers[25] and increases in computing power, has opened new possibilities[26]. These models are first trained on massive amounts of data[27,28] using "unsupervised" learning in which the model's task is to predict a given word in a sequence of words. The models can then be tailored to a specific task using methods, including prompting with examples or fine-tuning, some of which use no or small amounts of task-specific data (see Fig. 1)[28,29]. LLMs hold promise for clinical applications because they can parse human language and generate human-like responses, classify/score (i.e., annotate) text, and flexibly adopt conversational styles representative of different theoretical orientations.

Fig. 1 [Images not available. See PDF.]

Methods for tailoring clinical large language models.

Figure was designed using image components from Flaticon.com.

LLMs and psychotherapy skills

For certain use cases, LLM show a promising ability to conduct tasks or skills needed for psychotherapy, such as conducting assessment, providing psychoeducation, or demonstrating interventions (see Fig. 2). Yet to date, clinical LLM products and prototypes have not demonstrated anywhere near the level of sophistication required to take the place of psychotherapy. For example, while an LLM can generate an alternative belief in the style of CBT, it remains to be seen whether it can engage in the type of turn-based, Socratic questioning that would be expected to produce cognitive change. This more generally highlights the gap that likely exists between simulating therapy skills and implementing them effectively to alleviate patient suffering. Given that psychotherapy transcripts are likely poorly represented in the training data for LLMs, and that privacy and ethical concerns make such representation challenging, prompt engineering may ultimately be the most appropriate fine-tuning approach for shaping LLM behavior in this manner.

Fig. 2 [Images not available. See PDF.]

Example clinical skills of large language models.

Note. Figure was designed using image component from Flaticon.com.

Clinical LLMs: stages of integration

The integration of LLMs into psychotherapy could be articulated as occurring along a continuum of stages spanning from assistive AI to fully autonomous AI (see Fig. 3 and Table 1). This continuum can be illustrated by models of AI integration in other fields, such as those used in the autonomous vehicle industry. For example, at one end of this continuum is the assistive AI ("machine in the loop") stage, wherein the vehicle system has no ability to complete the primary tasks – acceleration, braking, and steering – on its own, but provides momentary assistance (e.g., automatic emergency breaking, lane departure warning) to increase driving quality or decrease burden on the driver. In the collaborative AI ("human in the loop") stage, the vehicle system aids in the primary tasks, but requires human oversight (e.g., adaptive cruise control, lane keeping assistance). Finally, in fully autonomous AI, vehicles are self-driving and do not require human oversight. The stages of LLM integration into psychotherapy and their related functionalities are described below.

Fig. 3 [Images not available. See PDF.]

Stages of integrating large language models into psychotherapy.

Figure was designed using image components from Flaticon.com.

Table 1. Stages of Development of Clinical LLMs

Stage	Car Analogy	Characteristics of Assessment	Intervention Focus/Scope	Intervention Nature	Clinical Example	Potential Risks or Costs
Assistive AI (*"machine in the loop"*)	AI-based features (e.g., automatic emergency breaking, lane departure warning) in the vehicle.	Standalone, modularized (e.g., assessments hand-picked by therapist and administered by survey).	Limited to concrete/ circumscribed (e.g., activity planning).	No full intervention packages; limited to components of interventions.	LLM trained to conduct skills from CBT-I might converse with the patient to collect their sleep diary data from the previous week to expedite a traditional therapy session.	Overhead and complexity for therapist for AI supervision.
Collaborative AI (*"human in the loop"*)	Vehicle mostly completing the primary task; human in the driver seat actively monitors the vehicle's progress and overrides it as needed (e.g., adaptive cruise control, lane keeping assist).	Increasingly integrated (e.g., assessments recommended by LLM and summarized with context for therapist review).	Includes less concrete, more abstract interventions (e.g., planning and processing exposures).	Limited to structured/standardized (e.g., CBT for insomnia).	CBT-I LLM might generate a) an overview of the sleep diary data, b) a rationale for sleep restriction and stimulus control, and c) a sleep schedule prescription based on the diary data. This content would be reviewed and tailored by the psychotherapist before being discussed with the patient.	Drafts that require significant corrections may not save much time; Busy therapists may fail to check or tailor content, especially if given higher caseloads due to AI assistance.

Fully autonomous AI	Fully autonomous vehicles that operate without direct human oversight.	Fully integrated, informs intervention (e.g., unobtrusive, automated symptom assessment running in background).	Includes very abstract/diffuse interventions (e.g., Socratic questioning).	Includes unstructured/unstandardized (e.g., acceptance and commitment therapy, idiographic or modular approaches).	LLM could implement a full course of CBT-I. The LLM would directly deliver multi-session therapy interventions and content to the patient, which would not be subject to tailoring or initial oversight by the psychotherapist.	Critical information could be missed (e.g., suicide risk); Provision of inappropriate or harmful care.

AI artificial intelligence, *LLM* large language model, *CBT-I* cognitive behavioral therapy for insomnia.

Stage 1: assistive LLMs

At the first stage in LLM integration, AI will be used as a tool to assist clinical providers and researchers with tasks that can easily be "offloaded" to AI assistants (Table 1; first row). As this is a preliminary step in integration, relevant tasks will be low-level, concrete, and circumscribed, such that they present a low level of risk. Examples of tasks could include assisting with collecting information for patient intakes or assessment, providing basic psychoeducation to patients, suggesting text edits for providers engaging in text-based care, and summarizing patient worksheets. Administratively, systems at this stage could also assist with clinical documentation by drafting session notes.

Stage 2: collaborative LLMs

Further along the continuum, AI systems will take the lead by providing or suggesting options for treatment planning and much of the therapy content, which humans will use their professional judgement to select from or tailor. For example, in the context of a text- or instant-message delivered structured psychotherapeutic intervention, the LLM might generate messages containing session content and assignments, which the therapist would review and adapt as needed before sending (Table 1; second row). A more advanced use of AI within the collaborative stage may entail a LLM providing a structured intervention in a semi-independent manner (e.g., as a chatbot), with a provider monitoring the discussion and stepping in to take control of the conversation as needed. The collaborative LLM stage has parallels to "guided self-help" approaches[30].

Stage 3: fully autonomous LLMs

In the fully autonomous stage, AIs will achieve the greatest degree of scope and autonomy wherein a clinical LLM would perform a full range of clinical skills and interventions in an integrated manner without direct provider oversight (Table 1; third row). For example, an application at this stage might theoretically conduct a comprehensive assessment, select an appropriate intervention, and deliver a full course of therapy with no human intervention. In addition to clinical content, applications in this stage could integrate with the electronic health record to complete clinical documentation and report writing, schedule appointments and process billing. Fully autonomous applications offer the most scalable treatment method[30].

Progression across the stages

Progression across the stages may not be linear; human oversight will be required to ensure that applications at greater stages of integration are safe for real world deployment. As different forms of psychopathology and their accompanying interventions vary in complexity, certain types of interventions will be simpler than others to develop as LLM applications. Interventions that are more concrete and standardized may be easier for models to deliver (and may be available sooner), such as circumscribed behavior change interventions (e.g., activity scheduling), as opposed to applications which include skills that are abstract in nature or emphasize cognitive change (e.g., Socratic questioning). Similarly, when it comes to full therapy protocols, LLM applications for interventions that are highly structured, behavioral, and protocolized (e.g., CBT for insomnia [CBT-I] or exposure therapy for specific phobia) may be available sooner than applications delivering highly flexible or personalized interventions (for example[31]).

In theory, the final stage in the integration of LLMs into psychotherapy is fully autonomous delivery of psychotherapy which does not require human intervention or monitoring. However, it remains to be seen whether fully autonomous AI systems will reach a point at which they have been evaluated to be safe for deployment by the behavioral health community. Specific concerns include how well these systems are able to carry out case conceptualization on individuals with complex, highly comorbid symptom presentations, including accounting for current and past suicidality, substance use, safety concerns, medical comorbidities, and life circumstances and events (such as court dates and upcoming medical procedures). Similarly, it is unclear whether these systems will prove sufficiently adept at engaging patients over time[32] or accounting for and addressing contextual nuances in treatment (e.g., using exposure to treat a patient experiencing PTSD-related fear of leaving the house, who also lives in a neighborhood with high rates of crime). Furthermore, several skills which may be viewed as central to clinical work currently fall outside the purview of LLM systems, such as interpreting nonverbal behavior (e.g., fidgeting, eye-rolling), appropriately challenging a patient, addressing alliance ruptures, and making decisions about termination. Technological advances, including the approaching advent of multimodal language models that integrate text, images, video, and audio, may eventually begin to fill these gaps.

Beyond technical limitations, it remains to be decided whether complete automation is an appropriate end goal for behavioral healthcare, due to safety, legal, philosophical, and ethical concerns[33]. While some evidence indicates that humans can develop a therapeutic alliance with chatbots[34], the long-term viability of such alliance building, and whether or not it produces undesirable downstream effects (e.g., altering an individual’s existing relationships or social skills) remains to be seen. Others have documented potentially harmful behavior of LLM chatbots, such as narcissistic tendencies[35] and expressed concerns about the potential for their undue influence on humans in addition to articulating societal risks associated with LLMs more generally[36,37]. The field will also need to grapple with questions of accountability and liability in the case of a fully autonomous clinical LLM application causing damage (e.g., identifying the responsible party in an incident of malpractice[38]). For these and other reasons, some have argued against the implementation of fully autonomous systems in behavioral healthcare and healthcare more broadly[39,40]. Taken together, these issues and concerns may suggest that in the short and medium term, assistive or collaborative AI applications will be more appropriate for the provision of behavioral healthcare.

Applications of clinical LLMs

Given the vast nature of behavioral healthcare, there are seemingly endless applications of LLMs. Outlined below are some of the currently existing, imminently feasible, and potential long-term applications of clinical LLMs. Here we focus our discussion on applications directly related to the provision of, training in, and research on psychotherapy. As such, several important aspects of behavioral healthcare, such as initial symptom detection, psychological assessment and brief interventions (e.g., crisis counseling) are not explicitly discussed herein.

Imminent applications

Automating clinical administration tasks

At the most basic level, LLMs have the potential to automate several time-consuming tasks associated with providing psychotherapy (Table 2, first row). In addition to using session transcripts to summarize the session for the provider, there is potential for such models to integrate within electronic health records to aid with clinical documentation and conducting chart reviews. Clinical LLMs could also produce a handout for the patient that provides a personalized overview of the session, skills learned and assigned homework or between-session material.

Table 2. Imminent possibilities for clinical LLMs

Task	Target Audience	Example Input to LLM	Example LLM Output
Aid in administrative tasks	Clinician	Psychotherapy session recording	"… Met with patient for cognitive behavioral therapy for depression. Reviewed homework; patient completed three thought records over the past week. Introduced 'thinking biases' worksheet; assisted patient in identifying patterns of problematic thinking applicable to her automatic negative thoughts from the past week…"
Offer feedback on therapy homework worksheets	Patient	Digital CBT worksheet; Patient writes, "I've always felt this way," as evidence in support of the negative automatic thought: "I'm unlovable" on the worksheet	"Remember, 'evidence' means facts that support the belief. Sometimes it's helpful to think about facts so strong they would stand up in a court of law. What is the evidence that you are unlovable?"
Produce adherence and competence ratings for elements of therapy	Researcher	Psychotherapy session recording	"…*Therapist helped patient identify negative automatic thoughts* Adherence rating (0-1): 1 Competence rating (0-6): 5…"
Identify trainee psychotherapist's areas of success and areas for improvement	Psychotherapy trainee	Psychotherapy session recording	"…In the following exchange, the therapist successfully used Socratic questioning to ask open-ended, non-leading questions: *[Patient: I should have known that it wasn't safe to get in that car. Therapist: Hm, help me understand… how could you have known that it wasn't safe?]*…"

Suggest an improved therapeutic response, offer education about therapeutic exchanges	Peer counselor or lay mental health worker	Message-based exchange between patient and peer counselor; peer counselor has drafted a response: “You’ll be fine”	“This could be improved by offering validation of the client’s feelings. For instance, you might say, ‘it sounds like you’re going through a difficult time, and it’s understandable to feel overwhelmed.’ Would you like to rewrite before sending?”

Measuring treatment fidelity

A clinical LLM application could automate measurement of therapist fidelity to evidence-based practices (EBPs; Table 2, second row), which can include measuring *adherence* to the treatment as designed, *competence* in delivering a specific therapy skill, *treatment differentiation* (whether multiple treatments being compared actually differ from one another), and *treatment receipt* (patient comprehension of, engagement with, and adherence to the therapy content) [41,42]. Measuring fidelity is crucial to the development, testing, dissemination, and implementation of EBPs, yet can be resource intensive and difficult to do reliably. In the future, clinical LLMs could computationally derive adherence and competence ratings, aiding research efforts and reducing therapist drift[43]. Traditional machine-learning models are already being used to assess fidelity to specific modalities[44] and other important constructs like counseling skills[45] and alliance[46]. Given their improved ability to consider context, LLMs will likely increase the accuracy with which these constructs are assessed.

Offering feedback on therapy worksheets and homework

LLM applications could also be developed deliver real-time feedback and support on patients’ between-session homework assignments (Table 2, third row). For example, an LLM tailored to assist a patient to complete a CBT worksheet might provide clarification or aid in problem solving if the patient experiences difficulty (e.g., the patient was completing a thought log and having trouble differentiating between the thought and the emotion). This could help to “bridge the gap” between sessions and expedite patient skill development. Early evidence outside the AI realm[47] points to increasing worksheet competence as a fruitful clinical target.

Automating aspects of supervision and training

LLMs could be used to provide feedback on psychotherapy or peer support sessions, especially for clinicians with less training and experience (i.e., peer counselors, lay health workers, psychotherapy trainees). For example, an LLM might be used to offer corrections and suggestions to the dialog of peer counselors (Table 2, fourth row). This application has parallels to “task sharing,” a method used in the global mental health field by which nonprofessionals provide mental health care with the oversight by specialist workers to expand access to mental health services[48]. Some of this work is already underway, for example, as described above, using LLMs to support peer counselors[7].

LLMs could also support supervision for psychotherapists learning new treatments (Table 2, fifth row). Gold-standard methods of reviewing trainees’ work, like live observation or review of recorded sessions[49], are time-consuming. LLMs could analyze entire therapy sessions and identify areas of improvement, offering a scalable approach for supervisors or consultants to review.

Potential long-term applications

It is important to note that many of the potential applications listed below are theoretical and have yet to be developed, let alone thoroughly evaluated. Furthermore, we use the term “clinical LLM” in recognition of the fact that when and under what circumstances the work of an LLM could be called psychotherapy is evolving and depends on how psychotherapy is defined.

Fully autonomous clinical care

As previously described, the final stage of clinical LLM development could involve an LLM that can independently conduct comprehensive behavioral healthcare. This could involve all aspects related to traditional care including conducting assessment, presenting feedback, selecting an appropriate intervention and delivering a course of therapy to the patient. This course of treatment could be delivered in ways consistent with current models of psychotherapy wherein a patient engages with a "chatbot" weekly for a prescribed amount of time, or in more flexible or alternative formats. LLMs used in this manner would ideally be trained using standardized assessment approaches and manualized therapy protocols that have large bodies of evidence.

Decision aid for existing evidence-based practices

Even without full automation, clinical LLMs could be used as a tool to guide a provider on the best course of treatment for a given patient by optimizing the delivery of existing EBPs and therapeutic techniques. In practice, this may look like a LLM that can analyze transcripts from therapy sessions and offer a provider guidance on therapeutic skills, approaches or language, either in real time, or at the end of the therapy session. Furthermore, the LLM could integrate current evidence on the tailoring of specific EBPs to the condition being treated, and to demographic or cultural factors and comorbid conditions. Developing tailored clinical LLM "advisors" based on EBPs could both enhance fidelity to treatment and maximize the possibility of patients achieving clinical improvement in light of updated clinical evidence.

Development of new therapeutic techniques and EBPs

To this point, we have discussed how LLMs could be applied to current approaches to psychotherapy using extant evidence. However, LLMs and other computational methods could greatly enhance the detection and development of new therapeutic skills and EBPs. Historically, EBPs have traditionally been developed using human-derived insights and then evaluated through years of clinical trial research. While EBPs are effective, effect sizes for psychotherapy are typically small[50,51] and significant proportions of patients do not respond[52]. There is a great need for more effective treatments, particularly for individuals with complex presentations or comorbid conditions. However, the traditional approach to developing and testing therapeutic interventions is slow, contributing to significant time lags in translational research[53], and fails to deliver insights at the level of the individual.

Data-driven approaches hold the promise of revealing patterns that are not yet realized by clinicians, thus generating new approaches to psychotherapy; machine learning is already being used, for example, to predict behavioral health treatment outcomes[54]. With their ability to parse and summarize natural language, LLMs could add to existing data-driven approaches. For example, an LLM could be provided with a large historical dataset containing psychotherapy transcripts of different therapeutic orientations, outcome measures and sociodemographic information, and tasked with detecting therapeutic behaviors and techniques associated with objective outcomes (e.g., reduction in depressive symptoms). Using such a process might make it possible for an LLM to yield fine-grained insights about what makes existing therapeutic techniques work best (e.g., Which components of existing EBPs are the most potent? Are there therapist or patient characteristics that moderate the efficacy of intervention X? How does the ordering of interventions effect outcomes?) or even to isolate previously unidentified therapeutic techniques associated with improved clinical outcomes. By identifying what happens in therapy in such a fine-grained manner, LLMs could also play a role in revealing mechanisms of change, which is important for improving existing treatments and facilitating real-world implementation[55].

However, to realize this possibility, and make sure that LLM-based advances can be integrated and vetted by the clinical community, it is necessary to steer away from the development of "black box," LLM-identified interventions with low explainability (e.g., interpretability[56]). To guard against interventions with low interpretability, work to finetune LLMs to improve patient outcomes could include inspectable representations of the techniques employed by the LLM. Clinicians could examine these representations and situate them in the broader psychotherapy literature, which would involve comparing them to existing psychotherapy techniques and theories. Such an approach could speed up the identification of novel mechanisms while guarding against the identification of "novel" interventions which overlap with existing techniques or constructs (thus avoiding the jangle fallacy, the erroneous assumption that two constructs with different names are necessarily distinct[57]).

In the long run, by combining this information, it might even be possible for an LLM to "reverse-engineer" a new EBP, freed from the constraints of traditional therapeutic protocols and instead maximizing on the delivery of the constituent components shown to produce patient change (in a manner akin to modular approaches, wherein an individualized treatment plan is crafted for each patient by curating and sequencing treatment modules from an extensive menu of all available options based on the unique patient's presentation[31]). Eventually, a self-learning clinical LLM might deliver a broad range of psychotherapeutic interventions while measuring patient outcomes and adapting its approach on the fly in response to changes in the patient (or lack thereof).

Toward a precision medicine approach to psychotherapy

Current approaches to psychotherapy often are unable to provide guidance on the best approach to treatment when an individual has a complex presentation, which is often the rule rather than being the exception. For example, providers are likely to have greatly differing treatment plans for a patient with concurrent PTSD, substance use, chronic pain, and significant interpersonal difficulties. Models that use a data-driven approach (rather than a provider's educated guess) to address an individual's presenting concern alongside their comorbidities, sociodemographic factors, history, and responses to the current treatment, may ultimately offer the best chance at maximizing patient benefit. While there have been some advances in precision medicine approaches in behavioral healthcare[54,58], these efforts are in their infancy and limited by sample sizes[59].

The potential applications of clinical LLMs we have outlined above may come together to facilitate a personalized approach to behavioral healthcare, analogous to that of precision medicine. Through optimizing existing EBPs, identifying new therapeutic approaches, and better understanding mechanisms of change, LLMs (and their future descendants) may provide behavioral healthcare with an enhanced ability to identify what works best for whom and under what circumstances.

Recommendations for responsible development and evaluation of clinical LLMs

Focus first on evidence-based practices

In the immediate future, clinical LLM applications will have the greatest chance of creating meaningful clinical impact if developed based on EBPs or a "common elements" approach (i.e., evidence-based procedures shared across treatments)[60]. Evidence-based treatments and techniques have been identified for specific psychopathologies (e.g., major depressive disorder, posttraumatic stress disorder), stressors (e.g., bereavement, job loss, divorce), and populations (e.g., LGBTQ individuals, older adults)[55,61,62]. Without an initial focus on EBPs, clinical LLM applications may fail to reflect current knowledge and may even produce harm[63]. Only once LLMs have been fully trained on EBPs can the field start to consider using LLMs in a data-driven manner, such as those outlined in the previous section on potential long-term applications.

Focus next on improvement (engagement is not enough)

Others have highlighted the importance of promoting engagement with digital mental health applications[15], which is important for achieving an adequate "dose" of the therapeutic intervention. LLM applications hold the promise of improving engagement and retention through their ability to respond to free text, extract key concepts, and address patients' unique context and concerns during interventions in a timely manner. However, engagement alone is not an appropriate outcome on which to train an LLM, because engagement is not expected to be sufficient for producing change. A focus on such metrics for clinical LLMs will risk losing sight of the primary goals, clinical improvement (e.g., reductions in symptoms or impairment, increases in well-being and functioning) and prevention of risks and adverse events. It will behoove the field to be wary of attempts to optimize clinical LLMs on outcomes that have an explicit relationship with a company's profit (e.g., length of time using the application). An LLM that optimizes only for engagement (akin to YouTube recommendations) could have high rates of user retention without employing meaningful clinical interventions to reduce suffering and improve quality of life. Previous research has suggested that this may be happening with non-LLM digital mental health interventions. For instance, exposure is a technique with strong support for treating anxiety, yet it is rarely included in popular smartphone applications for anxiety[64], perhaps because developers fear that the technique will not appeal to users, or have concerns about how exposures going poorly or increasing anxiety in the short term, which may prompt concerns about legal exposure.

Commit to rigorous yet commonsense evaluation

An evaluation approach for clinical LLMs that hierarchically prioritizes risk and safety, followed by feasibility, acceptability, and effectiveness, would be in line with existing recommendations for the evaluation of digital mental health smartphone apps[65]. The first level of evaluation could involve a demonstration that a clinical LLM produces no harm or very minimal harm that is outweighed by its benefits, similar to FDA phase I drug tests. Key risk and safety related constructs include measures of suicidality, non-suicidal self harm, and risk of harm to others.

Next, rigorous examinations of clinical LLM applications will be needed to provide empirical evidence of their utility, using head-to-head comparisons with standard treatments. Key constructs to be assessed in these empirical tests are feasibility and acceptability to the patient and the therapist as well as treatment outcomes (e.g., symptoms, impairment, clinical status, rates of relapse). Other relevant considerations include patients' user experience with the application, measures of therapist efficiency and burnout, and cost.

Lastly, we note that given that possible benefits of clinical LLMs (including expanding access to care), it will be important for the field to adopt a commonsense approach to evaluation. While rigorous evaluation is important, the comparison conditions on which these evaluations are based should reflect real-world risk and efficacy rates, and perhaps employ a graded hierarchy with which to classify risk and error (i.e., missing a mention of suicidality is unacceptable, but getting a patient's partner's name wrong is nonideal but tolerable), rather than holding clinical LLM applications to a standard of perfection which humans do not achieve. Furthermore, developers will need to strike the appropriate balance of prioritizing constructs in a manner expected to be most clinically beneficial, for example, if exposure therapy is indicated for the patient, but the patient does not find this approach acceptable, the clinical LLM could recommend the intervention prioritizing effectiveness before offering second-line interventions which may be more acceptable.

Involve interdisciplinary collaboration

Interdisciplinary collaboration between clinical scientists, engineers, and technologists will be crucial in the development of clinical LLMs. While it is plausible that engineers and technologists could use available therapeutic manuals to develop clinical LLMs without the expertise of a behavioral health expert, this is ill-advised. Manuals are only a first step towards learning a specific intervention, as they do not provide guidance on how the intervention can be applied to specific individuals or presentations, or how to handle specific issues or concerns that may arise through the course of treatment.

Clinicians and clinician-scientists have expertise that bears on these issues, as well as many other aspects of the clinical LLM development process. Their involvement could include a) testing new applications to identify limitations and risks and optimize their integration into clinical practice, b) improving the ability of applications to adequately address the complexity of psychological phenomena, c) ensuring that applications are developed and implemented in an ethical manner, and d) testing and ensuring that applications don't have iatrogenic effects, such as reinforcing behaviors that perpetuate psychopathology or distress.

Behavioral health experts could also provide guidance on how best to finetune or tailor models, including addressing the question of whether and how real patient data should be used for these purposes. For example, most proximately, behavioral health experts might assist in *prompt engineering*, or the designing and testing of a series of prompts which provide the LLM framing and context for delivering a specific type of treatment or clinical skill (e.g., "Use cognitive restructuring to help the patient evaluate and reappraise negative thoughts in depression"), or a desired clinical task, such as evaluating therapy sessions for fidelity (e.g., "Analyze this psychotherapy transcript and select sections in which the therapist demonstrated the particularly skillful use of CBT skills, and sections in which the therapist's delivery of CBT skills could be improved"). Similarly, in *few-shot learning*, behavioral health experts could be involved in crafting example exchanges which are added to prompts. For example, treatment modality experts might generate examples of clinical skills (e.g., high-quality examples of using cognitive restructuring to address depression) or of a clinical task (e.g., examples of both high- and low-quality delivery of CBT skills). For *fine-tuning*, in which a large, labeled dataset is used to train the LLM, and *reinforcement learning from human feedback* (RLHF), in which a human-labeled dataset is used to train a smaller model which is then used for LLM "self-training," behavioral health experts could build and curate (and ensure informed patient consent for use of) appropriate datasets (e.g., a dataset containing psychotherapy transcripts rated for fidelity to an evidence-based psychotherapy). The expertise that behavioral health experts could draw on to generate instructive examples and curate high-quality datasets holds particular value in light of recent evidence that *quality* of data trumps *quantity* of data for training well-performing models[66].

In the service of facilitating interdisciplinary collaboration, it would benefit clinical scientists to seek out a working knowledge about LLMs, while it would benefit technologists to develop a working knowledge of therapy in general and EBPs in particular. Dedicated venues that bring together behavioral health experts and clinical psychologists for interdisciplinary collaboration and communication will aid in these efforts. Historically, venues of this type have included psychology-focused workshops at NLP conferences (e.g., the Workshop on Computational Linguistics and Clinical Psychology [CLPsych], held at the Annual Conference of the North American Chapter of the Association for Computational Linguistics [NAACL]) and technology-focused conferences or workgroups hosted by psychological organizations (e.g., APA's Technology, Mind &Society conference; Association for Behavioral and Cognitive Therapies' [ABCT] Technology and Behavior Change special interest group). This work has also been done at nonprofits centered on technological tools for mental health (e.g., the Society for Digital Mental Health). Beyond these venues, it may be fruitful to develop a gathering that brings together technologists, clinical scientists, and industry partners with a dedicated focus on AI/LLMs, which could routinely publish on its efforts, akin to the efforts of the World Health Organization's Infodemic Management Conference, which has employed this approach to address misinformation[67]. Finally, given the numerous applications of AI to behavioral health, it is conceivable that a new "computational behavioral health" subfield could emerge, offering specialized training that would bridge the gap between these two domains.

Focus on trust and usability for clinicians and patients

It is important to engage therapists, policymakers, end-users, and experts in human-computer interactions to understand and improve levels of trust that will be necessary for successful and effective implementation. With respect to applications of AI to augment supervision and support for psychotherapy, therapists have expressed concern about privacy, the ability to detect subtle non-verbal cues and cultural responsiveness, and the impact on therapist confidence, but they also see benefits for training and professional growth[68]. Other research suggests that while therapists believe AI can increase access to care, allow individuals to disclose embarrassing information more comfortably, continuously refine therapeutic techniques[69], they have concerns about privacy and the formation of a strong therapeutic bond with machine-based therapeutic interventions[70]. Involvement of individuals who will be referring their patients and using LLMs in their own practice will be essential to developing solutions they can trust and implement, and to make sure these solutions have the features that support trust and usability (simple interfaces, accurate summaries of AI-patient interactions, etc.).

Regarding how much patients will trust the AI systems, following the stages we outlined in Fig. 3, initial AI-patient interactions will continue to be supervised by clinicians, and the therapeutic bond between the clinician and the patient will continue to be the primary relationship. During this stage, it is important that clinicians talk to the patients about their experience with the LLMs, and that the field as a whole begins to accumulate an understanding and data on how acceptable interfacing with LLMs is for what kind of patient for what kind of clinical use case, in how clinicians can scaffold the patient-LLM relationship. This data will be critical for developing collaborative LLM applications that have more autonomy, and for ensuring that the transition from assistive to collaborative stage applications is not associated with large unforeseen risk. For example, in the case of CBT for insomnia, once an assistive AI system has been iterated on to reliably collect information about patients' sleep patterns, it is more conceivable that it could be evolved into a collaborative AI system that does a comprehensive insomnia assessment (i.e., it also collects and interprets data on patients' clinically significant distress, impairment of functioning, and ruling out of sleep-wake disorders, like narcolepsy)[71].

Design criteria for effective clinical LLMs

Below, we propose an initial set of desirable design qualities for clinical LLMs.

Detect risk of harm

DETAILS

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Artificial Intelligence in Nursing: Technological Benefits to Nurse's Mental Health and Patient Care Quality

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ABSTRACT (ENGLISH)

Nurses are frontline caregivers who handle heavy workloads and high-stakes activities. They face several mental health issues, including stress, burnout, anxiety, and depression. The welfare of nurses and the standard of patient treatment depends on resolving this problem. Artificial intelligence is revolutionising healthcare, and its integration provides many possibilities in addressing these concerns. This review examines literature published over the past 40 years, concentrating on AI integration in nursing for mental health support, improved patient care, and ethical issues. Using databases such as PubMed and Google Scholar, a thorough search was conducted with Boolean operators, narrowing results for relevance. Critically examined were publications on artificial intelligence applications in patient care ethics, mental health, and nursing and mental health. The literature examination revealed that, by automating repetitive chores and improving workload management, artificial intelligence (AI) can relieve mental health challenges faced by nurses and improve patient care. Practical implications highlight the requirement of using rigorous implementation strategies that address ethical issues, data privacy, and human-centred decision-making. All changes must direct the integration of artificial intelligence in nursing to guarantee its sustained and significant influence on healthcare.

FULL TEXT

1. Introduction

Artificial intelligence (AI) is the application of technologies that allow machines to carry out tasks that require human intelligence, including decision-making, learning, and reasoning. Its uses span sectors, including banking for fraud detection, transportation for driverless cars, and education for individualised learning. In healthcare, artificial intelligence greatly enhances the nature of operations, diagnostics, and clinical procedures. Specifically, in nursing, it helps with patient monitoring, recordkeeping, and scheduling using predictive analytics, virtual companions, and chatbots. Its integration in healthcare has rapidly increased in recent years and is revolutionising the delivery of medical services. Studies suggest that there is a highly fruitful and practical application of various aspects of AI, such as machine learning algorithms, natural language processing, and predictive analytics, to improve patient care, simplify administrative processes, and support clinical decision-making [1,2,3,4,5]. Artificial intelligence can also enhance human capacities, streamline operations, provide creative answers to current issues in patient care, and reduce healthcare costs. In the US alone, healthcare expenditure rose to 18% from 5% from 1960 to 2022, and the US administration considered it due to ineffective technologies in healthcare management [6]. At the same time, healthcare institutions that have accepted artificial intelligence have met their 25% operating cost reduction targets and improved patient outcomes [7]. In addition, AI is also known to assist in alleviating professional crises in healthcare providers, like stress, burnout, and compassion fatigue [8,9].

Nurses, regarded as primary healthcare professionals, are the backbone of patient care. Nurses are frontline caregivers with numerous responsibilities, including direct patient care, medication administration, the monitoring of vital signs, assisting various medical procedures, managing challenging clinical environments, and patient emotional support [10]. They serve as crucial links between the patient and physicians. Their communication skills and compassionate approach to patients and families are essential for positive health outcomes [11]. Their expertise and dedication thus contribute to the advancement of public health standards.

Although nurses have considerable obligations in the healthcare industry, their potential to provide high-quality treatment is usually hampered by strict shift patterns, degrees of experience, occupational dynamics, nurse-to-patient ratios, and heavy workloads. When combined with professional discontent and conflicts, these demands can develop into occupational stresses that aggravate burnout and influence the quality of patient treatment [12]. Technological additions, especially emerging technologies like AI, can substantially improve the skills and outcomes of nursing care. Unlike the applications of AI in other industries, such as banking or manufacturing, where the main emphasis is on efficiency and automation, AI in nursing is especially meant to complement the human-centred character of patient care. It seeks to reduce nurses' workload so they may concentrate more on direct patient contact and ensure that technology improves rather than replaces the compassionate elements of providing care. Therefore, AI integration can enhance patient care efficiency, increase patient safety, and reduce the burden on nurses (Table 1). AI-driven tools can assist nurses in analysing large datasets, predicting potential complications, and thus improving decision-making and cognitive workload [13,14]. For example, AI can promptly alert a nurse ahead of time to the deteriorating conditions of a patient, and nurses can therefore provide early and effective intervention [15]. Additionally, AI tools can assist with patient education, symptom triage, and remote monitoring, thus freeing nurses to focus on more human-centred aspects of patient care [16].

This review aims to explore the transformative role of AI in enhancing mental support for nurses and look into opportunities for human–AI collaboration to reduce the workload, improve productivity, and provide personalised support for mental wellbeing. Furthermore, this review will analyse the ethical considerations of AI integration in nursing. This review aims to provide a balanced understanding of AI integration's potential benefits and challenges by addressing these aspects, offering insights into future AI–human collaboration prospects in nursing.

2. Materials and Methods

Literature Search

This comprehensive review was conducted by searching databases like Google Scholar and PubMed for relevant papers, book chapters, and reliable web sources. Using the following keywords, the search concentrated on English-written works: artificial intelligence, nursing, mental health support, mental distress, burnout, patient care, digital health, stress, predictive analytics, machine learning, chatbots, robots, conversational AI, patient monitoring system, ethics, data privacy, safety, security, bias. The Boolean operators "AND" and "OR" were applied to refine the search and explore interrelated topics. The search results were evaluated, and then Zotero software imported data for reference management. Duplicate entries were eliminated before additional investigation. Articles were shortlisted for thorough reading depending on their relevance to the study's main goals. Titles and abstracts were examined to identify studies addressing the integration of artificial intelligence in nursing, its use in mental health support, the enhancement of patient care, and related ethical questions. All of the authors equally participated in searching, sorting, and investigating the collected literature. The search was conducted over six months from 3 June 2024.

Inclusion Criteria

The reviewed articles comprised those that satisfied the following requirements:

1. Published in English.
2. Drawn from book chapters, theses, peer-reviewed publications, conference proceedings, and credible web sources.
3. Focusing on AI in mental health support, patient care, and related ethical issues.
4. Published within the past 40 years.

Exclusion Criteria

Articles were not included depending on the following standards:

1. Non-English works.
2. Research including dubious or lack of data.
3. Review articles or opinion pieces devoid of main conclusions.
4. Articles irrelevant to the theme, such as those concentrated only on artificial intelligence outside of the framework of nursing or healthcare.

This methodology guaranteed an extensive and targeted literature analysis, helping to identify pertinent studies to investigate artificial intelligence and nursing practice with respect to nurses' mental health and uncompromised patient care.

3. The Mental Health Landscape of Nurses

Nurses across the globe have played a remarkable role in healthcare. They handle patients in normal clinical settings and critical care units. Their heroic role during the COVID-19 outbreak is commendable, and many even lost their lives during their dedicated care delivery [26]. Numerous studies identify various occupational health hazards encountered by nurses [27,28]. Being frontline fighters, they are constantly exposed to patients' pain, trauma, and loss of life. They must maintain presence of mind under these circumstances, sometimes while working in compromised work settings and work attire, such as during the COVID-19 pandemic [29]. They also work extended hours, often have inadequate personal protective equipment, and must keep themselves away from their family. Even before the COVID-19 pandemic, nurses were susceptible to high rates of mental distress. The mental stress afflicting nurses constitutes stress, post-traumatic stress, burnout, anxiety, depression, and even depersonalisation (Figure 1). All of these circumstances adversely affect the wellbeing of nurses and healthcare delivery. It is no surprise that nursing is considered a stressful career around the world [30]. A recent study has shown that nursing stress predicts the emotional wellbeing of neonatal intensive care unit nurses, highlighting its significant impact on mental health [31]. Some of the common distress-related conditions that develop in nurses are anxiety, depression, and post-traumatic stress disorder, for which their profession itself is the primary underlying reason. Studies also suggest that nurses are more prone to developing these mental health problems than doctors working in the same setting [32,33]. The long-term impacts of stress can be profound and wide-ranging, negatively influencing their job performance and quality of care. Further, under this distress, there is a chance of developing job dissatisfaction, eventually leading to nurses leaving the profession [34]. Studies from Ethiopia and Iran have shown that 48.8% and 91.2% of nurses, respectively, experienced stress because of their job [35,36].

Burnout, another problem demonstrating similar symptoms to stress, tends to develop gradually over time but, at later stages, is greater in intensity. Burnout could be a consequence of stress or vice versa [12]. Sleeplessness, prolonged stress, fatigue, helplessness, diminished concentration, exhaustion, etc., are common symptoms of burnout. A recent study estimated the prevalence of burnout in nurses at 50% [37]. Several reasons can trigger burnout in nurses, including the work environment. For instance, a study from southern Italian hospitals conducted with 169 healthcare professionals, 64.5% of whom were nurses, assessed the connection between perceived burnout levels and the work environment. The results showed that levels of stress and burnout were much raised by inadequate environmental comfort and safety conditions [38]. The long-lasting effects of burnout can affect job performance, and the consequences are not limited to the nursing practitioner themselves, but also to the work environment and the individuals associated with and/or interacting with them [12,39]. Thus, it is also a social concern besides being a concern to the individual themselves. As in the case of stress, burnout can lead to job dissatisfaction, eventually resulting in the quitting of the profession altogether [40].

The incidence of mental distress is not limited to stress, post-traumatic stress, and burnout. Studies have demonstrated that anxiety and depression are also prevalent. A recent study from India has shown that, among the occupational mental health conditions experienced by nurses, stress, anxiety, and depression accounted for 50.8%, 74%, and 70.8%, respectively, with at least 79.1% of the nurses having any one of them [41]. Studies from other countries indicate that these problems are widespread across the globe. For example, studies showed that 43.1% and 38.5% (Saudi Arabia), 18.1% and 34.3% (China), 50.3% and 51.9% (UK), 38.8% and 37.4% (Iran), and 39.1% and 6.3% (France) of nurses in various countries had anxiety and depression, respectively [42,43,44,45,46].

4. Impact of Mental Distress of Nurses on Patient Care

The impact of mental trauma is a critical issue in healthcare, as the wellbeing of nurses is linked to patient care. It is well known that there is a severe shortage of nurses in the healthcare industry [47,48,49,50]. This results in nurses becoming overburdened as there is a unique requirement to show empathy while taking care of the needs of the patients. However, nurses become physically and mentally exhausted, which affects their ability to deliver safe, quality care [51]. The consequences of mental distress for nurses include compromised patient safety and an increased number of errors [52,53]. For instance, a study by Baye and colleagues [54] reported that higher workloads and stress were related to an increased rate of medication errors, which seriously impacted patient safety. Another study in 2021 found that nurses with diminished physical and mental health made more medical errors than those with better health [55]. An increased rate of healthcare-associated infections is also related to poor patient outcomes [56,57] due to nurses' mental distress. The consequences may even be life-threatening to patients [58]. Those nursing staff prone to making these mistakes typically endure one or more conditions like fatigue, impaired cognitive function, and lack of focus. Nurses may also progressively lose empathy or emotionally distance themselves from their patients, therefore seeing their patients as objects rather than as people who need caring treatment. One might describe such a state by means of the depersonalisation concept. Critical care nurses from a tertiary hospital in Malaysia exhibited a prevalence of depersonalisation as high as 72.9% [59]. As a result of depersonalisation, there are negative outcomes in terms of patient experience and the rapport between the nurse and the patient. The results of a 2021 study indicated that patients who were receiving care from nurses experiencing burnout had worse patient satisfaction [60]. A thorough study conducted in the same year revealed that patients treated by nurses with burnout (characterised by depersonalisation) reported lower satisfaction levels [61].

Absenteeism and staff turnover are two other consequences of mental health issues in nurses that negatively affect patient care and quality. Stress and burnout can lead to understaffing due to the inability of nurses to work under these conditions. As a result, the remaining nurses face increased workloads, resulting in a further decline in quality [61]. Higher turnover rates also mean that healthcare facilities are frequently forced to take on new nursing staff, which leads to a lack of continuity in care. The inverse relation between nurse turnover and health outcomes was documented in a study conducted in 2022 [62]. Nurse turnover also prolongs the stay of patients in the hospital and increases readmission rates as new staff tend to take time to adapt to the new work environment [63].

The growing concern about mental health, productivity, and quality of patient care calls for innovative solutions that address these interconnected challenges. To address these concerns, healthcare facilities must implement innovative solutions such as resilience training programmes, digital mental health tools, and organisational support systems. One such creative solution is to adapt various AI tools. Novel AI technologies like chatbots, virtual companions, predictive analytics, and AI-driven monitoring systems provide new hope for improving nursing care and the profession (Table 2). For instance, a recent study revealed the development of an artificial intelligence-driven mobile intervention proposing programmes depending on individual needs to minimise nurse burnout. Nurse managers made good use of the tools since they helped to lower turnover and preserve treatment quality. By raising nurse satisfaction, reducing running costs, and improving healthcare institution efficiency, this AI-driven approach raises the quality of healthcare. Personalised AI treatments can, thus, help to lower nurse burnout, increase staff retention, and foster strong and wellbeing-supportive surroundings [8].

5. Artificial Intelligence in Nursing and Healthcare

Over the past half-century, AI in healthcare has experienced significant evolution, especially with the introduction of machine learning (ML) and deep learning (DL) technologies [65,66]. In medicine and nursing, these technologies have extended the use of AI and enabled a change toward customised techniques rather than algorithm-only methods [71]. Predictive artificial intelligence models now provide preventative care and disease detection, monitor disease, and streamline clinical workflows to enhance patient outcomes; these models can also increase diagnostic accuracy, expedite clinical procedures, monitor disease and therapy, and improve procedural accuracy [20,72]. The early phases of AI, which occurred between the 1950s and the 1970s, included technologies such as Unimate, the first industrial robot launched in 1961, and Shakey, a mobile robot created at the Stanford Research Institute [73]. These early years focused on the development of devices able to provide typically human-made conclusions based on analysis. Though these developments marked standards in robotics and artificial intelligence, the healthcare sector, especially nursing, fell behind in adopting artificial intelligence since the emphasis was primarily on digitising data necessary for the growth of AI in healthcare. Significant achievements such as the development of early clinical informatics databases and the Medical Literature Analysis and Retrieval System (created in the 1960s) lay a solid basis for the following applications of AI in patient care and nursing support [74].

The so-called "AI winter" took place between the 1970s and the 2000s and led to less financing and fewer artificial intelligence discoveries, but notable AI-healthcare partnerships persisted. Clinical researchers were able to network with one another because of the programs developed at the Research Resource on Computers in Biomedicine, Rutgers University (1971), and the Medical Experimental–Artificial Intelligence program, Stanford University (1973) [75]. Early uses included the 1976 CASNET model for glaucoma diagnosis and MYCIN (1972), which examined bacterial infections and suggested antibiotic therapies [76]. The main ways that AI support tools were included in nursing during this period were electronic health records (EHRs) and decision support systems like DXplain (1986), which were developed at the University of Massachusetts [75]. As an electronic medical textbook and a clinical assistant, DXplain helped create differential diagnoses depending on symptoms. DXplain and other EHR systems provided an early layer of artificial intelligence in nursing. In 1980, the robot HelpMate was developed and mainly served as a transport system, but was first installed in hospitals in 1991 to transport materials [77]. While increasing workflow efficiency, these instruments assisted nurses with regular decision-making and patient data management.

Beginning a transforming phase between 2000 and 2020, new tools and applications were developed to increase the integration of AI in nursing. Paro, a social robot, was created in the early 2000s in Japan and was intended to be a therapeutic companion to patients, especially elderly people [78]. This innovation reduced some of the caregivers' workload, particularly in long-term care settings. Later, in 2009, Japan developed another robot, Robot for Interactive Body Assistance (RIBA), which could help nurses lift and transfer patients [79]. Designed by Diligent Robotics, Moxi, a nurse-assisting robot, was deployed during the COVID-19 pandemic to handle tasks including cleaning supplies, the delivery and retrieval of medical tools, and specimen handling. Moxi moves independently within hospital settings, reducing nurses' time on errands, and improves their availability for patient interaction [80].

In 2011, IBM's Watson represented a significant advancement in AI with its open-domain question answering skills, NLP, and data analysis from unstructured sources [81]. Watson's applications in medical research, such as the 2017 identification of RNA-binding proteins linked to amyotrophic lateral sclerosis, showcased the promise of AI in evidence-based clinical decision-making [82]. These programs also set the stage for related nursing decision support systems. AI applications in nursing, particularly through EHRs, expanded rapidly during this period by using predictive analytics to track patient outcomes and assist in managing nursing jobs [83]. Chatbots and virtual assistants are being developed using AI to streamline administrative tasks and enhance patient education. Introduced in 2015, Pharmabot gave young patients and their parents medicinal advice [21]. Developed in 2017, Mandy helped simplify patient intake in primary care, reducing the administrative tasks assigned to the nursing staff [84]. DL applications such as convolutional neural networks (CNNs) became extensively used in diagnostic imaging by the late 2010s to enable nurses and other healthcare workers make correct evaluations based on medical pictures [85,86]. These programs replicate neurological processes to allow these experts to make accurate evaluations.

These developments have made AI increasingly critical in nursing since it combines instruments necessary for nursing operations in monitoring, diagnosis, and patient education. More recent uses of AI, such as predictive algorithms to track nurse burnout, can reduce stress and provide customised solutions. These tools show growing dedication to clinical decision-making boosted by AI, efficiency, and patient care quality. AI-driven CDS systems were also designed to analyse real-time data and provide alerts to facilitate early intervention [2,3]. Additionally, AI-integrated automation in administrative tasks, such as scheduling and documentation, can reduce the nursing workload to a greater extent [23,24]. This trajectory emphasises the possibilities of AI to improve nursing, raise job happiness, and lower nurse turnover, helping to establish AI as a fundamental benefit in healthcare and nursing practice.

5.1. Chatbots in Nursing

The chatbot, a conversational agent, is an AI-powered computer program designed to simulate human-like conversations. It can chat through text, voice, or visual interactions, allowing users to engage as they would with a natural person [87]. It is one of the critical applications of AI, enabling users to communicate via text-based methods with agents that respond intelligently to their queries. Chatbots can be provided in various forms, such as text-based interfaces or voice assistants. The basic technology used is NLP and DL. NLP lets systems understand and interpret human language, which enables chatbots to perform user queries or commands effectively. Through this technology, chatbots can often include sentimental analysis to gauge user emotions and communicate accordingly [88]. Additionally, large language models (LLMs) have significantly advanced the field of NLP [89]. LLMs are based on neural networks capable of understanding complex linguistic patterns and contextual relations and generating human-like responses.

Due to LLMs, the technology has advanced capability for text recognition, translation, speech recognition, language generation, etc. [90]. These conversational agents can be used to support mental health and are suitable for addressing nurses' mental challenges. Chatbots like Wysa [69] and Woebot [70] would be best suited for nurses who face stress, burnout, post-traumatic stress disorder, depersonalisation, or any other psychological distress and are also reluctant to seek traditional therapy due to stigma or time constraints. They can deliver cognitive behavioural therapy (CBT), mindfulness, and positive psychology techniques that can reduce stress, anxiety, and depression [70]. A recently published meta-analysis study established the relevance of chatbots in alleviating anxiety and depression [91]. The results highlighted several essential aspects of depression, such as the positive outcome of chatbot-mediated psychological intervention and a short treatment period with efficacy on par with traditional psychological therapy. However, the long-term benefits of chatbots were unclear. Apart from their use in mental health support, they can also help reduce nurses' workload by automating routine tasks like providing medical reminders, scheduling appointments, and handling casual and repetitive queries from patients [92]. Providing timely reminders and improving patient adherence chatbots can help healthcare providers [93]. Thus, the automation of similar non-urgent tasks can help nurses focus more on direct patient care and reduce their work burden and resultant stress or burnout. However, using chatbots has limitations, such as poor patient adherence due to a lack of consistency or transparency, which genuine human care could provide.

5.2. Robots in Nursing

AI-powered robots were first introduced in healthcare in the 1980s [77]. These robots offer a better solution for the growing demands on nurses. They could help nurses reduce their workload by engaging in repetitive and physically demanding tasks, patient monitoring, and clinical decision-making. Robots are a better addition to the healthcare industry in reducing nursing stress and burnout. Though they are not replacements for the human workforce, they are regarded as assistants because they can help nurses and other healthcare providers when the workforce is overloaded or in special conditions like the COVID-19 pandemic [58,94]. They can be deployed in monitoring, testing, pre-diagnosis, delivery of medications and meals, collection and delivery of lab samples, etc. Relay and TUG are examples of robots logistically used in healthcare to carry and deliver medicines, biological samples, etc. [95]. Veebot is a robot that can insert a needle into a patient' s veins to draw blood with an accuracy of 83%. However, the AI-powered advancements in robotics progressed in the early 2010s. ROBEAR, a Japan-made robot, can help patients to stand up or can lift and assist them into wheelchairs. This robot can also recognise faces and voices and respond to voice commands [96]. The robot, Pepper, aided nursing care, especially during the COVID-19 pandemic, in monitoring body temperatures and reminding people to wear masks and disinfect their hands [97]. AI-powered robots use ML, DL, NLP and computer vision, which helps them move around complex environments, avoid obstacles, and interact with patients effectively [4]. While they greatly support healthcare providers, there are concerns about privacy and ethical implications [98].

5.3. Predictive Analytics

Owing to the nature of their work, nurses sometimes need to focus on patients who need emergency or critical care; nurses need to prioritise patients, and here, another AI tool—predictive analytics—can assist them. There is a bulk of data in hospitals, such as laboratory results, past medical history, medication history, and allergy information; predictive analytics, which runs on the principle of ML, builds algorithms from these existing data and analyses them to forecast possible outcomes or recommendations [14]. Predictive models can identify risk factors and guide clinical decision-making for better patient care and outcomes. They help healthcare providers tailor unique treatment plans to individual patient requirements and characteristics. The outcomes of such interventions will improve patient satisfaction [99]. From the perspective of healthcare institutions, predictive analytics can be best utilised for efficient resource allocation, maximising efficient healthcare delivery. ML algorithms, such as decision trees, random forests, support vector machines, k-nearest neighbours, and gradient boosting machines, are widely used in healthcare predictive modelling [100].

Some predictive models can analyse and identify high-risk patients regarding disease progression and intervention in chronic diseases like heart diseases, hypertension, and diabetes [1,101,102,103]. For instance, a 2018 study aimed to develop a model for estimating the probability of 30-day readmission in heart failure patients discharged from the hospital. At the optimal categorisation level, the deep, unified network predictive model achieved an accuracy of 76.4% to maximise healthcare cost-effectiveness. Such models help to identify patients with heart failure at high risk of readmission, allowing care teams to focus treatments on those most in need, thus improving clinical outcomes [104]. Similarly, a recent study involved developing and implementing a predictive analytics system to gauge readmission risk in Midwestern hospitals [105]. The study showed that the models effectively guided care teams in timing interventions and adapting strategies through the patient' s further care planning. Another predictive model observed whether a patient could be discharged to a nursing home, allowing hospitals to manage patient capacity and flow for timely surgical care [106].

5.4. AI-Driven Patient Monitoring Systems

AI-driven patient monitoring systems let nurses provide more customised and effective treatment by including multiple technologies for different healthcare situations. Remote monitoring systems are especially suitable for monitoring geriatric [107] and chronically ill patients [108] and general and surgical wards [20]. In both inpatient and outpatient environments, wearable gadgets with AI capacity constantly track vital signs like heart rate, oxygen levels, and movement patterns [109]. There are also intelligent beds and in-room sensors in hospitals that help to constantly monitor patients' vital signs, body position, and mobility [110]. In a study from 2023, patients' vital signs were monitored using Philips' IntelligVue Guardian (an automated electronic guidance system), and this approach showed cost-effectiveness and enhanced patient safety [111]. As well as helping nurses with remote patient monitoring, some devices even monitor chronic conditions such as diabetes, hypertension, and heart disease using AI, notifying nurses when readings go beyond safe levels [112]. This remote arrangement helps nurses to intervene as needed and adequately monitor large patient numbers. Especially in intensive care units and postoperative recovery environments, these AI-equipped systems are highly supportive by helping nurses to intervene quickly by identifying early signs of issues such as falls, sleep apnoea, or agitation [110]. Contact-based sensors and wearable devices (Internet of Things (IoT) models) help nurses and other healthcare providers make quick decisions and attend to those in need as soon as possible. With the integration of AI-powered monitoring devices, the strenuous task of manually charting every change in a patient's condition is now replaced by automatic data logging [113]. These devices reduce the need for hand-held checks, freeing nurses from some of their obligations and freeing time for other, more vital tasks. Overall, these monitoring devices reduce the possibility of significant events and help early response, improving patient safety.

6. Benefits of AI to Nurses

6.1. AI and Mental Health Support

The application of AI presents various advantages for the mental distress faced by nurses (Figure 2). While referring to the accessibility of help for nurses in addressing their various mental distresses, the irregular shifts and work schedules are a hindrance. These irregular shifts and work schedules in themselves create physical illness and time constraints, due to which they could have limited access to traditional health services during regular working hours [114,115,116]. With the integration of AI, nurses can manage their work schedules and workloads without compromising patient care. A recent study from Jordan with a group of 112 registered nurses showed that AI supported the nurses in patient monitoring and decision assistance, thereby enhancing time management and work efficiency [117]. While these tools can alleviate nurses' mental distress, there are also AI-powered mental support systems that they can use at their convenience as they are available 24/7. For instance, Wysa and Woebot offer them real-time support, and these systems provide on-demand mental health support such as mindful exercises, cognitive behavioural therapy, and stress relief exercises [69,70]. It is also noted that mental health stigma remains a significant barrier for nurses seeking traditional support for mental distress [118]. Fear of judgement from colleagues or admitting having mental health troubles can affect their professional reputation. With the support of AI-powered systems, they can maintain anonymity, thereby avoiding these circumstances and, in turn, making the mental health support system approachable [119]. Chatbots like Talkspace and BetterHelp are online treatment systems that link patients with certified therapists using various media, including voice, text, and video chat [120]. Both systems pair patients with therapists who are fit for their particular needs using AI technologies. To meet different mental health needs, BetterHelp offers a more extensive range of therapeutic modalities including cognitive behavioural therapy (CBT) and psychodynamic therapy, whereas Talkspace delivers a simplified experience for linking users to mental health professionals. This type of barrier-free access to mental health support can help to prevent stress and burnout, the two most prevalent issues.

Another benefit of using AI systems is that they provide personalised mental health support, addressing the unique needs of individual nurses [121]. Using inputs and behavioural patterns, AI algorithms can generate tailored recommendations, thus increasing the quality of personalised, accurate feedback. Shine is an example of an AI tool that provides tailored daily motivation and assistance. It uses AI to identify users' needs and preferences, providing tailored materials and resources for them [120]. Interventional tools should be able to adapt dynamically to the evolving needs of the users. Using gamification ideas and affordance-based design, gamified smartphone software for mental health management tool was developed that lets users participate in deep breathing exercises [122]. The device uses ML to provide real-time biofeedback, guiding users through breathing exercises with interactive visuals and modifying to fit individual breathing patterns to generate customised recommendations. The results showed notable declines in stress markers and higher user engagement, highlighting the possibilities of AI-driven therapies to enhance mental health outcomes.

Other AI tools like Ginger and Woebot continuously monitor users' interactions and adjust their interventions accordingly [123]. Nurses who use them receive real-time feedback, which helps them to manage stress before it escalates. Apart from real-time feedback, these systems can also analyse biometric data from wearables and smartphones. These data could be obtained from sleep patterns, heart rate, or activity levels. Such levels of personalisation enhance the overall result of interventions and encourage sustained engagement with the mental health support system with no additional cost, unlike traditional therapies.

AI-powered mental health support systems present much more cost-effective alternatives, and some platforms are free or at a minimal subscription fee compared to traditional therapy [69]. The cost-effectiveness would be feasible for healthcare institutions and individual nurses, who might struggle to afford regular therapy sessions. A study in 2017 highlights this aspect of AI-based mental health interventions, especially in large healthcare systems where nurse burnout is prevalent [124]. In another study involving 75 individuals from 15 different US colleges, an AI-driven mental health tool called Tess underwent a randomised controlled experiment [125]. The trial's goal was to ascertain whether Tess helped to reduce depression and anxiety symptoms. Three groups were formed from the participants: two groups had free access to Tess, one group had daily check-ins for two weeks, and the other group had bimonthly check-ins for four weeks. Conversely, the control group consisted of just receiving an instructional link to the eBook of the National Institute of Mental Health. The results showed that Tess significantly helped both intervention groups to lower their anxiety and depression symptoms when compared to the control group. This suggests that Tess influences mental health very well. Furthermore, members of the intervention groups claimed better mood, which emphasises Tess's possibilities as a reasonably affordable and readily available support aid for the treatment of mental health issues. Tess is not meant to be a trained therapist. Still, AI technologies like Tess can be used as scalable and reasonably priced options for providing psychological help.

6.2. AI Support in Nursing Care

Using advanced technology, AI-integrated nursing care helps nurses to deliver more efficient treatment and optimises workflows and patient outcomes. Combining AI-driven solutions with traditional nursing practices helps hospitals to satisfy complex patient needs and reduce nursing staff workloads [13]. Automating routine activities such as vital sign monitoring and data collection helps create effective workflow and time management by freeing nurses to focus on direct patient care [108]. Besides monitoring, automated alarms and notifications for critical test results or changes in patient conditions improve emergency response capacity [121]. Thus, real-time data and clinical decision assistance, which are readily available and support evidence-based treatment and educated clinical judgement, can improve therapeutic results. Concerning work schedules, when automated, it can reduce disputes and guarantee a sufficient workforce, improving the efficiency of administrative chores [117]. Better nursing care could be offered to patients if nurses endure less documentation and can incorporate AI tools into specific jobs to improve accuracy and optimise billing and documentation [25]. Using EHRs ensures complete, current patient records, reducing errors connected to manual record-keeping and improving patient care and safety [65]. Moreover, pharmaceutical management methods using barcoding and automation greatly reduce drug mistakes, enhancing patient safety [126].

Communication between nurses, patients, and other healthcare staff must also ensure safe and quality nursing care. Effective communication influences patient education, adherence to the treatment guidelines, early identification of health issues, and general patient satisfaction [127]. By giving patients access to health education resources, technology helps improve their understanding of their diseases and treatments, enhancing patient education and involvement. Wearable remote monitoring helps patients track their health, encouraging self-care and increased participation in health management [22]. AI applications like telehealth and telemedicine allow doctors and nurses to offer care to patients from afar, especially in underdeveloped areas. Digital tools also make it easy for healthcare workers to work together, which improves care coordination [18]. Even chronic diseases could be managed by AI. For instance, DIABTel is a telemedicine system used to manage patients with type 1 diabetes [19]. The system consists of a clinical operating system used by hospital nurses and doctors and a patient unit used for daily activities by patients. It is possible to collect, manage, and interpret data and allows the exchange of data and messages, thereby ensuring prompt care.

7. Challenges in Implementing AI in Nursing

Though there are sufficient reasons to suggest that AI could enhance nursing care, significant challenges exist in the healthcare context. Some of the challenges are mentioned below.

7.1. Reliability and Accuracy

AI systems applied in health assessments usually depend on algorithms that generate false positives or negatives, which can affect diagnosis and treatment [128]. Owing to this, concerns have been raised about the reliability and accuracy of AI systems. AI sometimes shows algorithmic biases, aggravating this issue considerably since they could disproportionately impact marginalised populations [129]. AI models’ training datasets may not entirely reflect the patient populations they are meant to serve. An example of this issue is given by a 2019 study by Obermeyer et al. Their analyses revealed that AI algorithms applied to predict health risks often overstated the care demands of black patients in contrast to white patients, therefore generating uneven treatment [130].

Avula et al. looked at the quality of data provided by AI tools in the healthcare sector and found incompatibilities in some AI systems [131]. Any flaw in analysis or recommendation can increase the chance of misinterpretation due to missing or outdated information. The possibility of errors in decision-making and treatment outcomes because of AI support in healthcare is also mentioned elsewhere [132]. Unreliable or inaccurate results could be produced due to data merging [133]. Many hospitals and clinics use several software tools, and these technologies may not always work together. There is a lack of standardisation of these AI solutions in the healthcare sector, developed independently by several companies. Among the several data sources that nurses are expected to handle, some of the most often used ones include patient reports, wearable technologies, and EHRs. Organising all of these distinct data in a way that AI systems can understand and exploit can be difficult. For example, AI-driven systems that help nurses monitor patients can spot problems, but these systems might not always have expert judgement from years of work experience [134].

7.2. Data Privacy and Security

The healthcare sector accounted for 15% of all global data breaches in 2017, the second-highest percentage at that time [135]. Data privacy and security are essential for applying AI in nursing, especially for delicate patient data like mental health records [136]. Exceptionally delicate information about mental health may be used or exposed to cyberattacks if it is not securely guarded [137]. The spread of AI technologies has heightened these concerns in the healthcare sector. For instance, in 2015 alone, 112 million healthcare data records were breached [138]. Since AI systems often use cloud-based servers to handle data, they make it easier for hackers to obtain access to systems. Many AI models are trained on massive datasets, including personal information, so it is crucial to safeguard these data both during storage and transmission [139]. Apart from the risks caused by outside players, internal stakeholders have voiced concerns about data abuse [140]. Patients may suffer greatly regarding reputation from the exposure or use of healthcare data, including discrimination, stigmatising, insurance loss, or unemployment [141]. Given these issues, strict government and privacy standards must be followed. For instance, regulatory bodies like the General Data Protection Regulation (GDPR) in the European Union and the Health Insurance Portability and Accountability Act (HIPAA) in the United States came into existence to help reduce these risks [142].

Inaccurate assessments compromise the quality of the given treatment and confidence in the technology. Regarding mental health assessments, nurses who depend on AI systems could be obliged to make tough ethical decisions should the AI recommendations contradict their clinical judgement. In a recent study on AI-assisted decision-making in nursing practice, the participants pointed out that depending too much on the AI system could lead to misguidance [143]. Further, they stated that this could lead to inappropriate care strategies and negative effects on nursing care resulting from unforeseen events or erroneous or suboptimal recommendations by the system. Being a technological assistant in healthcare lacks human qualities, unlike nurses, who lack contextual awareness. Hence, it may misinterpret circumstances owing to the speed with which information is processed [144].

7.3. Resistance to Adoption

Nurses have hesitated to incorporate AI in clinical applications as they mostly do not understand the process or logic it uses [145]. A recent study from Saudi Arabia found that nurses had only a moderate level of knowledge about AI, and only slightly over half (58.2%) of the participants had any practical knowledge of AI-integrated technology [146]. This study's analysis also showed a conservative attitude towards AI, which extends from mild caution to considerable resistance against incorporating AI into nursing practice. This apprehension arises from fears of job replacement, mistrust towards AI regarding reliability and accuracy, other ethical concerns about job displacement, doubts regarding AI's reliability and accuracy, and ethical fears concerning patient privacy and inadequate training. Because of their complex algorithms, AI models, commonly called black boxes, make it difficult for health practitioners to understand how they conclude decision-making or suggestions [147]. Particularly in high-stress settings like intensive care units, it is not unusual for nurses to voice concerns about the validity of AI solutions [148,149]. Hence, there is a lack of trust in AI systems in critical situations and resistance to adoption into healthcare. A study from 2023 found that 23% of nurses feared AI, and 36% had some negative attitude towards using AI [150]. Researchers recommend including AI awareness and training in nursing education, sprouting from the results of their study that 74.8% of nurses lacked a solid understanding of AI, and 12.7% of the participating nurses perceived AI as a threat to them rather than an opportunity [151]. Consistent with this study, another group of nurses showed that 70% had inadequate or no knowledge about AI techniques [152]. Most of the literature points to the fact that there is resistance to AI adoption primarily due to a lack of awareness and knowledge that could prevent nurses from effectively utilising the possibilities of AI and, hence, not exploiting the application to its full utility or even making mistakes while using it [153].

8. Ethical Implications of AI in Nursing

AI integration in nursing also presents some critical ethical concerns (Figure 3), such as privacy, bias, and accountability, along with the necessity to preserve the fundamental "human" aspect of nursing [154]. Examining these ethical issues will help guarantee the correct use of AI capacity while safeguarding patient welfare and the rights of both patients and nurses.

AI typically depends on large databases, including personal data, to improve treatment quality. Sensitive data, particularly from monitoring devices that could record physiological and psychological metrics including emotional states, are prone to privacy issues [137]. Even though these data-driven insights have many clear advantages such as the early identification of health hazards, they also pose the danger of exposing private data as these platforms are prone to breaches. The data utilised in AI algorithms can be shared with third-party entities without intending to do so [155]. This could result in the prospect of exploitation, therefore undermining patient faith in systems like AI. The privacy of nurses is also in danger, especially in hospitals where AI algorithms assess staff performance and workload and employee data in hospital systems [156]. These systems may collect and analyse sensitive employee information without explicit consent or adequate anonymisation, raising privacy concerns. In the event of a cyberattack, the whole hospital system could come under threat, including the leak of personal information of patients and staff [157]. A pronounced example of this is the 2017 "WannaCry" ransomware attack affecting 230,000 computers in 150 countries and disrupting the operations of the National Health Service (NHS) in England [158]. In this incident, hospital staff were locked out of their computers, and hackers demanded payment to restore access to encrypted data [159]. This incident stressed the susceptibility of healthcare systems to ransomware attacks, with far-reaching impacts on patient care and hospital operations.

All health sectors are concerned about data privacy and the risk of AI systems mismanaging personal information

[141]. To handle privacy concerns effectively, robust security policies and open data governance must be followed. This will guarantee that data concerning nurses and patients are preserved safely and used for authorised purposes. Another ethical concern with AI technology is AI bias, often leading to inaccurate or suboptimal treatment outcomes [160]. AI biases can lead to serious consequences by reinforcing societal biases. When specific groups, such as gender and ethnic minorities, are underrepresented in big data, AI systems may misdiagnose these patients more often with undesirable healthcare outcomes [161]. For instance, a bias in the algorithm assessing eligibility for kidney transplants favouring certain demographic groups resulted in a delay in kidney transplants amongst the minority group [162]. Thus, AI models repeatedly produce erroneous findings due to variations in how demographic variables such as gender, colour, or age are expressed in datasets. Another study showed how exclusion led to the underrepresentation of African Americans in clinical studies [163]. To solve such concerns, when designing AI tools, the developers should be able to combine diversity into algorithm training datasets, fairness-oriented data mining techniques, and frequent evaluations to identify and correct discriminating results. One of the ways health systems can lower bias is by assembling diverse teams comprising professionals from clinical, social, and technical domains. These groups are more suited to identifying possible prejudices and create fair and inclusive activities. Moreover, including a spectrum of patients and local populations in developing clinical algorithms enables us to consider various requirements and points of view. This can lead to framing algorithms that better aid underrepresented groups [164].

The next important ethical concern is accountability and transparency [154]. Complex models such as neural networks can provide highly accurate forecasts without information on how judgements are made, which makes it challenging for healthcare providers to depend entirely on these outputs since they typically act as “black boxes” [147]. Transparent and ethical AI systems enable the avoidance of possibly negative or permanent consequences on patients, promoting responsible and reliable AI utilisation for important medical purposes [165]. AI models that clearly explain their decisions can achieve transparency. They also need clear lines of accountability for choices affecting AI-driven systems’ results. This would help nurses have better confidence in their work and enable them to hold those in charge of mistakes liable should they happen [166]. Several methods can achieve transparency: explainable AI, open-sourced algorithms, transparent data practices, and regular audits [154]. However, enabling transparency has several challenges, including implementation complexity, security risks, and resource-intensive maintenance.

One of the most important and core ethical considerations is balancing technology and the “human touch”. The nursing profession embodies profound significance through the essential values of human touch and compassionate care [167]. This is because the “human touch” determines the mental state of nurses and patients. In mental healthcare, where human interaction can be equally crucial as treatment, the sympathetic bond between nurses and patients usually results in therapeutic gains. A recent study reported human touch in care as a challenge in AI–healthcare integration [168]. Yet another study emphasises that regardless of technological convenience, AI integration should be approached carefully due to the significance of the nurse–patient relationship [108], thus stressing the need to find a balance between the efficiency of technology and the provision of personal care. This would demand creating a setting where empathy and technology coexist to raise the standard of treatment without erasing the nurse–patient relationship. Appropriate attention to definite policies, transparent algorithms, and fair procedures could assure ethical integration and accountability. Addressing these concerns will make tremendous progress in AI-integrated nursing care.

9. Future Directions and Recommendations for AI in Nursing

Studies have corroborated that AI transforms nursing practice by increasing productivity, lowering stress, and improving patient care quality. For instance, in a study on intelligent surveillance systems, AI was demonstrated to reduce nurses' 18 min- to 10 min interaction time with patients [169]. Real-time updates on the patient's health situation helped them to do this. This helped nurses to focus on delivering vital treatment and avoid subsequent injuries and patient crises. A study conducted in Colombia revealed that more than half of nurses' time is spent on non-professional activities [170]. These tasks include waiting for the doctor's approval (which may take 85 min daily) and inputting duplicate data, which might be automated to save up to 10% of their time and maximise resource utilisation. Based on studies on robot-assisted nursing, 67.2% of nurse managers said that, without replacing nurses, robots might significantly lower workloads [171]. Integrated studies also underlined the value of robots in delivering medications and patient monitoring, enhancing safety and satisfaction. Moreover, there is a relationship between the use of robots to help with professional work and increased job satisfaction, as well as claimed improvements in health, which, in turn, lowers the possibility of nurses leaving their present jobs. Research comprising 331 nurses carried out in Taiwan confirmed these benefits [172]. The study underlined how robotic technologies could help nurses focus their efforts from non-professional tasks into professional ones. Furthermore, another study revealed that AI technologies, such as CDS systems, have helped simplify processes. Forty per cent of nurses have reported better patient monitoring, thirty-six per cent have experienced reduced stress levels, and twenty-seven per cent have noted more accuracy in daily tasks whilst using AI [173]. The accomplishment of an 87% agreement rate with the diagnosis given by nurses by means of adaptive-network-based fuzzy inference systems is another illustration of the superior diagnostic accuracy demonstrated by AI-powered nursing information systems [174]. Apart from cutting the non-essential time spent working, these technologies improved the quality of data collection, thereby enabling faster response to issues related to patient health. It has been shown that humanoid robots, such as Pepper, could increase interaction with the long-term care of dementia patients [171]. However, to fulfil their potential, more technical developments are needed. Together, these results show the transforming power of robotics and AI in lowering workloads, improving diagnosis accuracy, and supporting nurse wellbeing while concurrently sustaining high-quality patient care.

However, ongoing research is essential to validate the use of AI technologies in nursing. This guarantees that these technologies are based on facts and tailored to satisfy nursing care requirements. AI will likely use general solutions that overlook nurses' specific circumstances, such as high-stress environments and patient diversity, in the lack of validation. Studies conducted in the field of AI support this [175,176]. Developers can establish their safety and efficacy through trials and longitudinal studies on AI products. Using their respective applications, these technologies are meant to lower nursing burnout risk, increase patient care accuracy, and boost mental health. Customised AI systems must include input from nurses and stress practical applications, including patient triage, mental health surveillance, and task management, to serve nursing professionals' objectives properly.

Nursing education has to include AI if we want to raise healthcare workers' degree of understanding and readiness concerning this technology. Incorporating AI training into nursing courses will help to ensure that future nurses fully grasp the possibilities and constraints of AI within the framework of the healthcare sector. This might promote early acceptance of AI and help to lower the usually adverse reaction against technological advancement. If nurses had primary training in algorithmic decision-making or patient data analysis, they would be more suited to working successfully with AI tools. AI methods would help them enhance clinical judgement instead of replacing it, benefiting society. Early involvement with AI can help produce a workforce confident in its capacity to employ AI technology responsibly in medical care settings.

Clear policies and ethical standards help to guarantee that AI is applied with responsibility in nursing. Since healthcare is a sensitive topic, these guidelines should concentrate on ensuring that AI helps to maintain patient and staff safety. Emphasising that privacy and morality are the most critical concerns in these kinds of AI uses, laws could demand explicit algorithms, safe data, and moral usage in mental health tracking. Policies supporting "explainable AI" ensure that nurses comprehend and accept the recommendations of the AI, therefore ensuring that its decisions correspond with the nursing code of ethics and values stressing the patient.

Working together, technologists, medical professionals, and legislators should produce safe and morally and practically effective AI solutions. By working with healthcare professionals, AI developers can create solutions that satisfy practical needs by integrating modern technologies with the experience of daily caregivers. Although legislators support the proper use of AI, they also significantly contribute to creating legislation safeguarding the interests of providers and patients. By working collaboratively, nurses can employ AI to enhance treatment; one way to accomplish administrative tasks to lower staffing requirements is by automation. This can be achieved while acknowledging the vital human and personal nursing elements.

10. Conclusions

AI has shown great promise in transforming how nurses obtain mental health support by developing fresh approaches to handling complex issues like burnout, stress, and compassion fatigue. AI tools like predictive analytics, virtual companions, and tracking systems run by AI help mental healthcare and help nurses and technology collaborate more efficiently. The capacity of AI to forecast the future allows healthcare systems to identify which nurses are more likely to have mental health issues, enabling quick assistance for them and lowering occupational stress. People can also use virtual companions and chatbots, making mental health resources available twenty-four hours a day, seven days a week. These instruments offer individualised help in addition to conventional treatment. These advancements demonstrate how well AI can help protect nurses' emotional and mental wellbeing, enhancing patient care and easing their employment. Nonetheless, using AI in nursing care must have a clear ethical foundation. Protecting data privacy, addressing biases, and maintaining open AI systems help avoid ethical issues and foster trust in healthcare environments. Any AI solution designed to support nurses' mental health must abide by rigorous data security policies if we are to keep this information safe. While maintaining the compassionate, person-centred approach at the core of nursing, one should also consider how AI tools might alter how a nurse and patient engage. AI should enhance rather than replace the loving ties that define nursing care. We must ensure that AI is thoroughly used in nursing in the future, using additional research, wise investments, and monitoring of ethical issues. Legislators, research institutes, and hospitals should cooperate to create comprehensive guidelines supporting morally sound and effectively operating AI capabilities. Training courses should also be designed to inform nurses about the advantages and drawbacks of AI so that they may apply these tools with assurance and effectiveness. Using AI wisely would enable the healthcare sector to strengthen its staff, enhance patient care, and safeguard nurses' health.

Author Contributions

Conceptualisation, H.G.D. and M.K.; writing—original draft preparation and review, H.G.D., M.K., A.S., T.K. and M.Z. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

All data related to this study are provided in the manuscript. The data presented in this study are available on request from the corresponding author.

Conflicts of Interest

The authors declare no conflicts of interest.

Footnotes

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Figures and Tables

Figure 1. Mental distress experienced by nurses.

Figure 2. Advantages of AI in mental health support.

Figure 3. Ethical implications of AI in healthcare.

Table 1

Benefits of AI in nursing.

Benefit	Description	Reference
Improved Patient Care and Safety	• Accurate Documentation: EHRs ensure comprehensive, up-to-date patient records, minimising errors in manual records.	[17]
	• Medication Management: Barcoding and automated systems reduce medication errors.	
Enhanced Communication and Collaboration	• Telehealth and Telemedicine: Enables remote consultations, monitoring, and care for patients in underserved areas.	[18,19]

	• Care Coordination: Digital tools enable seamless collaboration among healthcare teams.	
Efficient Workflow and Time Management	• Automation of Routine Tasks: Vital sign monitoring and data collection automation, freeing up time for patient care.	[20]
	• Quick support: Quick access to guidelines and patient information aids rapid decision-making.	
Real-Time Data and Clinical Decision Support (CDS)	• Evidence-Based Care: Access to current research and guidelines supports informed clinical decisions.	[2]
	• Alerts and Notifications: Automated alerts for critical labs or condition changes enhance emergency responses.	
Enhanced Patient Education and Engagement	• Health Education Resources: Technology provides educational materials to improve patient understanding.	[21,22]
	• Remote Monitoring: Wearables allow patients to track their health, enhancing self-care and engagement.	
Increased Efficiency in Administrative Tasks	• Scheduling and Staffing: Automated scheduling ensures adequate staffing and reduces conflicts.	[23,24,25]
	• Billing and Documentation: Streamlined billing and documentation reduce paperwork and improve accuracy.	

Table 2

Overview of AI integration in nursing.

Type of AI	Description	Example of Healthcare Application	Reference
Predictive Analytics	Forecasts patient deterioration, enabling early intervention	Early warning systems (e.g., heart rate observation that alert nurses about potential patient risks	[64]
Natural Language Processing (NLP)	Assists in clinical documentation and extracts critical information from patient records	DeepCura, Nightingale Notes by Trusted Health, Suki AI Assistant for generating nursing care plans based on patient records	[65]
Machine Learning (ML)	Analyses data to classify and predict patient conditions	Sepsis Watch model to predict sepsis onset, supporting faster nursing response	[66]
Robotic Process Automation (RPA)	Automates administrative tasks, reducing workload	Automating appointment scheduling and medication reminders for patients	[67]
Computer Vision (CV)	Interprets visual data for patient monitoring and alerting nurses	Physiologic monitoring or detection of patient movement	[68]
Conversational AI	Engages in patient communication and symptom assessment	Chatbots like Wysa and Woebot provide mental health support to reduce nurse workload	[69,70]

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A Novel Approach to a Hybrid Security System Using Operator Machine Augmentation Resource (OMAR)

Ameen, Mohammed . Ameen, Mohammed.

ABSTRACT (ENGLISH)

The recent increase in the threat level concerning the public has made government and security organizations look for better and more secure ways of monitoring crowds. These systems employ both vision and non-vision techniques in order to control crowds of people and avoid situations that might be difficult to predict or control. This paper looks at these methodologies and explores how they can be combined with artificial intelligence (AI) to improve surveillance. Another contribution of this work is the proposition of the Operator Machine Augmentation Resource (OMAR) framework that leverages state-of-the-art technologies such as computer vision and specific training for CCTV operators to overcome the weaknesses that characterize legacy surveillance systems. The OMAR framework is designed to provide the operators with better tools for improving productivity and, thereby, surveillance system efficiency and security. The research also looks at the outcome of the hybrid security systems based on the level of training of the personnel involved and the level of AI support. The study does this by developing a human security information model and then using it to forecast the potential performance of these systems using elements such as response time, accuracy, cognitive load, visual discrimination, trust, and confidence. Subjects were split into trained and non-trained groups and were assigned surveillance tasks with and without AI. The analysis of the results of the trained models, such as Linear Regression and Random Forest, showed that training enhances performance through error reduction and accuracy increase and that AI enhances speed and efficiency but sometimes may increase the errors, especially in the non-trained groups. AI support also helped decrease the cognitive workload in the trained participants and increased the trust and confidence of non-trained participants. The study's results also identify the relationships between the operator, AI support, and training in hybrid surveillance systems. These findings underscore the necessity of creating measures to foster the trust of operators in AI-based systems and improve the cooperation between the operators and AI. The study indicates that future studies should test the OMAR framework and possibly expand these models to examine their usefulness in contributing to public safety and security.

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Essays on Digital Technology-Enabled Mental Healthcare Delivery

Tang, Yi . Tang, Yi.

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ABSTRACT (ENGLISH)

Mental health disorders are a leading cause of disability worldwide, affecting over 700 million people and incurring significant economic costs consisting of direct healthcare spending and lost earnings due to mental health-induced disabilities. The COVID-19 pandemic has exacerbated these issues, highlighting the urgent need for accessible mental health services. Traditional healthcare systems often fall short, particularly due to unique challenges in mental health care delivery, such as stigma and the reluctance of individuals to seek help, as well as a significant shortage of mental health care providers. These barriers are especially pronounced for underserved populations facing economic, geographic, and social obstacles. This dissertation examines the potential of digital technologies to address these gaps through three essays focused on different stages of the mental health help-seeking pathway: initiating care, escalating to professional care, and delivering professional care.

The first essay investigates whether mental health mobile apps (MHMAs) can mitigate the inequities seen in traditional mental health services by helping patients gain equitable self- and peer-support. Using detailed usage data from 1,688 users, the study examines the extent to which MHMAs are utilized and beneficial across different socio-demographic groups. The findings indicate that MHMA usage and benefits are statistically equivalent between underserved and better-served populations, suggesting that these apps can potentially promote equity in mental health support and encourage help-seeking behavior, especially among underserved populations.

The second essay addresses the challenge faced by patients who have already initiated help-seeking on online

platforms but lack timely referrals to professional care when needed. It adopts an abductive reasoning research design and explores the development and exploratory evaluation of an AI-enabled platform designed to improve the mental health service referral process. This platform uses advanced algorithms such as large language models to match users with appropriate mental health services based on their specific needs and socio-demographic backgrounds and deliver the personalized referral process through a chatbot. Initial testing with healthcare providers demonstrates that our proposed AI-enabled online mental health service referral platform has the potential to connect certain patients who have unmet mental health needs with professional mental health services, effectively bridging gaps in service delivery and ensuring timely escalation to professional care for those patients. However, the technology is not universally applicable; it is most effective for certain target populations. The essay also highlights that this AI solution can promote equity by encouraging patients from underserved populations to seek professional care, addressing a key issue where providers, due to long waiting lists, lack the incentive to prioritize equitable service delivery.

The third essay investigates the delivery of professional mental health care through telemental health services, focusing on the factors that influence their uptake and impact on mental health condition at the population level. Using 3-digit Zip Code Tabulation Area-level longitudinal data across 19 U.S. states, the study examines how improvements in provider-side technological infrastructure, specifically enhanced broadband access, and telehealth coverage and payment parity laws affect the adoption of telemental health services. The key finding is that these improvements have a synergistic effect: both enhanced broadband access and telehealth parity laws must work together to drive higher uptake of telemental health services and result in better population mental health condition. This synergy is crucial for maximizing the benefits of telemental health and improving overall population mental health.

This dissertation makes significant contributions to the healthcare operations management literature, particularly in the underexplored context of mental health services. Addressing the unique challenges of mental health care delivery is vital for improving outcomes and reducing the overall burden of mental health disorders. Firstly, the dissertation underscores the importance of expanding healthcare operations management research to include the entire help-seeking pathway, not just the interaction between patients and professional care providers. By focusing on digital technologies that facilitate the initiation of care and the escalation to professional services, this research highlights how these early stages can significantly influence overall care accessibility and effectiveness, contributing to reducing inequities by ensuring that underserved populations can engage with mental health services from the outset. Secondly, the research emphasizes the need to go beyond the traditional 3A-framework of affordability, access, and awareness in healthcare service delivery. The findings suggest that patient acceptance is a critical factor in the effective delivery of mental health services. Ensuring that patients are willing to engage with the services offered, particularly through digital platforms, is essential for achieving equitable health outcomes.

In terms of practical implications, this dissertation offers valuable guidance for policymakers, healthcare providers, and technology developers. For policymakers, the research highlights the necessity of supporting telehealth infrastructure and enacting telehealth parity laws to enhance the uptake of telemental health services. Enhanced provider broadband access combined with telehealth parity laws can work synergistically to improve mental health condition. Healthcare providers can adopt AI-enabled referral platforms to improve the efficiency and accuracy of connecting patients with the appropriate services, thereby addressing a critical gap in the current healthcare system. For technology developers, the findings underscore the importance of designing digital health solutions that are not only accessible and affordable but also acceptable to the target populations. By focusing on these areas, stakeholders can leverage digital technologies to promote equity and efficiency in mental health care, ultimately leading to better population health outcomes.

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Revolutionizing Care: Developing an AI-Human Synergy Mental Health Application for Mental Health Worker’ s Well-Being

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ABSTRACT (ENGLISH)

The development of an Artificial Intelligence (AI) human partnership Mental Health Application (MHApp) for Mental Health Workers (MHWs) aims to integrate AI technology with human expertise to enhance mental well-being. It addresses limitations in existing support systems, such as stigma and accessibility issues, drawing on the Job Demands-Resources (JD-R) model and Perceived Organizational Support (POS) theory. The program development plans to incorporate randomized controlled trials (RCTs) in its future evaluation strategy, aiming to contribute to evidence-based care and generate empirical evidence that underscores the app's effectiveness and ethical integrity. Designed to address these identified challenges, the AI-MHApp offers personalized support by marrying AI's analytical capabilities with the nuanced understanding and empathy of human mental health providers and evidence-based psychological practices. This merging is crucial to ensure valid digital mental health interventions, addressing ethical dilemmas posed by employing AI within this realm, and improving digital therapeutic alliance in clinical treatment to app users. It aims to mitigate job-related stress and enhance organizational support by providing features like self-assessment tools, training modules, and resources for mental health management. This feature is vital for mental health workers who might encounter obstacles in reaching conventional mental health services due to the strenuous demands of their profession or issues related to privacy. Interdisciplinary collaboration ensures a user-centered app that adapts to MHWs' needs. This underscores its ability to close the existing divide in providing mental health care. With its customized approach, the AI-human collaboration within the MHApp aims to notably boost the job satisfaction, mental resilience, and overall well-being of MHWs. These improvements, in turn, are expected to elevate the quality of care they deliver to their clients and diminish turnover within organizations.

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