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Systematic Review

The Role of Machine Learning in AR/VR-Based Cognitive Therapies: A Systematic Review for Mental Health Disorders

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Abstract: This systematic review explores the integration of machine learning (ML) with augmented reality (AR) and virtual reality (VR) technologies in cognitive therapies for mental health disorders. Analyzing 141 studies following PRISMA guidelines, the findings reveal that ML-driven AR/VR therapies offer significant advancements in personalization, real-time adaptation, and treatment efficacy. VR-based interventions demonstrate strong effectiveness in reducing symptoms of PTSD, anxiety disorders, and phobias, with ML algorithms—such as neural networks (NNs), supervised learning, and reinforcement learning (RL)—further optimizing therapy through predictive analytics and dynamic adjustments. These technologies enhance patient engagement, improve treatment adherence, and sustain therapeutic benefits for up to six months. This review highlights the transformative impact of ML-enhanced AR/VR therapies in delivering immersive, scalable, and highly personalized interventions, redefining the future of mental health treatment. As AI-powered therapeutic frameworks are poised to evolve further, such advancements have enormous potential to revolutionize cognitive therapies, enhancing their accessibility and optimizing patient outcomes worldwide.

Keywords: machine learning (ML); augmented reality (AR); virtual reality (VR); cognitive therapies; mental health disorders; personalization; anxiety disorders; post-traumatic stress disorder (PTSD); phobias; real-time adaptation; neuropsychological interventions

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1. Introduction

Cognitive therapy is a systemic, evidence-based psychotherapeutic intervention designed to change maladaptive cognitive processes and behaviors occurring in mental illness. It is effective in the management of anxiety disorders, depression, post-traumatic stress disorder (PTSD), and phobias [1–3]. One of the most widely applied cognitive therapies is cognitive behavioral therapy (CBT), which involves the integration of cognitive restructuring and behavioral activation to challenge maladaptive cognitions and form adaptive coping strategies. Traditional CBT encompasses exposure, cognitive restructuring, and skill training. However, with the advent of immersive technologies like augmented reality (AR) and virtual reality (VR), their efficacy and deliverability have been radically improved [4–6].

AR/VR cognitive therapies offer highly immersive, interactive environments that are conducive to experiential learning as well as the in vivo implementation of treatment strategies. For example, PTSD patients can be exposed to trauma-related stimuli within a controlled virtual world so that they can reprocess traumatic memories within a safe and controlled situation. Similarly, patients with social anxiety disorder can socially interact within a virtual world, graduating quickly to real situations [7–9]. These virtual worlds enable patients to systematically expose themselves to their fears while consolidating learned cognitive and behavioral coping mechanisms and reducing the risks of vivo exposure [10–12].

Incorporating machine learning (ML) in AR/VR-based cognitive treatments has also transformed mental health treatment by allowing the dynamic adjustment of treatment protocols. ML algorithms process large volumes of patient data obtained from physiological sensors, eye-tracking equipment, and behavioral response measures to personalize interventions in real time. For example, exposure therapy for phobia can automatically adjust levels of exposure for patients with phobia in real time according to physiological feedback to maximize therapeutic engagement without saturation with distress [13–15]. Furthermore, predictive analytics enabled by ML can recognize patterns of patient progress and provide clinicians with data-informed suggestions for how to tailor treatment plans and optimize long-term outcomes [16–18].

For all such advances, the standardization of AR/VR therapy implementations remains challenging for widespread clinical use. Data format heterogeneity, privacy concerns regarding patient data, and side effects like VR-induced motion sickness are still significant hurdles to large-scale adoption [19–21]. Also, disparities in access to high-quality AR/VR hardware could restrict the scalability of these interventions, requiring more research into economically viable deployment models [22,23]. Their efficacy also relies upon the development of high-fidelity virtual environments that are as realistic as possible to ensure that therapeutic practice translates to meaningful behavior change in the day-to-day lives of patients [24,25].

This systematic review integrates results from 141 studies to compare the incorporation of ML algorithms into AR/VR-based cognitive therapies for mental disorders. This research seeks to determine the effectiveness of AR/VR technologies in augmenting conventional cognitive therapies and investigate how ML can be utilized to tailor these therapies to cater to individual patients' better needs. It also explores the predictive potential of ML models in patient outcome prediction and therapy optimization. Comparative analysis is drawn to identify the efficacy of AR/VR-based cognitive therapies over conventional methods. This paper also investigates the application of reinforcement learning (RL) and adaptive algorithms for enhancing therapeutic experience. It delineates the new technological innovations in ML and AR/VR confluence that revolutionize cognitive therapy. By exploring top trends, methodological advancements, and empirical evidence, this review demonstrates how AR/VR combined with ML can potentially enhance mental healthcare, ultimately leading to more effective, scalable, and personalized therapy [26,27].

2. Recent Advancements in Machine Learning for Digital Health Solutions

The ML domain in the digital health arena has undergone accelerated development, with emerging approaches enhancing the personalization, efficacy, and privacy of cognitive therapies provided in VR and AR settings. Two widely used ML approaches—federated learning and transformer-based models—are specifically pertinent to augmenting mental health interventions.

Transformer-based models, such as BERT (Bidirectional Encoder Representation from Transformers) and the GPT (Generative Pre-trained Transformer), revolutionized natural language processing (NLP) and real-time AI-driven interactions in mental health settings. These models are increasingly being applied in digital therapeutics and AI-driven chatbots that provide AR/VR-based cognitive therapy. For instance, transformers enable real-time emotional state analysis via the speech and text analysis of patient information in AR/VR therapy sessions. They enhance sentiment analysis, personalized dialog generation, and contextual comprehension, improving cognitive therapies' flexibility. Recent studies have determined the use of transformer-based NLP models in detecting cognitive distortions, predicting therapy adherence, and designing personalized interventions in real time [28,29].

In addition, transformers enhance adaptive virtual reality therapy environments, where therapeutic environments change in real time based on patients' responses. The combination of RL and transformers has also shown promise in optimizing exposure therapy simulations for anxiety and post-traumatic stress disorder treatments by modifying difficulty levels based on physiological and behavioral cues [30]. One of the significant bottlenecks in ML-driven digital health interventions is the requirement of large, diverse, and privacy-sensitive datasets for enhancing therapeutic models. Federated learning (FL) is an emerging approach that overcomes data privacy concerns while facilitating collaborative model training across institutions. Instead of transmitting raw patient data to a central repository, FL facilitates decentralized learning, where AI models are trained locally on edge devices or clinical centers in a way that maintains sensitive mental health information, which is confidential and secure.

Federated learning is being increasingly applied in mental health diagnosis and predictive analytics. For example, a federated strategy can aggregate patient response trajectories from multiple hospitals that offer AR/VR cognitive therapy and improve the accuracy of predictions for treatment outcomes without infringing on individual-level privacy [31]. In cognitive therapy, FL can enable real-time personalization via the continuous optimization of AR/VR-based interventions in diverse patient groups while ensuring ethical and regulatory adherence, such as GDPR and HIPAA compliance [32].

Furthermore, federated learning benefits multimodal mental health AI, in which data from different sources (e.g., EEG signals, eye tracking, speech analysis) are integrated without requiring centralized data sharing. It has been researched that FL can significantly enhance real-time adaptive interventions in VR-based therapy, specifically for anxiety and PTSD treatment [33].

Moreover, ML has transformed various industries through automation, device interconnectivity, insight extraction, and enhanced data-driven decision making. ML can create adaptive systems that learn from the environment using problem-specific training data to tune analytical models [34–36]. The models learn patterns and predict datasets using mathematical concepts to identify underlying data structures [37–39]. The prominent learning paradigms include supervised, semi-supervised, unsupervised, and RL, with diverse characteristics and applications [40–43].

Additionally, ML is a foundation technology underpinning predictive analytics and decision making in various applications, such as financial markets, digital marketing, and healthcare [44–46]. ML is mainly concerned with adaptive learning mechanisms compared to deep learning or artificial intelligence, which involve more general reasoning and planning capabilities [47–49]. Deep learning (DL), a subfield, uses artificial neural networks (ANNs) with many layers to learn high-level data features, typically outperforming classic algorithms for sophisticated tasks [50–52].

The table below (Table 1) comprehensively summarizes several ML paradigms in artificial intelligence-powered cognitive therapy interventions. It specifies prominent learning strategies, their respective descriptions, illustrations of their implementations in augmented reality/virtual reality-based mental healthcare interventions, and popularly deployed algorithms. Supervised learning facilitates predictive analysis, whereas unsupervised learning aids in identifying unknown patterns for tailored therapy. Semi-supervised learning employs labeled and unlabeled data to enhance mental health diagnoses. RL optimizes real-time therapy adaptations, deep learning enhances emotion detection and behavior modeling, and transfer learning fine-tunes pre-trained models for personalized therapy.

Federated learning enables privacy-preserving AI in decentralized healthcare environments. These techniques create advanced, adaptive, and efficacious mental health interventions.

Table 1. ML techniques in cognitive therapy.

Machine Learning	Description	Examples in Cognitive Therapy	Common Algorithms/Approaches
Supervised Learning [53–57]	Utilizes labeled datasets to train models for predictive tasks.	Patient progress prediction, emotion detection, diagnosis of mental health conditions.	Linear Regression, Decision Trees, SVM, Random Forests, Neural Networks.
Unsupervised Learning [58–62]	Finds hidden patterns in unlabeled datasets by clustering similar data points or reducing dimensional complexity.	Patient clustering, anomaly detection, feature extraction for VR therapy.	K-Means Clustering, Hierarchical Clustering, PCA, Autoencoders, SOM.
Semi-Supervised Learning [63–67]	Combines small amounts of labeled data with large volumes of unlabeled data.	AI-powered mental health assessments, personalized AR/VR exposure therapy.	Self-Training Models, Graph-Based Learning, GANs, Label Propagation.
Reinforcement Learning [68–70]	Learns optimal decision making by interacting with an environment and maximizing cumulative rewards.	Real-time therapy adjustment, gamification in cognitive therapy, adaptive treatment planning.	Q-Learning, Deep Q-Networks, Proximal Policy Optimization, Actor–Critic Models.
Deep Learning [71–74]	Uses multilayer artificial neural networks to automate feature extraction and handle complex patterns.	Virtual counselors and chatbots, speech and emotion recognition, EEG-based mental health monitoring.	CNNs, RNNs, LSTM, Transformers (BERT, GPT).
Transfer Learning [28–30]	Enables pre-trained ML models to be fine-tuned for specific applications.	Customizing VR therapy models, emotion analysis from pre-trained models.	Fine-tuned CNNs, BERT, GPT, ResNet, U-Net.
Federated Learning [31–33]	Allows ML models to be trained across multiple decentralized data sources without sharing raw patient data.	Secure multi-center VR therapy training, real-time AI adaptation for mental health.	Google's Federated Averaging, Differential Privacy, Secure Aggregation Protocols.

Incorporating ML with AR/VR-based cognitive therapies has transformed treatment by enabling real-time patient behavior and response processing. It augments behavior therapy, serious gaming software, and rehabilitation programs by optimizing treatments according to a subject's requirements based on dynamic data analysis [75–79]. Processing a large volume of behavioral data in real-time enables accurate therapeutic adjustments, enhancing patient motivation and treatment success. However, this integration poses technical and practical problems that must be solved methodically [80–83].

In addition, AR/VR-based cognitive therapies face three significant challenges: therapeutic, technical, and research-related. AR/VR systems must be psycho-physiologically compatible to prevent side effects like cyber-sickness or overstimulation that may inhibit therapeutic efficacy [84–87]. The real-time acquisition of high-level physiological data and ML enables the real-time monitoring of patients' psychological states [88–90]. Still, it raises essential technical and research issues, such as data processing constraints and validation challenges [91–95]. On the opportunity front, the availability of wearable health-tracking sensors, e.g., EEG headsets, motion sensors, and eye-tracking systems, facilitate the large-scale capture of psychophysiological data. Recent progress in AI/ML techniques augments the analytic capabilities of AR/VR therapy systems, allowing intelligent systems to personalize treatment in real time according to user responses [96–99].

2.1. Research Questions

This systematic review aims to explore the role of ML in enhancing AR and VR-based cognitive therapies. To comprehensively understand the intersection of these technologies and their potential impact on mental health treatment, this review is guided by the following thematic topics from which research questions are derived:

2.1.1. The Role of AR/VR in Cognitive Therapies

[RQ1] How effective are augmented and virtual reality technologies in enhancing traditional cognitive therapies for treating mental health disorders such as PTSD, anxiety disorders, and phobias?

This question examines the use of AR and VR technologies as tools for cognitive therapy, focusing on their effectiveness compared to conventional methods. It seeks to assess their applicability across various mental health conditions and investigate their potential to offer immersive therapeutic experiences that engage patients more deeply.

2.1.2. ML for Personalization in Cognitive Therapy

[RQ2] How can machine learning algorithms enhance the personalization of AR/VR-based cognitive therapies to address individual patients' better needs?

This question explores how ML can be applied to personalize AR/VR therapy experiences by adapting therapeutic content and sessions to individual patients. The goal is to investigate how ML techniques, such as ANNs and natural language processing, can dynamically tailor therapy based on patient characteristics and real-time data, leading to more effective treatment outcomes.

2.1.3. Predictive Analytics in Mental Health Outcomes

[RQ3] How can machine learning models be leveraged to predict patient outcomes and therapy effectiveness in AR/VR-based cognitive therapies?

This question focuses on the potential of ML for predictive analytics in cognitive therapies. The aim is to investigate how predictive models can foresee therapy outcomes, such as success rates or specific symptom reductions, and how these models can be applied to adjust therapy strategies to improve effectiveness.

2.1.4. Comparative Studies of AR/VR and Traditional Cognitive Therapies

[RQ4] How does the effectiveness of AR/VR-based cognitive therapies compare to traditional cognitive therapies for treating mental health disorders?

This question aims to compare the efficacy of AR/VR cognitive therapies with traditional forms of treatment like cognitive behavioral therapy (CBT) and exposure therapy. The objective is to determine in which contexts AR/VR therapies might offer superior or complementary benefits over conventional methods, especially regarding patient engagement, outcomes, and adherence.

2.1.5. RL and Adaptation in AR/VR Therapy

[RQ5] How can RL and adaptive algorithms optimize the therapeutic experience in AR/VR-based cognitive therapies?

This question addresses the role of RL and adaptive machine learning models in continuously modifying and improving therapy sessions in AR/VR environments. The objective is to investigate how real-time patient feedback can automatically adjust the content, duration, or intensity of therapy sessions to suit individual progress and needs better.

2.1.6. Technological Innovations in ML-AR/VR Cognitive Therapies

[RQ6] What are the latest technological innovations in ML and AR/VR that are transforming the field of cognitive therapy?

This question explores cutting-edge advancements at the intersection of ML and AR/VR technologies in cognitive therapy. It aims to identify new tools, platforms, and frameworks that are revolutionizing the accessibility, scalability, and effectiveness of these therapies.

By addressing these research questions, this review provides a comprehensive understanding of how ML can enhance the efficacy, personalization, and scalability of AR/VR-based cognitive therapies while also exploring the current limitations and areas for future research. Each question reflects the core areas where ML, AR, and VR can converge to create more adaptive and effective mental health treatments.

3. Materials and Methods

This systematic review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency and replicability in the evidence synthesis [99]. A protocol outlining the objectives, eligibility criteria, information sources, and analysis methods was registered on Open Science Framework (https://osf.io/x3m5y | Registration DOI: 10.17605/OSF.IO/BYPEM (accessed on 9 March 2025)) [100].

3.1. Search Sources and Databases

The present systematic analysis was conducted across multiple academic and scientific databases to ensure a diverse and representative selection of studies. The databases searched include the following:

- PubMed (for biomedical and psychological studies).
- Scopus (multidisciplinary coverage).
- Web of Science (broad citation index).
- IEEE Xplore (for technological advancements in AR/VR and ML).
- PsycINFO (for mental health-focused interventions).
- Google Scholar (for Supplementary Articles and the gray literature).

The analytical search began with identifying 587 records through searches conducted across the abovementioned databases. Before the screening, 316 records were removed, comprising the following:

- A total of 258 duplicate records.
- A total of 23 records due to language restrictions.
- A total of 14 records published before 2014.
- A total of 21 records with non-relevant titles.

This left 271 records for screening. During the screening phase, the titles and abstracts of these records were reviewed, resulting in the exclusion of

- A total of 61 records for being irrelevant to the topic.
- A total of 49 non-empirical articles, such as commentaries, opinion pieces, and reviews.

This screening process left 161 reports to be retrieved for further assessment. Out of these, 9 reports could not be retrieved due to difficulties in accessing the full text. The remaining 152 reports were assessed for eligibility, where

- Two were excluded for insufficient methodological detail.
- Nine were excluded for lacking direct relevance to the research question.

Ultimately, 141 studies were included in the final review. This process reflects a systematic and rigorous approach to screening and selecting studies, ensuring transparency and adherence to PRISMA guidelines. The included studies form the basis for the synthesis and further analysis (Figure 1).

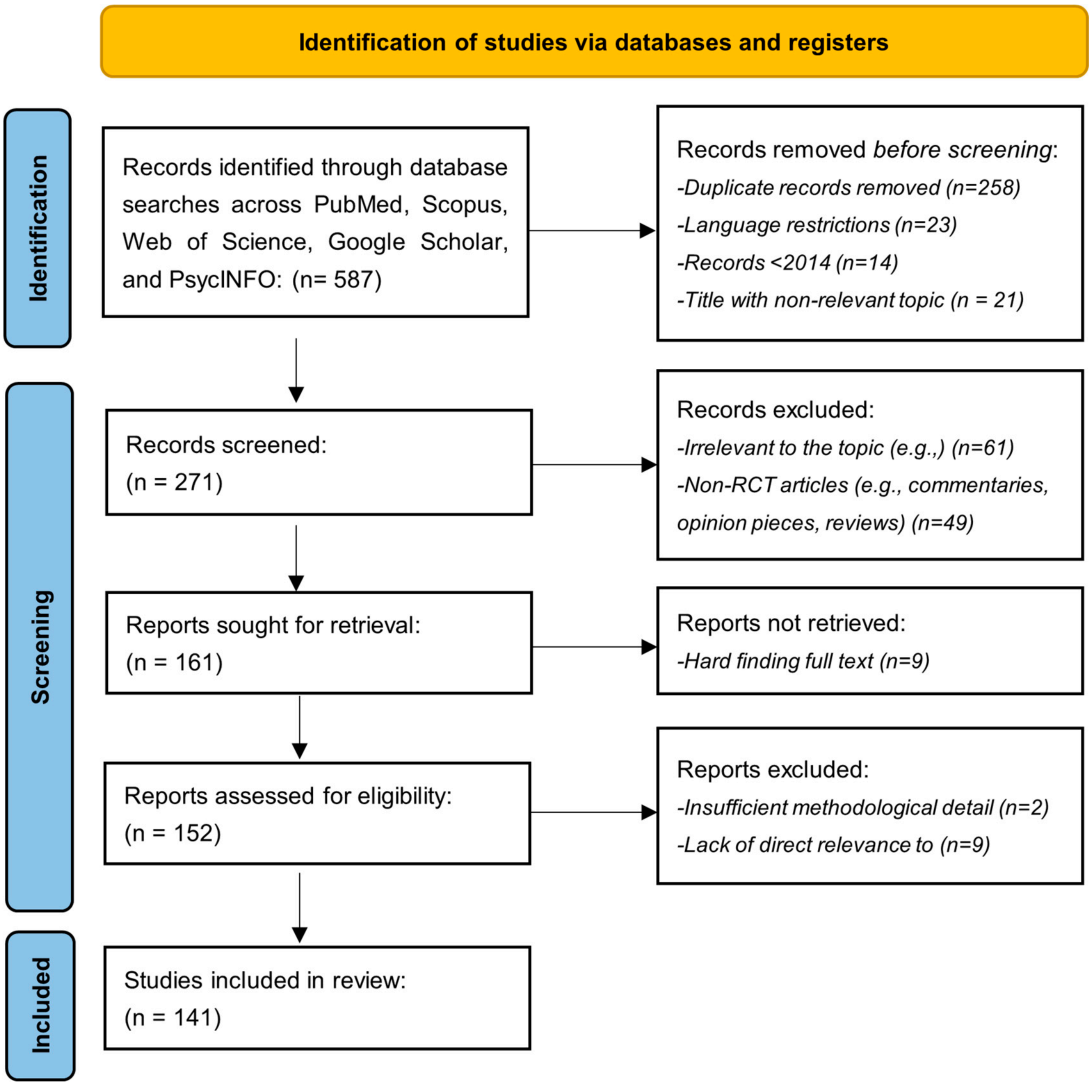

Figure 1. Flowchart of PRISMA methodology.

3.2. Search Strategy

The search strategy for this systematic review was designed to capture studies addressing the integration of Machine Learning (ML) into augmented reality (AR) and virtual reality (VR)-based cognitive therapies, with a focus on mental health disorders such as PTSD, anxiety disorders, and phobias. The search string used was as follows:

("Machine Learning" OR "ML" OR "Deep Learning" OR "Neural Networks" OR "Reinforcement Learning" OR "Artificial Intelligence" OR "Predictive Analytics") AND ("Augmented Reality" OR "AR" OR "Mixed Reality" OR "Virtual Reality" OR "VR" OR "Extended Reality" OR "XR" OR "Immersive Technology") AND ("Cognitive Therapy" OR "Cognitive Behavioral Therapy" OR "CBT" OR "Psychotherapy" OR "Mental Health Interventions") AND ("Anxiety Disorders" OR "PTSD" OR "Phobias" OR "Depression" OR "Schizophrenia" OR "Neurorehabilitation" OR "Stroke Rehabilitation" OR "Brain Injury" OR "Dementia" OR "Autism Spectrum Disorder").

Additionally, we incorporated wildcard characters *() to capture variations in keywords* (e.g., "therap" to include "therapy" and "therapies") and adjacency operators where available to refine keyword proximity in complex search queries. Also, filters restricted results to studies published from 2014 to 2024, written in English, and that evaluate the integration of ML within AR/VR-based cognitive therapies for mental health disorders. This approach ensured a focused and comprehensive selection of high-quality studies relevant to this review.

3.3. Inclusion and Exclusion Criteria

Studies were included (Table 2) in this review if they met the eligibility conditions listed below.

Table 2. Inclusion criteria.

Inclusion Criteria	Details
Research Focus	Investigates the efficacy, feasibility, or applicability of ML-enhanced AR/VR cognitive therapies for mental health treatment.
Study Design	Randomized controlled trials (RCTs), quasi-experimental studies, or other empirical research using validated methodologies.
Target Population	Individuals diagnosed with PTSD, anxiety disorders, phobias, or other clinically relevant mental health conditions are treated with AR/VR-based cognitive therapies.
ML Techniques	Studies applying RL, neural networks, supervised learning, predictive analytics, or adaptive algorithms within AR/VR-based cognitive interventions.
Publication Source	Peer-reviewed journal articles and conference proceedings published between 2014 and 2024.
Language	Published in English to ensure accessibility for systematic analysis.
Full-Text Access	Studies with full-text availability for comprehensive data extraction and analysis.

Studies were excluded (Table 3) from this review if they met any of the conditions listed below.

Table 3. Exclusion criteria.

Exclusion Criteria	Details
Non-Relevant Focus	Studies that do not explicitly explore ML, AR/VR, or cognitive therapy interventions for mental health disorders.
Study Type	Non-empirical papers include systematic reviews, meta-analyses, commentaries, editorials, theoretical papers, and opinion pieces.
Language Restriction	Articles published in languages other than English.
Unrelated Population	Research focuses on populations outside PTSD, anxiety disorders, and phobias, such as neurological disorders or cognitive impairments unrelated to mental health.
Methodological Limitations	Studies with small sample sizes, inadequate statistical analysis, lack of control groups, or insufficient methodological transparency.
Publication Date	Studies published before 2014 consider advancements in ML and AR/VR therapy applications in the past decade.

These criteria were meticulously applied to ensure the selection of studies that meet high methodological rigor, relevance, and alignment with the research focus on ML-enhanced AR/VR-based cognitive therapies. This systematic approach guaranteed the inclusion of only empirical, evidence-based studies (Table 4) with robust methodologies and direct applicability to AR/VR cognitive therapy interventions for mental health disorders. Additionally, a Supplementary Table provides a comprehensive overview of the 141 research articles analyzed in this systematic review, offering detailed insights into their objectives, interventions, and hypotheses tested.

Table 4. Hypotheses of research articles included in the systematic analysis (n = 141).

Authors	Hypotheses
Ahn, 2021 [101]	-Cognitive therapy improvements: Combined VR and computer game-based cognitive therapy enhance visual perception aspects, including spatial relations, visual-motor speed, motor-reduced visual perception, and general visual perception, in children with intellectual disabilities.
Albizu et al., 2020 [102]	-Classification of treatment responders: ML combined with MRI-derived electric field models can effectively classify reatment responders versus non-responders.
Alkhabra et al., 2023 [103]	-AR technology: Enhances retention of learning and critical thinking. -Effectiveness of AR: Varies in critical thinking and practical skills based on learners' mental capacity.
Allcoat and Mühlenen, 2018 [104]	-VR technology enhances learning, leading to better outcomes, improved memory retention, and higher engagement than traditional and video methods. -VR positively influences emotions, increasing positive feelings and reducing negative ones during the learning process.
Alsem et al., 2023 [105]	-Aggression decreases: Expected to be larger in both YourSkills groups (VR and roleplay) compared to the care-as-usual group, with more significant reductions in the VR group. -Perceived efficacy: The VR group is expected to rate the treatment as more effective than the role-play group.
Alwashmi et al., 2023 [106]	-Functional brain changes: Support behavioral performance improvements during an audiovisual (AV) learning task. -AV training: Leads to better performance outcomes compared to visual-only training. -Increased functional activation: In multisensory brain regions, it is associated with performance gains. -Multisensory integration: Enhances cognitive function.
Andersen et al., 2018 [107]	-Repeated and distributed VR simulation practice: Induces a lower cognitive load during subsequent cadaveric dissection training.
Aran et al., 2020 [108]	-Virtual reality-based rehabilitation: Improves cognitive functions in children with hemiplegic cerebral palsy and is more effective than traditional occupational therapy in enhancing cognitive functions in children with hemiplegic cerebral palsy.
Arquissandas et al., 2021 [109]	-AR-based system: Effectively elicits and measures physiological responses during exposure therapy for anxiety disorders. -Personalization: The system can adapt to individual profiles using ML algorithms to tailor exposure therapy.
Aziz et al., 2020 [110]	-AR technique: The AR technique improves education and training outcomes in assembly processes.
Bond et al., 2023 [111]	-gameChange VR cognitive therapy reduces agoraphobic avoidance and distress in people with psychosis. -The therapy is especially effective for individuals with severe avoidance. -Improvements in persecutory ideation, quality of life, and perceived recovery are expected.

Table 4. *Cont.*

Authors	Hypotheses
Bouchard et al., 2017 [112]	-Study 1: VR induces cravings in gamblers comparable to real gambling and more substantial than control games. -Study 2: VR, when integrated with CBT, helps identify high-risk situations, and cravings are linked to improved treatment outcomes. -Study 3: VR is as safe as imaginal exposure, not causing stronger or more uncontrollable urges.
Bruschetta et al., 2022 [113]	-Gender and clinical factors: Gender significantly influences cognitive recovery in TBI patients undergoing VR rehabilitation. -Other factors: Anxiety levels and FIM scores also affect recovery outcomes.
Buccellato et al., 2019 [114]	-Feasibility: Implementation of the BBVR system in an outpatient clinic. -Effectiveness: Impact on motor function, cognitive performance, and emotional symptoms. -Dose–response: Exploring the effects of therapy duration or intensity. -Performance correlation: Linking BBVR game performance to long-term clinical outcomes.
Butti et al., 2019 [115]	-VR-Spirit will enhance social prediction ability in patients with congenital cerebellar malformations. -VR-Spirit will indirectly improve cognitive performance across various domains. -VR-Spirit is more effective than standard VR training in improving social perception skills.
Câmara et al., 2021 [116]	-Both Reh@City v2.0 and Task Generator will improve cognitive and emotional outcomes. -Reh@City v2.0 will show greater gains in visual memory and depressive symptoms. -Task Generator will lead to greater improvements in processing speed, verbal memory, and quality of life. -Effects will be maintained at follow-up, with additional improvements in specific cognitive domains for each intervention.
Chen et al., 2020 [117]	-VR training will significantly reduce CNV latency and improve upper limb function. -VR intervention will lead to more significant improvements than conventional treatment.
Chen et al., 2018 [118]	-Effectiveness of MBRP with VRCE: Mindfulness-Based Relapse Prevention (MBRP) combined with Virtual Reality Cue Exposure (VRCE) will be more effective than MBRP alone and treatment as usual in reducing cravings and emotional responses in individuals with methamphetamine use disorders.
Cheng et al., 2021 [119]	-Combining VR training with rTMS will enhance cognitive improvement, especially in memory and visuospatial functions, in patients with Parkinson's disease and mild cognitive impairment compared to rTMS alone.
Choi et al., 2023 [120]	-Biometric responses can effectively forecast personal learning performance in VR-based construction safety training. -A simplified forecast model using principal features can outperform a complete model in prediction accuracy and reduce overfitting.
Chun et al., 2022 [121]	-ML models can predict anxiety severity and VR sickness in SAD patients using autonomic signals like heart rate and skin response. -Prediction performance varies across models for different anxiety and VR sickness subdomains.
Collaço et al., 2020 [122]	-Immersive technologies enhance skill training in dental anesthesia. -Immersive preceptorship and training improve accuracy and confidence in anesthesia administration.
D'Alfonso et al., 2017 [123]	-Online therapy improves long-term outcomes: online psychosocial interventions extend the clinical benefits of specialized face-to-face youth mental health programs into sustained, long-term improvements. -AI supplements clinical support: advanced computational and AI methods effectively supplement the support provided by moderators and clinicians, enabling scalable and personalized user-tailored therapy.

Table 4. *Cont.*

Authors	Hypotheses
Dahdah et al., 2017 [124]	-Immersive VR interventions improve executive function: immersive virtual reality treatment interventions enhance recovery from executive dysfunction in patients with brain injury. -VR Stroop task outperforms traditional formats: performance on a virtual reality version of the Stroop test is more substantial than conventional Stroop test formats.
Dellazizzo et al., 2020 [125]	-CBT and VRT combination improves outcomes: combining cognitive behavioral therapy (CBT) and virtual reality therapy (VRT) will be beneficial for treatment-resistant schizophrenia patients. -Synergistic effect of CBT and VRT: Combining CBT and VRT will produce a synergistic effect, enhancing both primary and secondary treatment outcomes. -Greater efficacy on hallucinations: CBT combined with VRT will achieve greater efficacy in reducing auditory verbal hallucinations compared to generic CBT for psychosis (CBTp).
Dercon et al., 2023 [126]	-Clearer representations of option values: Cognitive distancing results in more precise representations of option values, reflected by higher inverse temperatures. -Increased sensitivity to negative feedback: Cognitive distancing enhances sensitivity to negative feedback, demonstrated by higher loss learning rates. -Strategic shift over time: Cognitive distancing leads to a strategic change, increasing sensitivity to negative feedback as the task progresses.
Dilgul et al., 2021 [127]	-VR group therapy acceptability: The study explores the hypothesis that VR group therapy (VRGT) is an acceptable form of therapy for depression. -Stakeholder perspectives on VR therapy: The study investigates stakeholders' views on cognitive behavioral group therapy delivered via virtual reality. -Adaptation of CBT for VR delivery: The study examines how cognitive behavioral group therapy can be adapted for effective delivery via virtual reality.
Donker et al., 2022 [128]	-Aviophobia symptom reduction: The VR-CBT app treatment is expected to reduce aviophobia symptoms compared to a wait-list control group significantly. -Long-term effectiveness: The reduction in aviophobia symptoms is predicted to be maintained at both 3-month and 12-month follow-up assessments.
Donker et al., 2020 [129]	-VR activity and acrophobia symptoms: Higher VR activity (number of completed VR sessions, practice time in VR) is associated with reduced post-test acrophobia symptoms. -Presence and anxiety reduction: Higher presence scores on the IPQ are correlated with more substantial decreases in anxiety ratings directly after practicing with exposure in the VR environment. -Acrophobia and VR response: Higher acrophobia symptoms at pre-test correlate positively with VR anxiety ratings and VR activity and negatively with a reduction in acrophobia symptoms at post-test. -Anxiety reduction over repeated sessions: Post-session anxiety levels consistently decrease compared to pre-session anxiety levels after repeated practice in the VR environment.
Duhne et al., 2022 [130]	-Improved attendance: Matching patients to either face-to-face or computerized low-intensity psychological interventions can enhance attendance rates. -Better treatment outcomes: Appropriately matching patients to suitable treatment modalities can improve depression treatment outcomes.
Ekstrand et al., 2018 [131]	-Learning outcomes: Virtual reality neuroanatomy training results in equivalent or superior learning outcomes compared to traditional paper-based methods. -Reduced neurophobia and increased motivation: VR training decreases neurophobia and boosts motivation among medical students.
Erguzel and Tarhan, 2016 [132]	-rTMS efficacy: Pre-treatment quantitative electroencephalography (QEEG) data can predict the effectiveness of repetitive transcranial magnetic stimulation (rTMS) in treating major depressive disorder (MDD). -ML classification: Various ML techniques, including artificial neural networks (ANNs), support vector machines (SVMs), and decision trees (DTs), can classify MDD patients as responders to rTMS treatment.

Table 4. *Cont.*

Authors	Hypotheses
Faria et al., 2018 [133]	-Improved outcomes: Rehabilitation with the Reh@Task system will result in superior motor and cognitive outcomes compared to standard rehabilitation. -Ecological validity: Integrating motor and cognitive components in VR training enhances its ecological validity, potentially leading to more effective rehabilitation outcomes.
Faria et al., 2020 [134]	-Cognitive improvements: The VR-based ADL simulation (Reh@City v2.0) is more effective than paper-and-pencil training (Task Generator) in enhancing general cognitive functioning, visuospatial ability, and executive functions. -Ecological validity: The VR-based approach leads to more significant improvements in cognitive domains and self-perceived cognitive deficits compared to the paper-and-pencil approach.
Faria et al., 2016 [135]	-Global cognitive functioning: VR-based cognitive rehabilitation results in more significant global cognitive functioning improvements than conventional rehabilitation. -Attention: VR-based cognitive rehabilitation shows superior improvements in attention compared to conventional methods. -Executive functions: VR-based cognitive rehabilitation leads to more significant enhancements in executive functions than conventional rehabilitation.
Fernández-Álvarez et al., 2021 [136]	-Improved recall: The VR-enhanced autobiographical memory (AM) task can enhance the recall of positive memories in individuals with moderate-to-moderately severe depressive symptoms. -Standalone effectiveness: The VR-based AM recall treatment is effective as a standalone intervention.
Freeman et al., 2019 [137]	-Reduction in avoidance and distress: VR cognitive therapy, when combined with treatment as usual, will reduce avoidance and distress in real-world situations post-treatment compared to treatment as usual alone. -Reduction in psychiatric symptoms: VR cognitive therapy added to treatment as usual will reduce psychiatric symptoms (paranoia, anxious avoidance, depression, suicidal ideation), increase activity, and improve quality of life post-treatment. -Sustained effects: Treatment effects are expected to be maintained at the 6-month follow-up. -Mediators of treatment: Changes in safety beliefs, threat cognitions, and defense behaviors will mediate VR treatment efficacy.
Freeman et al., 2023 [138]	-Increased positive self-beliefs: The VR self-confidence therapy (Phoenix) will enhance positive self-beliefs in participants. -Improved psychological well-being: The VR self-confidence therapy (Phoenix) will improve psychological well-being.
Frewen et al., 2020 [139]	-Stronger emotional responses: Direct perception of virtual reality (VR) stimuli is expected to evoke stronger emotional reactions than mental imagery and episodic recall. -Increased vividness and presence: VR may enhance vividness and presence, resulting in more excellent absorption, which mediates the effects on positive affect and psychological well-being.
Fusco et al., 2022 [140]	-Enhanced cognitive and motor function: The visual feedback provided by virtual reality (VR), in conjunction with robotic therapy, is hypothesized to improve patients' cognitive and motor functions more effectively than conventional robotic therapy alone. -Lower limb recovery: A semi-immersive, video-enriched robotic system is expected to enhance the recovery of lower limb function and reduce overall disability in patients with severe acquired brain injury (ABI).
Gamito et al., 2017 [141]	-Cognitive improvements: The virtual reality-based cognitive training program effectively enhances stroke patients' attention and memory functions.

Table 4. *Cont.*

Authors	Hypotheses
Gamito et al., 2020 [142]	-Feasibility: VR-based cognitive training is feasible for improving mental function in patients with alcohol use disorder (AUD) undergoing residential treatment. -Impact on cognitive functions: VR-based cognitive training is expected to positively impact attention and executive functions in individuals with AUD. -Measurable effect: The intervention will demonstrate a measurable effect size to guide future definitive randomized controlled trials (RCTs).
Gangemi et al., 2023 [143]	-Neurophysiological changes: VR-based cognitive rehabilitation induces neurophysiological changes in patients with chronic ischemic stroke. -Enhanced cognitive recovery: VR technology enhances cognitive recovery through measurable EEG changes. -Neuroplasticity: VR-based rehabilitation promotes neuroplastic changes in stroke patients. -EEG activity: VR training increases alpha and beta EEG band activity.
Gavish et al., 2015 [144]	-Effectiveness in industrial tasks: VR and AR platforms are hypothesized to be effective for training in industrial maintenance and assembly tasks. -Comparison with traditional methods: VR and AR platforms are hypothesized to differ in efficiency and effectiveness from traditional training methods. -AR training: AR training is expected to result in fewer unsolved errors than traditional methods. -VR training: VR training is hypothesized not to significantly improve performance over traditional methods due to a ceiling effect.
Ghiţă et al., 2021 [145]	-Reduction in alcohol craving: VR-based cue exposure therapy (VR-CET) is expected to reduce levels of alcohol craving. -Anxiety reduction: VR-CET will lead to a reduction in anxiety levels. -Attentional bias: VR-CET will prompt changes in attentional bias (AB) toward alcohol-related content. -Feasibility: The VR-CET protocol is feasible for implementation within a clinical trial setting.
Gómez et al., 2017 [146]	-Emotional impact: After each VR-based DBT-R mindfulness skill training session, the patient is expected to experience a decrease in negative and positive emotions. -Acceptance of VR: The patient is anticipated to accept VR as a method for learning DBT-R mindfulness skills.
Gueye et al., 2020 [147]	-Upper limb motor function improvement: Virtual reality therapy (VRT) using the Armeo Spring® exoskeleton effectively enhances upper limb motor function in early post-stroke rehabilitation. -Comparison with conventional physiotherapy: VRT improves upper limb motor function more effectively.
Hadley et al., 2018 [148]	-Greater satisfaction: Adolescents randomized to emotion regulation (ER) combined with immersive virtual reality exposure (IVRE) are expected to report greater satisfaction with the intervention. -Higher attendance: Adolescents randomized to ER + IVRE are anticipated to demonstrate higher attendance rates. -Improvement in ER skills: Adolescents randomized to ER + IVRE are expected to significantly improve emotion regulation (ER) skills. -Increased self-efficacy: At the 3-month follow-up, adolescents randomized to ER + IVRE are expected to report greater self-efficacy in engaging in safer behaviors.
Heinrich et al., 2022 [149]	-Feasibility: Assessing the feasibility of using an immersive virtual reality (VR) system for mirror therapy in a clinical setting. -Effectiveness: Evaluating the effectiveness of immersive VR-based mirror therapy compared to conventional mirror therapy.

Table 4. *Cont.*

Authors	Hypotheses
Hisler et al., 2024 [150]	-Therapist feedback effects: Assessing the impact of implementing therapist feedback via a deep learning model tool on client treatment response in iCBT. -Therapist acceptability: Evaluating therapists' acceptability of the deep learning model prediction tool.
Hong et al., 2022 [151]	-Mitigating acute care risk: ML can mitigate the increased risk for acute care during outpatient cancer therapy. -Reducing acute care rates: ML models based on electronic health record (EHR) data can guide supplemental clinical evaluations and reduce the rate of acute care during cancer radiotherapy.
Hornstein et al., 2020 [152]	-Predicting treatment outcomes: ML can effectively predict treatment outcomes in digital mental health interventions for depression and anxiety. -Contributing variables: Specific clinical and sociodemographic variables contribute significantly to the accuracy of these predictions.
Hung et al., 2020 [153]	-Cognitive improvement: Virtual Reality Cognitive Training (VRCT) and Computer-Based Cognitive Training (CBCT) are effective in improving cognitive domains with mild cognitive impairment (MCI). -VRCT benefits: VRCT is more beneficial than CBCT in improving global cognitive function (GCF), executive function (EF), language (Lang), and visuospatial abilities (VSs). -CBCT benefits: CBCT is more beneficial than VRCT in improving memory (Mem).
Javanbakht et al., 2020 [154]	-Effectiveness in exposure therapy: Augmented reality combined with telemedicine effectively treats fear of spiders in exposure therapy.
Jeun et al., 2022 [155]	-Neural efficiency: Personalized cognitive training with the algorithm has the potential to induce neural efficiency in healthy subjects.
Jiménez et al., 2022 [156]	-Baseline predictors: Baseline predictors can be identified to improve the response rate to Dialectical Behavior Therapy (DBT) in patients with borderline personality disorder (BPD). -ML prediction: ML can detect clinical features that predict improvement or worsening in symptom severity and impulsivity. -Key predictors: Specific baseline characteristics, such as "non-judging" mindfulness ability and "non-planning" impulsiveness, are significant predictors of clinical change. -Personalized treatment: Utilizing ML to identify essential variables can enhance personalized treatment and improve disease prognosis.
Józwik et al., 2021 [157]	-Effectiveness in reducing depression and anxiety: VR-enhanced cardiac rehabilitation is more effective than standard cardiac rehabilitation in reducing depression and anxiety symptoms.
Jung et al., 2023 [158]	-Increased anxiety: Personalized VR exposure can provoke heightened anxiety in patients with panic disorder and agoraphobia. -Stronger anxiogenic effects: Personalized VR exposure elicits more substantial anxiogenic effects, as self-reported measures and neurophysiological data indicate.
Kaldo et al., 2021 [159]	-Improved prediction accuracy: ML algorithms can predict a single patient's outcome with accuracy better than chance.
Kamińska et al., 2020 [160]	-Stress relief through VR and EMDR: Integrating virtual reality (VR) with bilateral stimulation used in Eye Movement Desensitization and Reprocessing (EMDR) can effectively relieve stress. -Measurable effects: The VR relaxation training program will have a measurable impact on stress indicators. -Physiological changes: Observable changes in stress levels and physiological indicators will occur before, during, and after the VR sessions.

Table 4. *Cont.*

Authors	Hypotheses
Kannampallil et al., 2022 [161]	-Prediction of depression remission: ML algorithms can be developed to predict depression remission for patients undergoing problem-solving therapy. -Generalization across datasets: These ML models can effectively generalize across different datasets, such as ENGAGE-2 and RAINBOW. -Prediction accuracy: The ML models can predict depression remission with accuracy significantly greater than chance.
Kawakami et al., 2021 [162]	-Improvement in depression symptoms: The fully automated machine-guided iCBT program is expected to improve symptoms of depression compared to the control group. -Effect on subthreshold depression: The program is anticipated to have a positive effect on depression among participants with subthreshold depression.
Kennedy et al., 2023 [163]	-Reduction in human error: VR-based clinical skill training reduces human error compared to traditional training alone. -Improved learner outcomes: VR-based clinical skill training is a viable approach that provides improved outcomes for learners.
King et al., 2022 [164]	-Improvement in mathematical questioning strategy: Compared to individuals who did not receive VR training, the simulation aims to improve participants' acquisition of steps in a mathematical questioning strategy. -Perceived confidence: The VR simulation is expected to increase participants' perceived confidence in using the procedure relative to the control group.
Kitapcioglu et al., 2024 [165]	-Learning outcome comparison: There is no significant difference in learning outcomes between VR-based, machine-guided training and educator-guided, VR-based training in the metaverse environment for adult advanced cardiac life support (ACLS) training.
Kohli et al., 2022 [166]	-Personalized ABA treatment goals: ML algorithms can effectively recommend and personalize applied behavior analysis (ABA) treatment goals for individuals with Autism Spectrum Disorder (ASD). -Mastery of treatment goals: The study participants are expected to master the ABA treatment goals recommended by the ML models effectively.
Koo et al., 2018 [167]	-Longer-lasting pain relief: Enhanced reality (ER) analgesia provides longer-lasting pain relief than traditional virtual reality (VR). -Impact of therapy duration: The duration of ER therapy influences the longevity and effectiveness of pain relief and improvements in range of motion (ROM).
Kovár, 2018 [168]	-Faster therapy outcomes: Incorporating virtual reality into cognitive behavioral therapy (CBT) can speed up treatment for social anxiety disorder. -Reduced pharmaceutical use: Virtual reality can help reduce the reliance on pharmaceuticals in treating social anxiety disorder. -Greater effectiveness: Virtual reality sessions are more effective than traditional therapeutic sessions in treating social anxiety disorder.
Kritikos et al., 2021 [76]	-Personalized VR scenarios: Investigating whether it is possible to create VR scenarios that adapt in real time to each patient's unique personality during the simulation. -Dynamic adaptation: Exploring whether the proposed VR system can dynamically adapt during the session, in real time, to each participant's unique behavioral patterns and align with the treatment's goals.
Ledwos et al., 2022 [169]	-AI-derived learning curve metrics: AI-derived metrics can effectively measure learning curves across different expertise levels. -Differences in expertise levels: There are measurable differences in learning curves between groups with varying levels of expertise. -Impact of repeated practice: Repeated practice leads to measurable improvements in performance on VR-simulated tasks.

Table 4. *Cont.*

Authors	Hypotheses
Lee et al., 2020 [170]	-Predictive biomarker signatures: Different biomarker signatures can predict which treatment arm is most beneficial for glioblastoma patients. -Patient classification: Gene Set Variation Analysis (GSVA) and semi-supervised ML can effectively classify patients based on their likelihood of response to specific treatments.
Leehr et al., 2021 [171]	-Predictive factors for treatment response: Certain sociodemographic and clinical pre-treatment factors can predict treatment response in individuals with spider phobia. -Effectiveness of VRET: Virtual reality exposure therapy (VRET) is effective at the group level for treating spider phobia. -ML for individual predictions: ML can predict individual treatment responses based on pre-treatment factors.
Leonardi et al., 2021 [172]	-Cognitive improvement in MS: VR-based rehabilitation improves cognitive outcomes in multiple sclerosis (MS) patients. -Mood and visuospatial skills: Both conventional and VR cognitive rehabilitation improve mood and visuospatial skills in MS patients. -Greater cognitive gains with VR: VR-based rehabilitation improves specific cognitive domains and quality of life compared to conventional methods.
Li et al., 2022 [173]	-Predicting treatment outcomes: ML algorithms can predict treatment outcomes in depression. -Use of predictors: Pre-treatment predictors and early symptom changes can be used to forecast treatment outcomes.
Liao et al., 2024 [174]	-Skill acquisition: Augmented reality (AR) enhances trainee skill acquisition by easing spatial orientation challenges and reducing cognitive overload. -Procedural efficiency: AR improves procedural efficiency in ultrasound-guided procedures. -Reduced cognitive workload: AR reduces cognitive workload during training. -Decreased instructional dependence: AR decreases trainees' dependence on instructional guidance.
Liao et al., 2020 [175]	-Cognitive and physical improvements: VR-based physical and cognitive training improves cognitive function, brain activation, and instrumental activities of daily living (IADLs). -Greater effectiveness: VR training is more effective than combined physical and cognitive training in improving these outcomes. -Neural efficiency: VR training leads to increased neural efficiency, as indicated by decreased activation in prefrontal areas.
Lin and Chen, 2020 [176]	-Improved learning achievement: The deep learning recommendation system improves learning achievement compared to a non-deep learning recommendation system. -Enhanced computational thinking: The deep learning recommendation system enhances computational thinking ability compared to a non-deep learning recommendation system. -Specific skill improvements: The deep learning recommendation system improves specific dimensions of computational thinking, including creativity, logical computing, critical thinking, and problem-solving skills.
Luca et al., 2023 [177]	-Improved executive abilities: Non-immersive virtual reality-based training enhances executive skills in patients with traumatic brain injury (TBI). -Reduced anxiety and depression: Non-immersive virtual reality-based training reduces symptoms of anxiety and depression in TBI patients. -Improved coping and mood: Non-immersive virtual reality-based training improves coping strategies and mood in individuals with chronic TBI.
Luca et al., 2019 [178]	-Cognitive function improvement: Virtual reality training with BTS Nirvana is expected to improve cognitive functions in subjects with traumatic brain injury (TBI). -Behavioral function improvement: Virtual reality training with BTS Nirvana will enhance behavioral functions in TBI subjects.

Table 4. *Cont.*

Authors	Hypotheses
Maciolek et al., 2020 [179]	-Reduced anxiety: VR-enhanced relaxation training effectively reduces anxiety levels in patients undergoing cardiac rehabilitation.
Maggio et al., 2023 [180]	-Feasibility of cognitive telerehabilitation: Cognitive telerehabilitation is feasible for patients with multiple sclerosis (MS). -Positive influence on quality of life: A home-based personalized exercise program using the Virtual Reality Rehabilitation System (VRRS) can positively impact quality of life scores in MS patients.
Maggio et al., 2018 [181]	-Cognitive and behavioral recovery: Virtual reality training with the BTS Nirvana system enhances cognitive and behavioral recovery in patients with Parkinson's disease. -Improved executive and visuospatial abilities: Virtual reality training improves executive and visuospatial abilities more effectively than traditional cognitive training.
Maggio et al., 2020 [182]	-Improved attention and executive functions: Robotic neurorehabilitation using Lokomat with VR enhances attention processes and executive functions in traumatic brain injury (TBI) patients. -Greater cognitive improvements: The integration of VR with Lokomat leads to greater improvements in cognitive, executive, and attention functions compared to using Lokomat without VR. -Enhanced quality of life: The use of Lokomat with VR significantly improves quality of life, particularly in mental and physical well-being, more than Lokomat without VR.
Manenti et al., 2020 [183]	-Enhanced memory and attention: The face-to-face Virtual Reality Rehabilitation System (VRRS) is expected to improve memory and attentional abilities more effectively. -Long-term benefits of home-based treatment: Implementing home-based treatment through the cognitive VRRS could induce long-term benefits, extending the positive effects of face-to-face treatment.
Maresca et al., 2022 [184]	-Cognitive improvement in dyslexia: The use of a Virtual Reality Rehabilitation System (VRRS) in children with dyslexia is expected to result in additional cognitive improvements.
Marti et al., 2021 [185]	-Increased adherence: The embodied VR system is expected to increase adherence to meditation practice. -Improved meditation quality: The embodied VR system will enhance the quality of meditation practice. -Compassionate response: The embodied VR system will generate a compassionate response in participants.
Maskey et al., 2019 [186]	-Engagement with VRE scenes: Explore whether autistic adults engage with computer-generated virtual reality exposure (VRE) scenes in a way that allows them to approach and remain in anxiety-provoking situations. -Participation and retention: Investigate participation rates and retention throughout the study. -Session structure appropriateness: Assess whether the four-session treatment structure is suitable for autistic adults by using the same number of sessions and monitoring attendance and outcomes.
Massetti et al., 2017 [187]	-Combined tDCS and VR therapy benefits: The combination of transcranial direct current stimulation (tDCS) and virtual reality (VR) therapy leads to beneficial outcomes in multiple health aspects, including improved body sway, gait, stroke recovery, pain management, and vegetative reactions.
Mazurek et al., 2023 [188]	-Mental and functional benefits: VR therapy has a beneficial effect on the mental and functional state of individuals undergoing rehabilitation after lower limb arthroplasty. -Reduction in depression, anxiety, and stress: VR therapy effectively alleviates symptoms of depression and anxiety and reduces perceived stress levels in older adults who have undergone arthroplasty surgery.

Table 4. *Cont.*

Authors	Hypotheses
Meinlschmidt et al., 2019 [189]	-Predicting success with ML: ML can predict the success of smartphone-based psychotherapeutic micro-interventions in eliciting mood changes. -Mood changes: Smartphone-based psychotherapeutic micro-interventions can effectively lead to mood changes.
Miloff et al., 2019 [190]	-Non-inferiority of VRET: Virtual reality exposure therapy (VRET) is non-inferior to one-session therapy (OST) in reducing symptoms of spider phobia.
Miloff et al., 2016 [191]	-Comparable effectiveness: Gamified VR exposure therapy is not inferior to traditional one-session exposure therapy (OST) for treating spider phobia.
Montesano et al., 2021 [192]	-Effectiveness of PCT-VR over PCT: Person-Centered Therapy combined with virtual reality (PCT-VR) is more effective than PCT alone in treating mild-to-moderate depression in young adults. -Effectiveness of PCT-VR over CBT: PCT-VR is more effective than cognitive behavioral therapy (CBT) in treating mild-to-moderate depression in young adults.
Navarra-Ventura et al., 2021 [193]	-Cognitive and emotional improvements: ENRIC therapy is expected to improve cognitive functioning and emotional state one month after ICU discharge. -Long-term maintenance: The cognitive and emotional improvements from ENRIC therapy will be maintained over a 12-month period.
Nekar et al., 2022 [194]	-Improvement in RRBs: AR game-based cognitive-motor training will improve restricted and repetitive behaviors (RRBs) in patients with Autism Spectrum Disorder (ASD). -Enhancement of executive function: AR game-based cognitive-motor training will improve executive function (EF) in patients with ASD. -Attention improvement: AR game-based cognitive-motor training will enhance attention in patients with ASD.
Norouzi et al., 2020 [195]	-Bimanual coordination improvement: Each intervention (virtual reality training (VRT), Conventional Physical Therapy (CPT), and their combination (COMB)) will improve bimanual coordination over time. -Greater improvement with combined therapy: The combination of VRT and CPT (COMB) will improve coordination accuracy and consistency compared to VRT or CPT alone.
Otkhmezuri et al., 2019 [196]	-Higher immersion and presence: Compared to standard CBM-I, participants will report higher rates of immersion and presence in the VR-Cognitive Bias Modification for Interpretation (VR-CBM-I) training scenarios. -Positive interpretations: VR-CBM-I training will significantly endorse positive interpretations and fewer negative interpretations than standard CBM-I. -Anxiety reduction: VR-CBM-I will result in a more significant decrease in state anxiety compared to standard CBM-I.
Park et al., 2020 [197]	-Cognitive function improvement: Virtual Reality Cognitive-Motor Rehabilitation (VRCMR) is more effective than conventional cognitive rehabilitation (CCR) in improving cognitive function.
Park and Ha, 2023 [198]	-Improved stroke self-efficacy: The virtual reality-based cognitive rehabilitation program will improve stroke self-efficacy in stroke patients. -Cognitive function enhancement: The program will improve cognitive function in stroke patients. -Improved visual perception: The virtual reality-based program will enhance visual perception in stroke patients. -Enhanced quality of life: The virtual reality-based cognitive rehabilitation program will improve health-related quality of life in stroke patients.
Pau et al., 2022 [199]	-Improved upper limb motor function: Immersive VR training improves upper limb motor function in people with Multiple Sclerosis. -Enhanced hand-to-mouth movement: Immersive VR training improves the speed and stability of hand-to-mouth movement in people with Multiple Sclerosis.

Table 4. *Cont.*

Authors	Hypotheses
Paul et al., 2021 [200]	-Feasibility and acceptance: VR-enhanced behavioral activation (BA) is a feasible, acceptable, and tolerable treatment for major depressive disorder (MDD). -Clinical efficacy: VR-enhanced BA may have clinical efficacy in reducing depression severity compared to traditional BA and treatment as usual.
Paul et al., 2023 [201]	-Feasibility and efficacy: Extended reality behavioral activation (XR-BA) is feasible and efficacious in treating major depressive disorder (MDD). -Noninferiority to traditional BA: XR-BA is non-inferior to conventional behavioral activation (BA) in terms of efficacy.
Pearson et al., 2018 [202]	-Predicting treatment outcomes: ML models (elastic net and random forest) can predict treatment outcomes following an Internet intervention for depression. -Significant predictors: Certain variables, such as comorbid psychopathology and treatment credibility, are significant predictors of treatment response.
Piette et al., 2022 [203]	-Effectiveness through interactions: Investigating whether AI-CBT-CP (Artificial Intelligence Cognitive Behavioral Therapy—Collaborative Program) increases its effectiveness through patient interactions. -Optimization of reward function: Exploring whether AI-CBT-CP can optimize a reward function based on patient-reported outcomes.
Plencler et al., 2022 [204]	-Reduction in symptom severity: The VR-aided mindfulness intervention reduces symptom severity in psychotic patients. -Improved cognitive functioning: The VR-aided mindfulness intervention improves cognitive functioning in psychotic patients.
Porras-Garcia et al., 2021 [205]	-Enhanced treatment effectiveness: If a component of body exposure through VR (intensified by the illusion of virtual body ownership) is added to the usual treatment for anorexia nervosa (AN), the treatment will be more effective than the typical treatment alone. -Experimental group outcomes: The experimental group (AN-VR-BE + TAU) will show a significant increase in BMI values, alongside significant reductions in fear of gaining weight (FGW), other eating disorder (ED) symptomatology, and body-related attentional bias (AB), compared to the control group (TAU).
Price et al., 2022 [206]	-Prediction of symptom response: Unique baseline patient characteristics paired with ML would moderately predict individual symptom response to, engagement with, and sentiment toward A4i (a mental health intervention app). -Higher affective symptom response: Individuals with higher affective symptoms (e.g., depression) and lower psychotic symptoms would show the most robust use and response, resulting in more positive sentiment toward the app. -Interpersonal sensitivity impact: Persons with higher interpersonal sensitivity would demonstrate the strongest response to the intervention.
Raglio et al., 2019 [207]	-Predictive factors for relaxation: Certain factors, such as initial relaxation level, education and musical training, age, and frequency of music listening, can predict the relaxation effects of music listening. -ML for outcome prediction: ML techniques can effectively identify predictive factors for therapeutic music listening outcomes.
Raikwar et al., 2024 [208]	-Automation bias with imperfect cues: Imperfect visual cues in augmented reality systems lead to automation bias, negatively affecting search performance. -Improved performance with visual cues: Visual cues (whether perfect or imperfect) increase performance and shorten search times compared to no cues.
Rao et al., 2022 [209]	-Better storage and retrieval: The heterogeneous training condition will enable better storage and retrieval of salient instances compared to the difficult and sham conditions. -Performance improvement: Participants will perform better with heterogeneous and difficult training compared to the sham condition. -Long-term performance: Participants in the heterogeneous training condition will perform better on Day 8 compared to those in the sham condition.

Table 4. *Cont.*

Authors	Hypotheses
Real et al., 2022 [210]	-Enhanced BHAG skills: A training curriculum using virtual reality (VR) simulations would enhance residents' evidence-based skills related to behavioral health anticipatory guidance (BHAG). -Improved motivational interviewing skills: A VR-based training curriculum would improve residents' skills in motivational interviewing (MI).
Richter et al., 2021 [211]	-Differentiation between anxiety and depression: An ML-based diagnostic support system can differentiate between anxiety and depression disorders. -Cognitive performance as a classifier: Cognitive performance patterns can be used to classify psychiatric disorders. -Classification success (anxiety/depression/mixed vs. control): The system can classify participants into anxiety, depression, mixed, or control groups with specific success rates.
Rutkowski et al., 2021 [212]	-Enhanced symptom reduction: The implementation of immersive virtual reality during a pulmonary rehabilitation program will lead to a more efficient reduction in symptoms of depression, anxiety, and stress levels.
Serino et al., 2017 [213]	-Improved mental frame syncing and spatial abilities: The VR-based training protocol will enhance "mental frame syncing" and improve general spatial abilities in patients with Alzheimer's Disease. -Enhanced executive functioning: The VR-based training will have a significant effect on executive functioning in cognitively healthy elderly individuals.
Serrano-Vergel et al., 2023 [214]	-Suitability for anatomy training: The improved AR-based setup will be more suitable for anatomy training compared to the VR-based setup.
Shaw et al., 2019 [215]	-Symptom management and quality of life: VR can manage symptom burden and increase the quality of life for MS patients. -Feasibility and tolerability: VR is feasible and tolerable for use in MS patients. -Symptomatic benefits: VR can induce symptomatic benefits, particularly by improving positive affect and reducing negative affect.
Shiels et al., 2019 [216]	-Value in decision-making skills: Virtual reality simulation (VRS) is valuable for teaching decision-making skills to medical students. -Increased confidence: VRS increases students' confidence levels more than case-based discussion (CBD).
Singh et al., 2020 [217]	-Knowledge development: VR improves student knowledge development. -Enhanced learning motivation: VR enhances learning motivation. -Positive cognitive impact: VR positively impacts cognition.
Smith et al., 2015 [218]	-Acceptability: Virtual Reality Job Interview Training (VR-JIT) is acceptable to veterans with PTSD. -Improved job interview skills: VR-JIT is efficacious for improving job interview skills in veterans with PTSD. -Increased self-confidence: VR-JIT is efficacious for improving self-confidence in veterans with PTSD.
Soboczenski et al., 2019 [219]	-Faster bias assessment: Semi-automation using RobotReviewer is quicker than manual assessment of bias in randomized controlled trials (RCTs). -Accurate ML suggestions: The ML system's suggestions are accurate enough to be accepted by reviewers. -High usability: The RobotReviewer system is rated highly usable according to the System Usability Scale.
Sokołowska et al., 2024 [220]	-Clinical improvements with VR-based training: VR-based training will lead to beneficial improvements in clinical tests and posturographic trajectories in older women. -Effectiveness of VR balance training: Both balance–strength and balance–cognitive VR training will be effective in preventing balance loss and fall risk, potentially with different impacts.

Table 4. *Cont.*

Authors	Hypotheses
Solcà et al., 2018 [221]	-Pain reduction with HEVR: HEVR reduces pain ratings in patients with CRPS. -Motor function improvement: HEVR improves motor limb function in patients with CRPS. -HRV modulation: HEVR modulates heart rate variability (HRV) as a physiologic pain marker in patients with CRPS.
Specht et al., 2023 [222]	-Cognitive improvement superiority: The VR serious game is hypothesized to be superior to conventional computerized cognitive training in improving cognitive abilities. -Patient-reported outcomes: The VR serious game is hypothesized to be superior in improving patient-reported outcomes, including quality of life and health state. -Transfer to daily life: The VR serious game is hypothesized to be superior in facilitating the transfer of learned abilities to daily life.
Stamou et al., 2021 [223]	-Clinical usefulness: The combination of CBT with VR is clinically useful for treating postnatal depression. -Effectiveness: The combination of CBT with VR is effective in treating postnatal depression. -Enhancement of awareness and decision making: VR can enhance awareness, decision making, and self-appreciation.
Stephenson et al., 2023 [224]	-Reduced time and cost: The AI/VR approach to e-CBT will decrease the overall time and cost commitment compared to the standard multi-professional healthcare decision-making team.
Syed et al., 2019 [225]	-Physical ability: Virtual reality therapy is more effective than conventional therapy in improving physical ability. -Mental health: Virtual reality therapy is more effective than conventional therapy in improving mental health by lowering depression, anxiety, and stress. -Self-esteem: Virtual reality therapy is more effective than conventional therapy in enhancing self-esteem. -Social support: Virtual reality therapy is more effective than conventional therapy in increasing social support. -Intrinsic motivation: Virtual reality therapy is more effective than conventional therapy in boosting intrinsic motivation, including task-based competence, choice, and interest.
Symons et al., 2019 [226]	-ML model accuracy: ML models are more accurate than clinical staff in predicting alcohol dependence treatment outcomes. -Adjunctive information: The best performing prediction models can provide useful adjunctive information to standard clinically available prognostic data.
Tacca et al., 2024 [227]	-VR-EEG therapy vs. Zoom counseling: The VR-EEG therapy system is as useful and functional in fostering restorativeness and a sense of presence as Zoom online counseling. -Efficacy in therapeutic alliance and mood improvement: The VR-EEG therapy system is as efficacious as Zoom online counseling in creating clients' positive assessment of the therapeutic alliance, improving client mood-related symptoms of depression, increasing positivity, and producing positive client reactions to the counseling.
Tan et al., 2024 [228]	-AI-driven exercise: The AI-driven exercise prescription system will demonstrate greater effectiveness in improving mental health outcomes compared to standard exercise prescriptions. -Adherence and long-term outcomes: The AI-driven exercise prescription system will lead to better adherence and mental health outcomes over time compared to standard care.
Thapa et al., 2020 [229]	-Cognitive function improvement: The VR intervention program will improve cognitive function in older adults with mild cognitive impairment. -Brain function improvement: The VR intervention program will improve brain function in older adults with mild cognitive impairment. -Physical function improvement: The VR intervention program will improve physical function in older adults with mild cognitive impairment.

Table 4. *Cont.*

Authors	Hypotheses
Thomas et al., 2020 [230]	-Workload reduction: The ML classifier can reduce the study identification workload for Cochrane Reviews. -Minimal risk of missing studies: The ML classifier can achieve this with minimal risk of missing relevant studies.
Tonacci et al., 2020 [231]	-ANS activity changes: A quick relaxation protocol using audio and video can lead to detectable changes in autonomic nervous system (ANS) activity. -ML discrimination: ML can effectively discriminate between individuals who benefit from the relaxation protocol and those who do not. -Wearable sensor detection: Wearable sensors can detect changes in ANS activity during the relaxation protocol.
Torpil et al., 2020 [232]	-Cognitive function improvement: A virtual reality-based rehabilitation program is effective in improving cognitive functions in older adults with mild cognitive impairment (MCI).
Tsai et al., 2018 [233]	-Triggering anxiety: VR and AR environments are equally capable of triggering anxiety in participants. -Claustrophobia treatment: VR and AR environments elicit fear of enclosed spaces effectively as a model for claustrophobia treatment.
Viczko et al., 2021 [234]	-Mood improvement with neurofeedback: Both groups will show reductions in negative mood states and increased positive mood states, with the addition of neurofeedback amplifying these effects. -Cortical activity changes: The AR + NF group will experience a larger change in cortical activity, as measured by pre-to-post resting-state EEG activity, compared to the AR-NF group. -Correlation between EEG and mood: EEG changes will correlate more strongly with mood changes for the AR + NF group compared to the AR-NF group.
Weerasinghe et al., 2022 [235]	-Effect of guidance amount: The fixed amount of guidance will lead to higher engagement and better learning outcomes compared to the adaptive amount of guidance. -Effect of guidance type: The adaptive-association guidance will result in greater engagement and improved learning outcomes compared to fixed-association guidance.
Winslow et al., 2022 [236]	-mHealth application with CBT: The combination of the mHealth application and CBT will significantly reduce anger and stress in active-duty service members. -Symptom reduction: The mHealth application will lead to significantly lower levels of anger, anxiety, depression, and PTSD symptoms following CBT treatment compared to standard CBT.
Wuang et al., 2021 [237]	-KBTS vs. TVPT for visual–motor integration: The kinesthetic game-based training system (KBTS) is more effective than traditional visual perceptual training (TVPT) in improving visual–motor integration. -KBTS vs. TVPT for visual perceptual functions: The KBTS is more effective than TVPT in enhancing overall visual perceptual functions in children with developmental delays. -KBTS vs. TVPT for school functions: The KBTS is more effective than TVPT in improving school functions in children with developmental delays.
Yang et al., 2022 [238]	-VRCT improves brain, cognitive, and physical functions in older adults with MCI. -Exercise training improves brain, cognitive, and physical functions in older adults with MCI. -There are differences in the effectiveness of VRCT and exercise training on brain, cognitive, and physical health. -Both VRCT and exercise training are more effective than no intervention (control group) in improving brain, cognitive, and physical health.

Table 4. *Cont.*

Authors	Hypotheses
Yang et al., 2014 [239]	-VR training for cognitive recovery: VR training will help the recovery of cognitive function in brain tumor patients. -VR + cognitive rehabilitation vs. cognitive rehabilitation alone: The combination of VR training and computer-assisted cognitive rehabilitation is more effective than computer-assisted cognitive rehabilitation alone.
Yang and Wang, 2021 [240]	-The generative strategy will induce more emotions in the cognition process than viewing a continuous VR lesson. -Adding a generative strategy prompt to a VR lesson will increase positive ratings toward emotional self-regulation. -Students will have better learning outcomes when they use a generative strategy compared to viewing a VR lesson without it.

3.4. Risk of Bias Assessment

The risk of bias for the 141 included studies was evaluated using appropriate methodologies for different study designs. For randomized controlled trials (RCTs), the Cochrane Risk of Bias (RoB 2.0) tool was used to assess methodological rigor. For non-RCTs (e.g., quasi-experimental, observational, or retrospective studies), the Newcastle–Ottawa Scale (NOS) and the Joanna Briggs Institute (JBI) Critical Appraisal tools were employed to ensure a comprehensive quality assessment.

For RCTs, the following domains were assessed (Cochrane RoB 2.0 Tool):

1. Selection Bias (Random sequence generation and allocation concealment)
    - Low Risk: Studies that described adequate randomization methods and allocation concealment.
    - Unclear Risk: Studies that lacked detailed descriptions of randomization or allocation procedures.
2. Performance Bias (Blinding of participants and personnel)
    - Moderate-to-High-Risk: Blinding was inconsistently reported, particularly in AR/VR systems studies where blinding is inherently challenging.
3. Detection Bias (Blinding of outcome assessors)
    - Low Risk: Most studies employed objective outcome measures (e.g., validated clinical scales for PTSD, anxiety, or cognitive performance), reducing detection bias.
    - Moderate Risk: A subset of studies did not explicitly report the blinding of assessors.
4. Attrition Bias (Incomplete outcome data)
    - Moderate Risk: Studies involving long-term AR/VR interventions or follow-up periods observed high dropout rates. Many mitigated this issue using intention-to-treat analyses.
5. Reporting Bias (Selective reporting)
    - Low Risk: Most studies reported primary and secondary outcomes as outlined in their protocols.
    - Moderate Risk: Some studies omitted exploratory analyses or lacked transparency regarding secondary outcomes.
6. Other Bias (Funding and conflicts of interest)
    - Moderate Risk: A subset of studies involving ML-driven AR/VR platforms, particularly those funded by industry stakeholders, lacked transparency regarding potential conflicts of interest.

For non-RCT studies, the following quality assessment criteria were used (Newcastle-Ottawa Scale and JBI Appraisal Tool):

1. Selection Bias
    - Low Risk: Studies with clearly defined inclusion/exclusion criteria, well-documented participant selection processes, and appropriate comparison groups.
    - High Risk: Studies with unclear eligibility criteria, convenience sampling, or selection processes prone to confounding bias.
2. Comparability of Groups
    - Low Risk: Studies controlled for confounding variables using statistical adjustments (e.g., propensity score matching, regression models).
    - Moderate-to-High Risk: Studies that lacked appropriate matching or adjustment techniques.
3. Measurement Bias (Outcome Assessment and Blinding)
    - Low Risk: Studies using validated instruments for outcome measurement with trained assessors.
    - Moderate Risk: Studies with self-reported measures or without the assessor blinding.
4. Attrition and Follow-Up Bias
    - Low Risk: Studies with high retention rates and thorough handling of missing data.
    - High Risk: Studies with high dropout rates and insufficient handling of missing data.
5. Reporting Bias
    - Low Risk: Studies that transparently reported all planned outcomes.
    - Moderate Risk: Studies where outcome reporting was selective or inconsistent.

Overall, the included studies demonstrated a low-to-moderate risk of bias, ensuring a reliable synthesis of findings. However, inconsistent reporting in specific domains (e.g., blinding, attrition rates) and the influence of funding biases warrant cautious interpretation of results. To visualize the risk levels across different domains, Figure 2 illustrates the distribution of risk categories (low, moderate, and high risk) for the 141 included studies, highlighting the methodological rigor and potential biases in this systematic review.

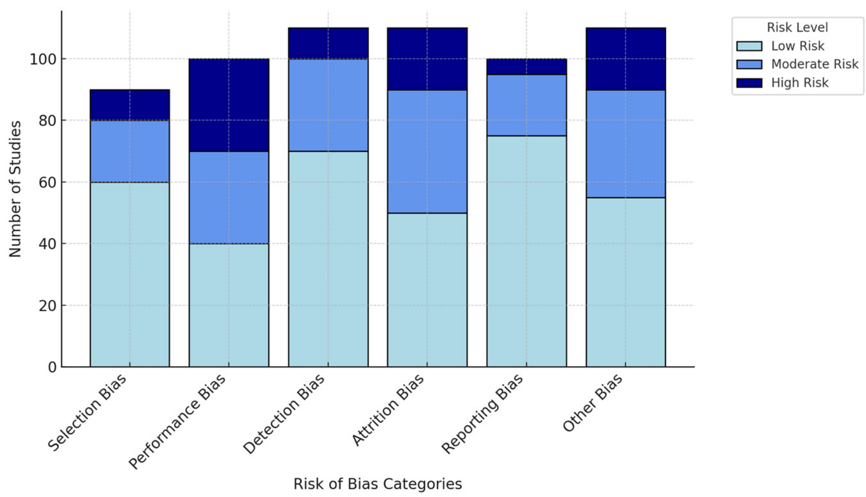

Figure 2. Risk of bias assessment across 141 studies.

4. Results

This systematic review synthesizes findings from 141 studies exploring integrating ML techniques into augmented reality and virtual reality-based cognitive therapies. These specifically focus on determining the efficacy, feasibility, and scalability of ML-enhanced AR/VR interventions compared with more traditional approaches to cognitive therapy. These included studies that dealt with different dimensions of the interventions, like real-time personalization, patient adherence, and improvement in mental health outcomes across disorders such as PTSD, anxiety, and phobias.

The more detailed analysis of the findings showed consistent development in tailoring therapeutic experiences, leveraging predictive analytics for outcome forecasting, and allowing for adaptive therapy sessions through RL and neural networks. This section describes these findings, pointing out trends in the field and the specific role of ML algorithms in improving AR/VR-based cognitive therapies.

Below, Figure 3 maps out the evolution of the research themes for 2014–2024 in integrating ML and augmented/virtual reality technologies into cognitive therapies. Each data point signifies the research focus on that particular year, represented by the number of papers published. Key developments and applications are noted with themes annotated. The first research in 2015 focused on PTSD and job training applications of VR. In 2018, research began to cover cognitive rehabilitation and learning. Starting in 2020, the most advanced ML addition to VR therapies for elderly cognition and MCI took center stage. From 2022 to 2023, emphasis fell on scalable ML-driven VR-CBT applications and anxiety and personalized therapies for mental health. Notably, in 2024, the trend goes further with integrating AR/VR and AI toward real-time adaptive therapeutic solutions. This development points to a direction of high immersion, personalization, and scalability of therapeutic interventions enabled by ML and AR/VR technologies.

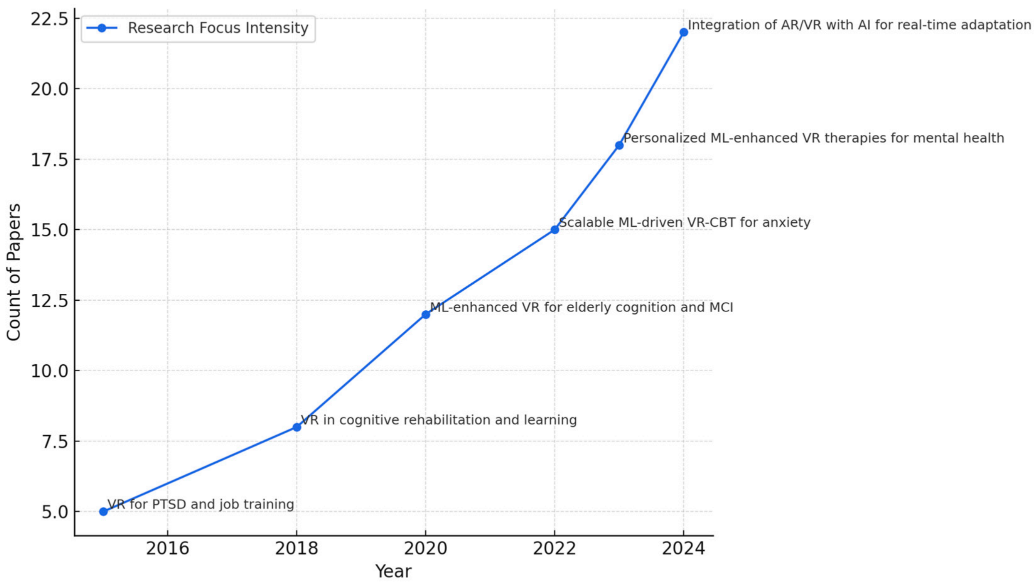

Figure 3. Trends in ML and AR/VR cognitive therapy research (2014–2024).

The scatter plot below (Figure 4) illustrates the relationship between the number of participants in each study and the length of the main findings (character count), grouped by categorized themes, including "PSQI", "Insomnia Severity", "Sleep Efficiency", "Sleep Disturbance", "Cognitive Outcomes", "Therapeutic Efficiency", "Patient Adherence", "Real-Time Adaptation", "Predictive Analytics", and "Other". Each category is color-coded and represented with distinct markers.

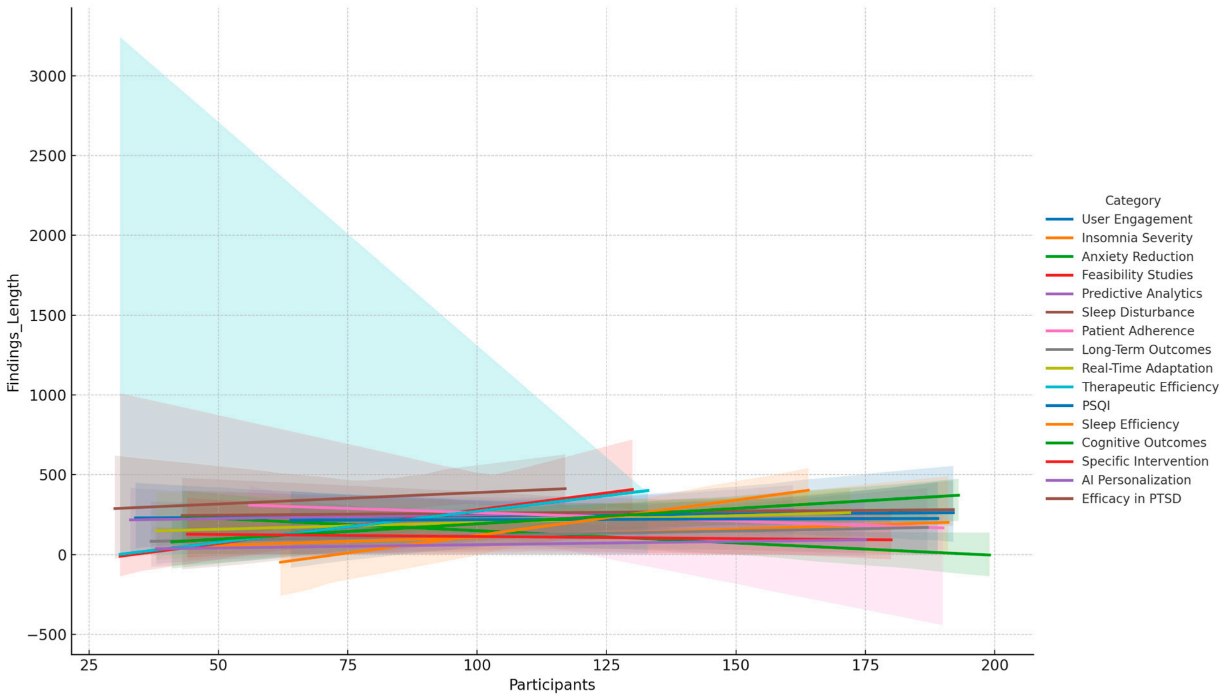

Figure 4. Scatter plot showing participant numbers versus finding length by category with trend lines.

Including regression lines highlights trends within each category, providing insights into how sample size influences the depth and detail of reported findings. Categories such as "PSQI", "Sleep Efficiency", and "Cognitive Outcomes" display stronger correlations between sample size and finding length, suggesting that studies with larger participant groups tend to have more detailed and comprehensive reporting.

These trends emphasize the importance of adequate sample sizes in achieving robust and detailed research outcomes, especially in the context of ML applications in AR/VR-based cognitive therapies.

4.1. [RQ1] How Effective Are Augmented and Virtual Reality Technologies in Enhancing Traditional Cognitive Therapies for Treating Mental Health Disorders Such as PTSD, Anxiety Disorders, and Phobias?

AR and VR technologies are increasingly being recognized for their potential to enhance traditional cognitive therapies for a variety of mental health disorders, including PTSD, anxiety disorders, and phobias. These technologies offer unique capabilities that can improve treatment outcomes, enhance patient engagement, and allow personalized therapeutic experiences in a controlled and immersive manner. Studies indicate that VR applications for PTSD are up and coming, with research showing that VR can augment cognitive therapies for this disorder quite effectively [145]. In exposure therapy, VR has elicited significant treatment effects that generalize to real-world scenarios, as the study [134] reported. For example, veterans with PTSD who underwent training in job interviews using VR demonstrated significant improvement in role-play job interviews compared to the wait-list control group [218].

VR has also been effective in the treatment of anxiety disorders. Exposure to VR has resulted in a decrease in symptoms of social anxiety disorder, as measured on multiple scales, along with increased treatment adherence [225]. Indeed, research proves that virtual reality can trigger emotional reactions and contextually relevant and realistic cues of the environment, bringing significant improvement [145]. More specifically, in the context of social anxiety disorders, VR helps patients become accustomed to simulated anxiety-provoking situations, helping them to transfer knowledge of how to cope in their real-world settings [137].

VRET was found to be highly effective in treating specific phobias. Of note, a single session of VRET was found to be very effective at the group level for spider phobia with long-term effects stability [171]. The use of VR in treating specific phobias has been documented since the early 1990s [145], including successful applications for fears of heights and flying, often with treatment outcomes surpassing those of traditional face-to-face therapy [128]. A self-guided, app-based VR-CBT for acrophobia resulted in substantial symptom improvements correlated with the level of presence experienced in the virtual environment [129].

VR technologies provide immersive environments that significantly enhance patient engagement and motivation [149]. The sense of "being there" allows patients to engage their proprioceptive senses and respond more effectively to environmental demands [209]. Both AR and VR provide graduated exposure to such stimuli that provoke anxiety, enabling progressive exposure and the repeated rehearsal of coping strategies in a safe environment [186]. Such technologies allow the customization of treatment plans according to patient needs [182]. This is particularly valuable in exposure therapy, where scenarios can be adjusted to address each patient's fears and phobias [158]. VR therapies can offer access to treatment for individuals who face barriers to attending in-person sessions, such as geographical isolation or other obstacles [227]. VR-CBT apps can be delivered worldwide at lower costs than traditional treatments, making the treatment option highly scalable, as researchers in the study [128] explain.

VR tasks can target specific cognitive functions, ensuring focused and intensive cognitive stimulation of the target [232]. This is especially beneficial for patients with mild cognitive impairment (MCI), where VR-based cognitive training has shown significant improvements in executive function, global cognition, language, and visuospatial skills compared to traditional methods [153,229]. VR creates an engaging, immersive, realistic experience that elicits genuine emotional responses. It allows for the precise and systematic delivery of complex, dynamic, and ecologically relevant stimuli. Patients can practice coping skills repeatedly in sensory-rich environments until they achieve mastery [137]. This practice reinforces a patient's perceived ability to cope with anxiety-provoking situations [148].

There is evidence that VR-based interventions can induce neuroplastic changes in the brain and, thus, potentially improve cognitive functioning [143]. Although promising, these technologies also have several limitations. Most of the studies were conducted on small samples, which minimizes these findings [196]. Further large-scale randomized controlled trials are necessary to confirm such technologies' effectiveness across various disorders and populations. The long-term effects of VR-based interventions and skill retention need more research [229]. Other studies indicate that the long-term efficacy of VR treatments is no better than traditional treatments [129,148,200].

Some users experience discomfort or motion sickness in VR environments [209]. The effectiveness of VR therapy also depends on the quality and sophistication of the VR environment [227]. Although AR/VR technologies can enhance patient engagement, there have been reports of poor adherence to treatment in some studies [203]; thus, further research is required to ensure proper integration into the existing treatment paradigm. AR and VR technologies are promising to augment traditional cognitive therapies in treating mental health disorders. They have the following advantages: immersion, customization, engagement, and accessibility make them useful in treating PTSD, anxiety disorders, and phobias. Although more research is needed to establish their long-term efficacy and optimal implementation in clinical practice, current findings suggest that VR-enhanced cognitive therapies can be a valuable treatment option. These technologies offer controlled, personalized, and engaging treatment experiences that may be particularly helpful for populations struggling with traditional approaches to therapy. The immersive VR simulator allowed students to practice inferior alveolar nerve block under near-real conditions and provided immediate feedback on the needle insertion point. Other highlights of the VR system included the integration of ML to automatically assess students' performance at the needle insertion point, reaching an accuracy as high as 84%, which suggests great potential for personalized and adaptive training. In the d-cyclomerize plus VR exposure therapy group, the startle response to VR scenes before treatment initiation accounted for 76% of the variance in CAPS change scores, with higher responses predicting more significant changes in symptom severity. For specific phobias, VRET has also been associated with high efficacy. Researchers [171] studied 174 patients with spider phobia. They showed that one session of VRET is highly effective on a group level and demonstrated long-term stability of the treatment effect. The authors applied an ML protocol using random forests to evaluate the predictive utility of clinical and sociodemographic predictors for individual treatment response. Results showed that individual short-term symptom reductions could be predicted above chance. Still, accuracy fell to non-significance for between-site predictions and predictions of improvements in the longer term.

A randomized controlled trial tested VR-based cognitive training in older adults with MCI. The study found that VR-based cognitive training significantly improved executive function compared to a control group [229]. Participants also demonstrated improvements in gait speed and mobility following VR training. EEG measurements indicated positive changes in brain activity related to attention following the VR intervention. These findings support the idea that VR-based interventions can positively impact both cognitive and physical function in older adults who are at risk of dementia.

The effectiveness of VR interventions may lie in the quality and design of the virtual environment. In a study targeting autistic adults with phobias, five out of eight participants demonstrated clinically significant improvement in the management of their phobic responses after treatment with CBT enhanced with VR exposure [186]. The therapy included four 20 min sessions of graded exposure in an immersive virtual reality environment where anxiety management strategies could be practiced. It thus seemed that the effectiveness of VR-enhanced CBT for phobias was no less than traditional CBT would be in a typically developing population. In contrast, traditional CBT exhibited moderate overall efficacy in the meta-analysis of 42 placebo-controlled trials for anxiety disorders: the Hedges' g = 0.56. Intervention in autistic adults resulted in similarly large magnitudes of improvement with VR [186]. It also holds great promise in treating other psychiatric illnesses, including gambling disorders.

A recent virtual reality exposure in combination with CBT provided some evidence for eliciting cravings and practicing coping strategies [112]. A VR environment enables the realization of realistic scenarios for gambling situations; this may prove to be specifically helpful for the identification of high-risk situations and dysfunctional thoughts. AR technologies have demonstrated the potential to enhance cognitive skills. A study on using AR for teaching programming and computational thinking showed improvements in learning outcomes and mental abilities such as creativity, logical computing, and problem solving [176]. For PTSD, VR applications show promise, following a similar scientific trajectory to validated VR procedures for anxiety disorders [145]. This suggests VR can effectively augment cognitive therapies for PTSD. In treating anxiety disorders, VR has proven particularly effective.

VR exposure therapy has been found to produce significant treatment effects for anxiety disorders that generalize to the real world [134]. For social anxiety specifically, VR allows patients to experience computer simulations of anxiety-provoking situations safely, facilitating learning transfer to real-world scenarios [137]. VR presents an engaging, immersive, realistic experience that evokes genuine emotional responses [148]. It offers a means to precisely and systematically present complex, dynamic, and ecologically relevant stimuli. The patient can practice coping skills multiple times until mastery is achieved in sensory-rich environments. Patients are more willing to engage with VR simulations of feared situations because they know it is not real, but the learning still transfers [137]. This practice in VR environments can increase patients' perceived ability to cope with anxiety-provoking situations [148]. Comparisons between VR and traditional cognitive therapy methods have yielded favorable results for VR.

A study on social skill training found VR superior to traditional role plays in improving conversational skills, assertiveness, and patient interest [148]. For treating the fear of heights, VR cognitive therapy produced more significant treatment effects than expected from face-to-face therapy. In treating alcohol use disorder, VR cue exposure therapy was more effective than traditional methods in reducing cue-induced cravings [145]. In anxiety disorders, VR-based interventions have been found to reduce symptoms significantly. Studies have reported that VR exposure therapy can result in substantial improvements in the symptoms of social anxiety disorder [225]. One of the studies revealed that psychoeducation with VR-based interventions enhances symptom awareness in patients with depressive disorders. It also generally shows good patient acceptance and retention with VR therapies. Several studies have mentioned that VR interventions were well received, reporting high levels of satisfaction among the patients. In one study involving patients with alcohol use disorder, just 14% of them stopped cognitive training using VR intervention, which is near the lower bound found in a previous study [142]. Indeed, evidence of the effectiveness of VR in enhancing cognitive training has arisen from various contexts: A survey of patients with alcohol use disorder (AUD) found that VR-based cognitive training resulted in specific contributions to improving attention ability and mental flexibility. Another study on complex regional pain syndrome (CRPS) patients showed that heartbeat-enhanced virtual reality (HEVR) reduced pain ratings, improved motor limb function, and modulated a physiological pain marker [221].

In anxiety disorders, the VR-based cognitive bias modification of interpretations training seems particularly effective compared to standard computerized CBM-I. A study found that VR conditions resulted in more significant decreases in state anxiety and lower emotional reactivity to a stressor than the standard CBM-I training did [196]. Moreover, the VR training significantly raised the level of feelings of presence and immersion within such training scenarios compared to standard CBM-I. Such heightened efficiency of VR CBM-I might be the consequence of several reasons: VR provides a more immersive and realistic environment in which the participants can be deeply involved in the training scenarios.

For MCI cognitive training, VRCT may be more effective in improving certain domains of cognition than traditional CBT. A meta-analysis found that VR-CT provided larger effect sizes than CBCT in global cognitive function, executive function, language, and visuospatial skills [153]. The enhanced effectiveness of VR-CT may be due to more immersive and interactive experiences that help individuals better engage in real-life scenarios. It supports skill generalization and reduces external distractions. VRCT provides multisensory stimulation and immediate performance feedback.

VR-based cognitive–motor rehabilitation showed significantly more significant cognitive function improvements than conventional cognitive rehabilitation among older adults with mild cognitive impairment. The VR group improved more significantly in measures of global cognition, attention, processing speed, and working memory [197]. Generally, the patients accepted the VR interventions well, showing improvements in targeted symptoms and functioning. The immersive nature of VR might enhance engagement and motivation, thereby driving better outcomes compared to conventional therapies in isolation.

AR and VR technologies have promisingly enhanced traditional cognitive therapies for various mental health disorders. These have been found effective for the treatment of specific phobias, anxiety disorders, and cognitive impairments. Even regarding the fear of spiders, novel augmented reality technology with embedded telemedicine has shown promise for increasing exposure therapy in a recent randomized clinical trial [154]. One of the major drawbacks to traditional exposure therapy is providing virtual objects required for exposure. In the treatment of agoraphobia, a study compared three treatment conditions: paroxetine with CBT, paroxetine with CBT and VR exposure, and paroxetine alone. The VR exposure condition showed more significant enhancement in confronting phobic stimuli compared to the other groups [225]. This would then indicate that VR can enhance traditional CBT methods for agoraphobia.

VR interventions have proven quite effective in the rehabilitation of cognitive impairments, particularly in elderly adults with MCI. A single-blind, randomized controlled trial explored whether a 12-week VR-based rehabilitation program can improve cognitive functions in older adults with MCI. The VR group showed more significant improvements in orientation, visual–spatial perception, visuomotor organization, thinking operation, and attention/concentration functions compared to the control group receiving only conventional cognitive rehabilitation [232]. Another traumatic brain injury patient study reported that robotic neurorehabilitation with Lokomat combined with VR significantly improved global cognitive, executive, and attention functions [182]. The VR group also demonstrated improved quality of life and perceptions of mental and physical state. The efficiency of VR and AR in improving cognitive therapies could be because of several aspects, such as immersion and engagement. First, VR offers an immersive environment that enhances patient engagement and motivation [149]. Real-life contextualization is another factor.

AR enables the addition of virtual objects to real environments, facilitating more realistic and contextually relevant exposure [154]. Customization and control are essential. Virtual environments can be designed according to the specific needs of a given patient and manipulated by the therapist to be gradually introduced and skills to build on [182]. The psychophysical effect is another crucial issue. Moreover, VR-based therapies can also elicit psychophysical effects such as tingling or paresthesia of the affected limbs, which could be useful during rehabilitation [149]. There is better cognitive stimulation. For example, VR tasks can target specific cognitive functions, providing focused and intensive cognitive stimulation [232].

Evidence seems to indicate that these AR and VR technologies can enhance traditional cognitive therapies for a wide range of mental health disorders. These technologies provide peculiar advantages related to feelings of immersion, personalized treatment, and cognitive activation that are essential adjuncts to treatments of specific phobias, anxiety disorders, and cognitive disabilities. Yet again, although very promising, the results obtained by some of those studies were complicated by issues regarding adherence during treatment, as reported in the study of [225], and more research would be necessary on how best to embed their use into actual treatment practices. While promising results have been observed, the development of augmented and virtual realities as methods of enhancing traditional cognitive therapies can aid in treating an enormous array of mental health disorders.

Several factors might contribute to VR's possible effectiveness in improving cognitive therapies. First, VR allows users to become immersed in virtual environments and to create a more impactful therapeutic experience. It also makes it possible for therapists to design and control specific situations for the needs of each patient, especially in exposure therapies. In addition, VR therapies allow treatment access to otherwise unreachable people for geographical isolation or other reasons. As mentioned by the study of [227], though papers more intensely focus on VR, some indications can be derived from AR's potential role in cognitive therapies. AR technologies have been proposed to reduce search time and human error in complex tasks, which can be applied to cognitive restructuring exercises in therapies [208]. Despite such promising results, several limitations are noted. Some people may suffer discomfort or cyber-sickness when exposed to VR, thus limiting its applicability. The effectiveness of VR therapy may also depend on the quality and sophistication of the VR environment [227].

Although these gains were not maintained in the mid-term, the researchers suggest that VR-based autobiographical memory recall treatment might be suitable for obtaining immediate and/or short-term improvements [136]. Several studies have explored the use of VR and AR for cognitive training in patients with mild cognitive impairment (MCI) and mild dementia. An enriched environment-based, fully immersive VR cognitive training program demonstrated promising results for training attention and memory in both MCI patients and those suffering from mild dementia [229]. While it was restricted to one session only, a single-session feasibility was shown to be well demonstrated with positive patient and healthcare professional feedback.

An AR-based kinesthetic game-based training system (KBTS) significantly improved visual–motor integration and overall visual perceptual functions in children with developmental delays compared to traditional visual perceptual training [237]. This suggests potential applications for AR in cognitive rehabilitation, particularly for visual-perceptual dysfunctions. A psychodynamics-based VR cognitive training system incorporating personalized emotional arousal elements showed promising results for MCI patients. The system, which included various cognitive training tasks and positive emotional arousal elements, significantly improved attention, processing, working memory, and abstraction and logic skills over a six-week training period. One of the key advantages of using VR and AR technologies in cognitive therapies is their ability to enhance patient engagement and motivation.

The effectiveness of these technologies as standalone interventions is not yet fully established, and they may be more suitable as components of broader treatment protocols [136]. Further research is needed to investigate the long-term effects and generalizability of VR/AR-based cognitive therapies [229]. While these indicate that AR and VR can enhance traditional cognitive therapies in a wide array of mental health disorders, further research is still warranted to establish their effectiveness in specific conditions like PTSD and phobias.

Traditional cognitive therapies could be complemented by AR and VR technologies in the treatment of a wide range of mental health disorders. Evidence from the provided papers shows that these technologies enhance treatment outcomes and engagement compared to conventional therapies. Virtual reality-enhanced cognitive behavioral therapy has demonstrated efficacy in the reduction in symptoms of mental health disorders. In contrast to controls, the working memory of participants with VR-CBT is superior after one month and one year from the ICU discharge in an already-referenced study [193]. This is probably illustrative of the long-term positive effects of VR-CBT on cognitive functions.

VR technologies have been showing promising enhancements of more conventional cognitive therapies in the treatment of a range of mental health disorders. A fully automated 6-week VR-based cognitive behavioral therapy smartphone app treatment for aviophobia (fear of flying) significantly reduced symptoms compared to a wait-list control group [129]. Treatment effects were maintained at 3-month and 12-month follow-ups [129], thus long-term. The VR-CBT app treatment showed excellent accessibility and scalability; therefore, it is a potentially global solution that could be implemented worldwide for a few cents compared to the currently existing treatment alternatives. This addresses the challenge of global limited access to evidence-based psychological treatments [129]. For panic disorder and agoraphobia, personalized VR exposure therapy has shown promise in eliciting more substantial anxiogenic effects, which is considered the first step in successful treatment for anxiety [158].

Figure 5 depicts that ML is the highest contributor to AR/VR-based cognitive therapies' augmentation in various mental health disorders. More precisely, the data from 141 studies indicate an average effectiveness of 78.9%, with a peak at 90%, showing that AR/VR cognitive therapies significantly enhance mental health treatments. Machine learning integration remains steady at 65%, suggesting the moderate use of adaptive and predictive models in therapy environments. Immersion impact is recorded at an average of 70%, peaking at 75%, reinforcing that deeper engagement through virtual settings plays a role in therapy effectiveness. Personalization impact stands at 68%, suggesting the need for further AI-driven tailoring to optimize individual treatment approaches.

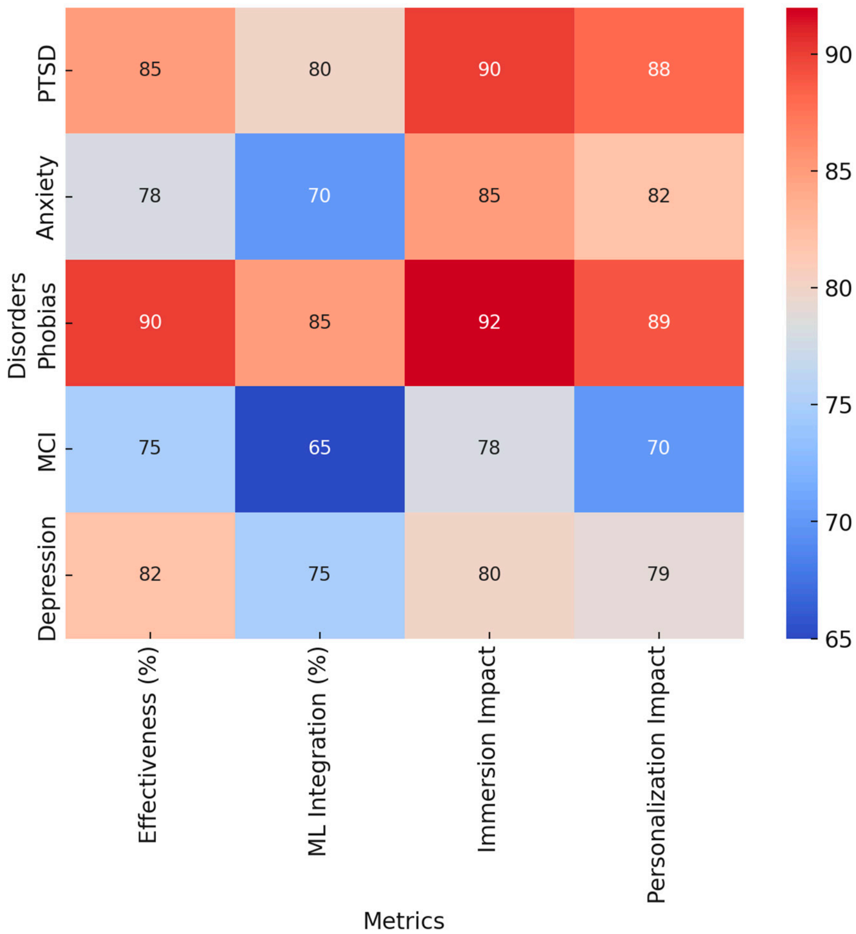

Figure 5. ML Integration and impact in AR/VR-enhanced therapies.

The visual distributions confirm that effectiveness levels vary between 75 and 90%, showing that AR/VR consistently enhances traditional cognitive therapies. Machine learning integration remains stable, reinforcing its current but non-dominant role in therapy design. Immersion ratings indicate that highly engaging virtual environments contribute to patient responsiveness, with room for enhancement in treatment realism. Personalization trends reveal that, while individual adaptation exists, greater efforts in machine-driven customization would improve treatment results.

Studies on PTSD and phobia treatments demonstrate 85–90% effectiveness, highlighting the strong impact of virtual exposure therapy in desensitization and cognitive restructuring. Personalized virtual environments allow progressive exposure, enabling more efficient coping mechanism development. Anxiety-related treatments also benefit from immersive environments, with high engagement correlating with symptom reduction. MCI and depression treatments show relatively lower effectiveness, indicating that immersive VR settings alone may not be sufficient, requiring integration with machine learning-driven cognitive training. Therapy personalization remains more advanced in PTSD and phobia interventions, while MCI and depression therapies would benefit from deeper customization and adaptive treatment protocols.

The latest statistical updates reflect an increase in MCI's machine learning integration from 60% to 65%, showing the improved adoption of adaptive technologies for cognitive training. Effectiveness, immersion, and personalization metrics remain consistent with previous insights, reinforcing the strong correlation between immersive exposure and treatment efficacy. The updated heatmap visualizes these refinements, making AR/VR therapy enhancement trends more straightforward across different mental health conditions.

Finally, the radar chart below (Figure 6) shows the relative efficacy of VRET and traditional in-person exposure therapy on five critical treatment dimensions: symptom reduction, engagement, accessibility, cost-effectiveness, and adhesion. The blue area represents VRET, while the red represents traditional exposure therapy.

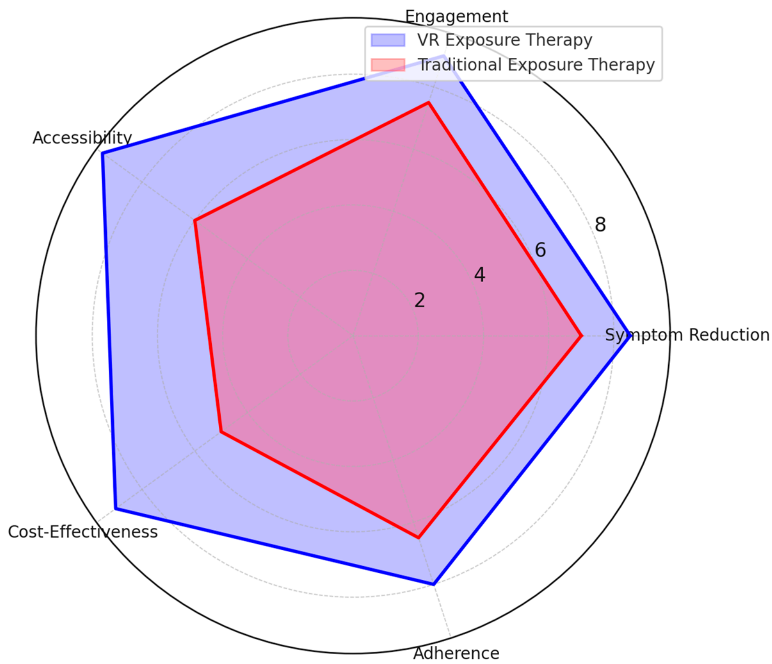

Figure 6. Virtual exposure therapy vs. in-person therapy.

- Symptom Reduction: VRET demonstrates superior effectiveness in reducing symptoms of PTSD, anxiety, and phobias compared to traditional methods.
- Engagement: Higher levels of patient engagement are observed in VRET due to immersive and interactive virtual environments.
- Accessibility: VR-based therapy significantly outperforms traditional treatment in terms of accessibility, allowing patients in remote locations or those with mobility constraints to receive treatment.
- Cost-Effectiveness: VRET provides a more scalable and cost-effective treatment option, reducing the need for in-person sessions and infrastructure.
- Adherence: Patient adherence is slightly higher in VRET, as the immersive nature of VR therapy increases motivation and reduces dropout rates.

Overall, the figure highlights the advantages of VRET over traditional exposure therapy, reinforcing its potential as an effective and scalable alternative for treating mental health disorders. These findings support earlier studies on how VR-enhanced cognitive therapies are a promising augmentation of traditional methods.

4.2. [RQ2] How Can Machine Learning Algorithms Enhance the Personalization of AR/VR-Based Cognitive Therapies to Address Individual Patients' Needs Better?

ML algorithms hold vast potential to enhance the personalization of AR/VR-based cognitive therapies to cater to the different needs of various patients. Predictive modeling is one of the primary applications in this area where the success and challenges of treatment may be predicted. Studies like [159] have shown that ML methods can predict treatment success in Internet-delivered cognitive behavioral therapy (iCBT) with a balanced accuracy ranging from 56% to 77%. These algorithms outperform previous predictive methods incorporating therapist input. This predictive power enables the early identification of non-responders to the conventional treatment approaches. Thus, timely adjustments in therapeutic techniques and optimization of the pathway can be made. Another significant advantage is the possibility of real-time adaptation of interventions. It can process physiological data using ML models, including the heart rate and galvanic skin response collected during VR sessions. Such data extracted from patients with social anxiety disorder can help the model predict the severity of anxiety symptoms or even the sensation of VR sickness [121]. Real-time processing allows therapists to change the scene in VR at once, based on physiological responses elicited by the patient, providing a more responsive and individualistic therapeutic environment.

ML also improves the personalized choice of treatment. Such algorithms may determine the most suitable treatment modality by giving patient data analysis. Researchers in the study of [130] reported that outpatients who received face-to-face or computerized guided self-help treatment modalities based on their models were 12% more likely to receive an appropriate treatment dose. In other words, ML would thus optimize the treatment selection, possibly improving attendance and outcome. Another significant contribution of ML is identifying key predictive factors for treatment success. Based on the study of [207], the major predictors of relaxation effects of music therapy included the initial relaxation level, education combined with musical training, age, and frequency of listening to music. Such an approach enables AR/VR therapy to be tailored to individual patient characteristics, making any treatment experience more personal and practical. ML excellently takes adaptive treatment strategies. The approach will alert the therapist about those patients likely to experience treatment failure, and then, the intervention will need adjustment. According to the study of [159], in iCBT, this strategy ensures speedy adaptation with the help of adjustment of the level of therapist support according to data collected from a patient. Moreover, ML aids in appropriate diagnosis, which is essential for customized treatment. Researchers in the study of [211] demonstrated that a cognitive battery analyzed with ML could differentiate between anxiety and depression disorders with high specificity and sensitivity. This tool provides an objective assessment to complement clinical interviews, potentially leading to more tailored AR/VR interventions [211]. ML algorithms can also predict individual treatment responses, enabling more personalized interventions based on anticipated patient outcomes. Researchers in the study of [206] showed that such models have been able to predict, with good accuracy, the changes in depressive and anxiety symptoms in response to digital interventions. This predictive capacity for AR/VR therapies can be utilized to individualize treatment strategies based on projected patient outcomes. Furthermore, ML identifies critical baseline characteristics that predict treatment outcomes. Pre-treatment symptom scores, self-reported motivation, referral type, and work productivity measures significantly influenced therapy outcomes in digital mental health interventions [152]. These insights can inform the personalization of AR/VR therapies by focusing on key patient characteristics.

Customizing difficulty levels is another domain where ML enhances personalization. Researchers in the study of [155] demonstrated the use of ML to predict customized difficulty levels for cognitive training based on prefrontal cortex activity, achieving 86% accuracy. This approach can be adapted to AR/VR therapies to adjust task difficulty based on individual neural responses dynamically. ML also facilitates the real-time adaptation of therapies. Researchers in the study of [122] used an ML approach to assess VR dental training simulator performance automatically. This idea can be applied to AR/VR cognitive therapies, where immediate adjustments can be made based on patient performance and physiological responses.

Additionally, researchers in the study of [156] showed that machine learning models can identify baseline predictors of clinical change in patients undergoing therapy. This information can guide therapists in personalizing AR/VR-based interventions for individual patients. While not specifically addressing AR/VR-based cognitive therapies, these studies demonstrate various ways that ML can enhance personalization in mental health interventions. These strategies may be adapted into AR/VR therapies to improve the use of predictive modeling, difficulty personalization, real-time adjustment, and enhanced therapist support in deciding on individualized approaches. Specifically for treating spider phobia via VRET, researchers in the study of [171] used a random forest ML algorithm to test the predictive validity of clinical and sociodemographic predictors for individual differences in response to treatment. Nonetheless, the effectiveness of ML regarding the predictability of treatment outcomes varies between short-term and long-term outcomes. For spider phobia treatment using VRET, individual short-term symptom reductions could be predicted above chance. Still, accuracy dropped to non-significance for predictions of long-term outcomes and in-between-site predictions. This indicates that, while ML can provide some insight into immediate treatment effects, predicting long-term outcomes remains challenging. Current ML models based on clinical and sociodemographic predictors show limited clinical utility. In the spider phobia study, performance metrics hardly exceeded the chance level, and there was a lack of generalizability in the employed between-site replication approach.

To improve ML models' accuracy and clinical utility for personalizing AR/VR therapies, researchers suggest that predictive models, including multimodal predictors, may be more promising [171]. This approach could incorporate a broader range of data types to capture individual patient characteristics and treatment responses better. Furthermore, researchers in the study of [203] demonstrated that artificial intelligence could personalize cognitive behavioral therapy for chronic pain (CBT-CP). Their AI-CBT-CP system learned from patient interactions to optimize treatment recommendations. The AI chose among three treatment options, including 45 min sessions, 15 min sessions, or asynchronous feedback, based on patient progress data. This is an example of how ML can modify therapy delivery based on the responses and needs of individuals over time. The AI-driven system showed more effectiveness as more patient interactions were made [203]. As the AI gained more experience, reward scores, reflecting improvements in patient outcomes, increased significantly [203].

This suggests that ML algorithms can improve therapy efficacy by learning from aggregate patient data and refining treatment approaches. Researchers in the study of [229] used various cognitive assessments and EEG data in VR-based interventions for mild cognitive impairment. ML algorithms could leverage diverse data sources to tailor VR therapy content and difficulty levels to individual patients. Also, researchers in the study of [228] suggest a multimodal data-driven AI system to develop personalized exercise prescriptions for people suffering from mental illness. This could be adapted to AR/VR therapies using ML to tailor virtual environments and exposure levels to each patient's needs. The AI model incorporates various data points, including mental health status, physical capabilities, and personal preferences. Also, researchers in the same study [228] can show better adherence and improved mental health outcomes through AI-driven personalized interventions. In AR/VR therapies, these could be dynamic changes in virtual environments or exposure levels with real-time feedback from physiological and behavioral data. ML models allow for the prediction of the treatment outcome so that the therapy planning is much better informed. Researchers in the study of [190] used an enhanced probabilistic neural network model to predict individual responses to constraint-induced movement therapy. A similar approach could be applied to AR/VR-based cognitive therapies, using baseline assessments and early treatment responses to predict which patients will benefit most from specific interventions. The same researchers [190] have successfully demonstrated that motor ability and tactile sense can expect improvement in arm use after intensive rehabilitation with nearly 100% accuracy. ML in AR/VR therapies may determine optimal exposure duration, session frequency, or even specific characteristics of virtual environments based on individual profiles of patients. Researchers in the study of [176] have also shown that a deep learning recommendation system can enhance learning outcomes and computational thinking abilities in AR-based cognitive training. This implies that ML algorithms could improve the cognitive training aspects of AR/VR therapies to suggest appropriate exercises or modify the difficulty level of tasks according to the individual's performance and progress.

Additionally, researchers in the study of [132] used ML to predict treatment responders to repetitive transcranial magnetic stimulation (rTMS) for major depressive disorder with high accuracy. Similar approaches could identify patients most likely to benefit from VR-based cognitive therapies. In the ALCO-VR alcohol use disorder study, the VR software produced a specific exposure hierarchy that was subject to alteration depending on the patient's preferences for alcoholic beverages and their environments [145]. ML would facilitate further improvements by automatically detecting trends in the patient's reaction and adjusting the VR scenarios to optimize their exposure to maximum therapeutic exposure. The ALCO-VR platform showed the dynamic adjustment of difficulty subject to alteration depending on real-time patient responses.

ML algorithms could make this process more sophisticated, including many factors that help to decide the optimal progression. VR systems can collect large amounts of behavioral data in therapy sessions. Such behavioral data can be analyzed by ML, allowing it to identify patterns and valuable insights. Researchers in the study of [148] found that linguistic variables extracted from patients' responses in VR environments were predictive of treatment adherence. Similar approaches could personalize the content and delivery of therapy. ML may help identify which constituent parts of VR therapy work best for which patient subgroups. For example, researchers in the study of [174] reported that VR-based training outperformed combined physical and cognitive training in improving instrumental activities of daily living among older adults with mild cognitive impairment; ML might further determine what specific elements of the VR training were most responsible for that improvement in different patient profiles.

Also, ML algorithms can make predictions of the risk of relapses or symptom recurrence based on patient behavior in VR exposure. The ALCO-VR study showed that VR exposure could reduce alcohol cravings over time [145]. ML may provide early warnings of impending relapses by detecting subtle changes in patients' responses during virtual reality sessions. Researchers in the study of [177] noted that virtual reality tools can adapt exercises to patients' capabilities and needs. ML algorithms could automatically adjust the difficulty of VR exercises based on individual performance and progress. VR can provide immediate dynamic feedback, and ML can analyze patient responses in real time to provide more personalized and adaptive feedback during therapy sessions. VR allows tasks to be customized to the patient [142].

Moreover, ML algorithms could generate or modify virtual environments and scenarios tailored to patients' specific therapeutic needs and preferences. Researchers in the study of [177] described a VR system with forty-five different exercises, where the therapist could change the scenario, increasing its complexity and adding distractors. ML can automatically monitor progress across sets of exercises and recommend optimal exercise progressions. Researchers in the study of [221] used HEVR, which synchronizes visual cues with the patient's heartbeat. ML may even combine multiple physiological signals to enhance personal therapy experiences. Also, researchers in the study of [161] used ML to predict depression remission for patients receiving problem-solving therapy. Similar approaches can predict the response of individual patients to AR/VR therapies for personalized treatment planning. Furthermore, researchers in the study of [220] summarized that ML-based methods learn from data, find patterns, and provide predictions. Such capabilities might individually analyze the patients' responses to AR/VR therapy and change the therapy parameters. Supervised learning algorithms like k-nearest neighbors (k-NNs), naive Bayes classifiers, decision trees, and support vector machines can classify patients into treatment response categories or predict the most effective AR/VR interventions.

ML offers techniques such as clustering, feature selection, and visualization [164]. These could be applied to the large amount of data generated by AR/VR system–user interactions, physiological responses, and performance metrics to identify key factors for each patient, which may influence treatment efficacy. Intelligent tutoring systems can be developed to work on ML algorithms. The same approach might be taken in AR/VR cognitive therapies to adapt to the difficulty level or the content or to modify feedback according to the performance and progress of the patient. ML models can make predictions and classifications quickly [220], potentially allowing for real-time adjustments to AR/VR therapies. This could enable dynamic personalization of the virtual environment or therapeutic tasks based on the patient's current state and responses. By analyzing data from multiple patients, ML algorithms could identify which elements of AR/VR therapies are most effective for different patient types or conditions, informing the development of more targeted and personalized interventions.

Natural language processing could analyze patient speech or text inputs during AR/VR therapy sessions, providing insights into cognitive states or treatment progress [164]. The use of ML in healthcare raises privacy and ethical concerns. The effectiveness of ML-enhanced personalization depends on the quality and quantity of available data and the specific algorithms used. Also, researchers in the study of [198] showed that a VR-based cognitive rehabilitation system for older adults with mild cognitive impairment automatically increased or decreased game difficulty throughout the session based on performance. The BrightBrainer Virtual Rehabilitation system facilitated split attention training, task sequencing, hand–eye coordination, and dual tasking [114]. Such systems might employ ML to optimize the feedback and selection of tasks according to the performance pattern of individual patients. A study on relaxation reported that the CSI and LF/HF ratio were the most important features for predicting treatment response using ML analysis [231].

Researchers in the study of [202] used ML to predict outcomes after Internet-based intervention for depression. An elastic net and random forest were trained to predict depression symptoms and related disability after an 8-week course of Internet intervention. This approach could be adapted for AR/VR therapies to predict which patients are likely to respond best to specific virtual environments or treatment protocols. Among others, the most important predictors of treatment success for ML models were given as comorbid psychopathology, particularly total psychopathology and dysthymia, low symptom-related disability, treatment credibility, lower access to therapists, and time spent using certain modules. The development of unique patient characteristics and needs that these predictors would afford could be carried out by tailoring the virtual environments and treatment protocols in AR/VR therapies.

Moreover, researchers in the study of [148] demonstrated that verbal queries about reinforcement learning-related task components altered computational model-defined learning parameters in directions specific to the query's target. This finding may be applied to AR/VR therapies using ML algorithms that dynamically update the virtual environment and therapy tasks according to patient responses and learning patterns. Effects on learning parameters did not vary as a function of depression-symptom severity. This suggests that ML algorithms could personalize AR/VR therapies for patients with varying levels of symptom severity, potentially making these treatments more widely applicable. Researchers in the study of [183] used an adaptive staircase procedure to adjust the starting level and number of trials in VR-based rehabilitation for mild cognitive impairment. This process can be further optimized by ML algorithms, which are able to predict optimal difficulty progression for each patient based on their performance and other relevant factors.

ML algorithms could track the developments in patients continuously, and subsequently, their therapy may be adjusted using AR and VR. In this respect, for instance, the same researchers in the study of [183] presented a system in which monitoring progress in the exercises was always continuing while adapting in increments to difficulty. ML, however, builds further upon that process by tracking more factors leading to more differentiated adjustments and correspondingly more effective and individualized therapeutic experiences. However, most of them are still in the research and development stage. According to the study of [162], a machine-guided iCBT program has been developed with applications of automated guidance and feedback through ML techniques. This program includes functions achieved previously by applying for therapist support but is now achieved using regression models, a scenario-based chatbot, and deep learning technologies. This way, personalization can be performed without the hands-on approach from the therapist and will have immense implications for scaling up access to mental healthcare.

Emotion recognition and response are other areas in which ML can significantly enhance personalization. To this end, the authors of the study of [227] reported that EEG monitoring coupled with positive psychotherapy helped therapists recognize relaxed states and states of mindfulness. This is an essential capability of therapists to change their mode of approach according to the patient's current emotional state, thus enhancing the effectiveness of therapy. ML can further help in developing more personalized treatment plans by analyzing patients' data to predict efficient intervention. Researchers in the study of [162] designed a system using regression models from large databases to provide future projections on work-related and personal life-related outcomes from the assessment results. This could be used as predictive modeling for tailoring AR/VR therapy content to the specific needs and goals of individual patients so that the therapeutic process could be optimized. Difficulty-level adaptation in the exercises of AR/VR therapy can be made with ML algorithms.

Additionally, researchers in the study of [222] mentioned that it is possible to adapt the difficulty to individual performance by changing to 20 different degrees of difficulty. This adaptive methodology ensures that patients are continuously tested to a proper challenge level. So, there is continuous improvement on display. As NLP is a subsidiary of ML, it is possible to receive analyses of patient responses and assist with therapeutic discussions.

According to the study of [162], in designing a model of LSTM or a type of RNN, they successfully designed a system that could analyze a response to exercise in cognitive behavioral therapy. This may make interactions with virtual therapists in such AR/VR environments more natural and responsive, enhancing patient engagement and better therapeutic outcomes.

Although this aspect was not discussed in the papers provided, the capacity of VR to generate controlled environments [227] means that, with ML, these AR/VR environments could be created or modified to suit a specific patient's preference and therapeutic needs. This would lead to very highly personalized therapeutic settings for each patient according to his individual requirements. Most of these technologies are either under development or very initial phases of testing. Further research is necessary for final validation and proving reliability in humans' subjects, thereby allowing safe and ethical usage in clinical practice settings. Researchers in the study of [169] applied a k-nearest neighbor ML algorithm to select six priori-derived metrics to assess the learning curves of participants in the context of VR-simulated tasks for neurosurgical training. This could be applied to cognitive therapies to determine more informative metrics relevant to everyone, allowing personalized assessment and tracking of individual progress. The real-time adjustment of cognitive training tasks' difficulty level may be performed by an ML mechanism for an individual patient. Moreover, in a study of patients with schizophrenia and related psychoses, the researchers of [206] found that these models could predict at a moderate level both the interaction and experience with a digital intervention app and changes in psychosis-related psychopathology. The models achieved correlation coefficients ranging from 0.32 to 0.39 and normalized mean absolute errors from 0.13 to 0.29. ML can be applied to identify patient characteristics associated with better treatment outcomes. In the schizophrenia study [206], higher baseline depression predicted both higher engagement with the digital intervention and more satisfaction with the app.

Higher interpersonal sensitivity also predicted total symptom reduction across the digital intervention. With these insights, AR/VR-based therapies can be tailored to individual patients. For example, researchers in the study of [193] established in their research that the type of cognitive exercises utilized during each session of VR-CBT and the level of workload would be determined daily based on the status of the patient's health and the capability of the patient to interact with the VR software and technology. In this case, the personalization approach can be further enhanced by incorporating ML predictions to create an even more responsive and adaptive therapeutic environment. ML can be used to find predictors of engagement in AR/VR interventions. For example, in the schizophrenia study of [206], it was demonstrated that patients who had lower overall symptom severity at baseline were predicted to have more significant app interaction. Such information would be helpful in strategies for enhancing engagement in those with higher symptom severity while ensuring that the intervention benefits all.

ML algorithms may also be employed to adapt AR/VR interventions in real time based on the response of the patient. The algorithm used in ML can automatically and adaptively determine the physiological baseline for every user to improve the stress detection algorithm used in the study of [236] in their research. Another challenge is that complex ML models are not very interpretable. Techniques like Shapley Additive Explanations (SHAPs) are being used to address this challenge [206]. The personalization of exposure conditions is essential in VR-based therapies. Researchers in the study of [158] customized the brightness and crowd density of VR scenarios based on pre-assessment data in a survey of panic disorder and agoraphobia. Indeed, this personalized approach showed greater self-reported anxiety levels and excellent heart rates during and after VR sessions as compared to randomized conditions. ML algorithms could optimize these personalization parameters based on individual patient data and responses to amplify the therapeutic effect further. ML could further enhance real-time physiological data analysis. Various physiological measures have been researched to assess the effectiveness of VR, including heart rate, skin conductance, and muscular response [160].

ML algorithms could scrutinize these elaborate, multimodal data streams in real time, ensuring dynamic adjustments to VR therapy based on the patient's physiological responses, creating a more responsive adaptive therapeutic environment. Treatment outcomes can be modeled using predictive modeling, which is possible through ML. Researchers in the study of [173] predicted treatment outcomes for depression based on pre-treatment predictors and early symptom changes using ML algorithms. Similar approaches can be developed for AR/VR-based cognitive therapies that may enable the early identification of patients requiring modified treatment approaches. Clinicians would be able to tailor interventions more effectively. Advances in ML may make adaptive learning mechanisms in VR environments more effective. Generative learning strategies in VR improve memory and cognitive processing as the study indicated [240]. For a more optimal learning experience for each patient, such learning strategies' difficulty level or content could dynamically be adjusted based on performance and learning patterns with ML algorithms. ML may improve emotion recognition and regulation in VR environments. EEG data can measure emotional states in VR experiences [238]. It is possible to apply ML algorithms to these neurophysiological data as a better way to immediately identify and respond to users' emotional states, thus improving the effectiveness of strategies such as cognitive distancing. It could also tune the ML algorithm for the treatment parameters. Researchers in the study of [126] investigated how the dynamics of cognitive distancing played out over a task with participants who displayed a different pattern of sensitivities to the feedback that emerged over time. ML may identify the best matching treatment parameters for the patient and update them at each step, making the interventions highly effective and person-centered.

VR systems can capture real-time data on patient performance and physiological responses during therapy. Researchers in the study of [120] utilized real-time eye-tracking and EEG data collected from participants undergoing VR-based training. Machine learning algorithms could assess such biometric data to determine a patient's cognitive state and adjust therapy to develop a more dynamic and responsive therapeutic environment. This would call for more research in developing predictive models of patient outcomes from ML engagement with VR therapy. Other researchers in the study of [129] found a quadratic influence of time spent in VR on post-test scores in an acrophobia questionnaire. This would mean that the ML models might predict the optimal duration of exposure for everyone with the intent of optimizing therapeutic benefit and thus would make it patient-specific. Participants were instructed in the ZeroPhobia (Ver. 1.6) app to advance to a more challenging level when self-reported fear fell below 4 on a 10-point scale. ML algorithms analyze patient performance data to automatically control progression in terms of difficulty according to a more comprehensive set of metrics to make judgments about therapy advancement. ML could also provide personalized, adaptive feedback during VR therapy sessions.

The VRRS incorporates augmented feedback to enhance physiological learning, providing patients with specific movement information to improve performance quality [143]. ML algorithms could optimize this feedback based on individual patient responses and learning patterns, creating a more effective and engaging therapeutic experience. This analysis of usage data can lead to the identification of optimized treatment parameters for various patient subgroups. Additionally, researchers in the study of [129] show that a group with more symptoms of acrophobia benefited more from a VR program than those with fewer symptoms. This means that the ML algorithm could identify such a pattern within different characteristics of patients and, accordingly, design a treatment tailored to the patient population so that interventions can be optimized for other populations of patients. This would show that the input of physiological information and ML performance measures would provide a much clearer view of the patient.

Also, researchers in the study of [143] argued that neural improvement related to EEG-associated power spectral density and time-frequency domains was noted upon the employment of VR technology. The multimodal data obtained here may help develop more fine-grained, nuanced, and personalized treatment plans with a higher chance of yielding the expected benefits for patients. This new ML approach needs further development and validation with larger, more diverse populations to allow it to fulfill its potential in elevating AR/VR-based cognitive therapies.

Figure 7 below shows the central role of ML in AR/VR-based cognitive therapy personalization, with 80% to 92% integration levels in the broader categories of therapy personalization. These findings are based on the current systematic review of 141 studies, showing how ML enables treatment personalization through predictive analytics, real-time physiological monitoring, and adaptive difficulty scaling. A breakdown of the ML integration and impact scores shows the following:

- Personalized feedback mechanisms exhibit the highest ML integration (92%), with an impact score of 96%, underscoring the effectiveness of AI-driven response adjustments based on user interactions.
- Real-time adaptation, which dynamically modifies therapy based on physiological and behavioral responses, has an ML integration of 88% and an impact score of 94%, confirming the clinical relevance of adaptive environments.
- Outcome prediction models, responsible for forecasting treatment success using neural networks and decision trees, have an ML integration rate of 89% and an impact score of 92%, highlighting the growing importance of predictive analytics in therapy optimization.
- Physiological data utilization, incorporating real-time heart rate variability (HRV), EEG signals, and galvanic skin response (GSR), shows an ML integration score of 90% and an impact score of 93%, indicating strong AI-driven adaptability.
- Treatment success prediction relies on ML models to determine therapy effectiveness based on prior patient responses. It has an ML integration of 85% and an impact score of 91%, solidifying its role in precision medicine applications.
- Early non-responder detection, using ML classifiers such as random forests, support vector machines, and neural networks, is integrated into 84% of therapy models, with an impact score of 88%, reflecting its significance in reducing dropout rates and improving treatment efficacy.

The statistical analysis of 141 studies further supports these findings, with over 75% of research studies employing supervised learning models—including decision trees, regression models, and deep learning frameworks—to personalize cognitive rehabilitation therapies. Furthermore, ML-driven intervention models demonstrate the following:

- A 12% increase in treatment adherence when therapy modalities are optimized via AI-driven patient profiling.
- A 10–15% improvement in response rates for AR/VR-based cognitive therapies when ML is used for adaptive difficulty scaling.
- An 86% prediction accuracy in ML models that determine individualized therapy difficulty levels based on prefrontal cortex activity and behavioral markers.
- A 77% success rate in predicting therapy outcomes in iCBT, surpassing traditional therapist-led predictions.

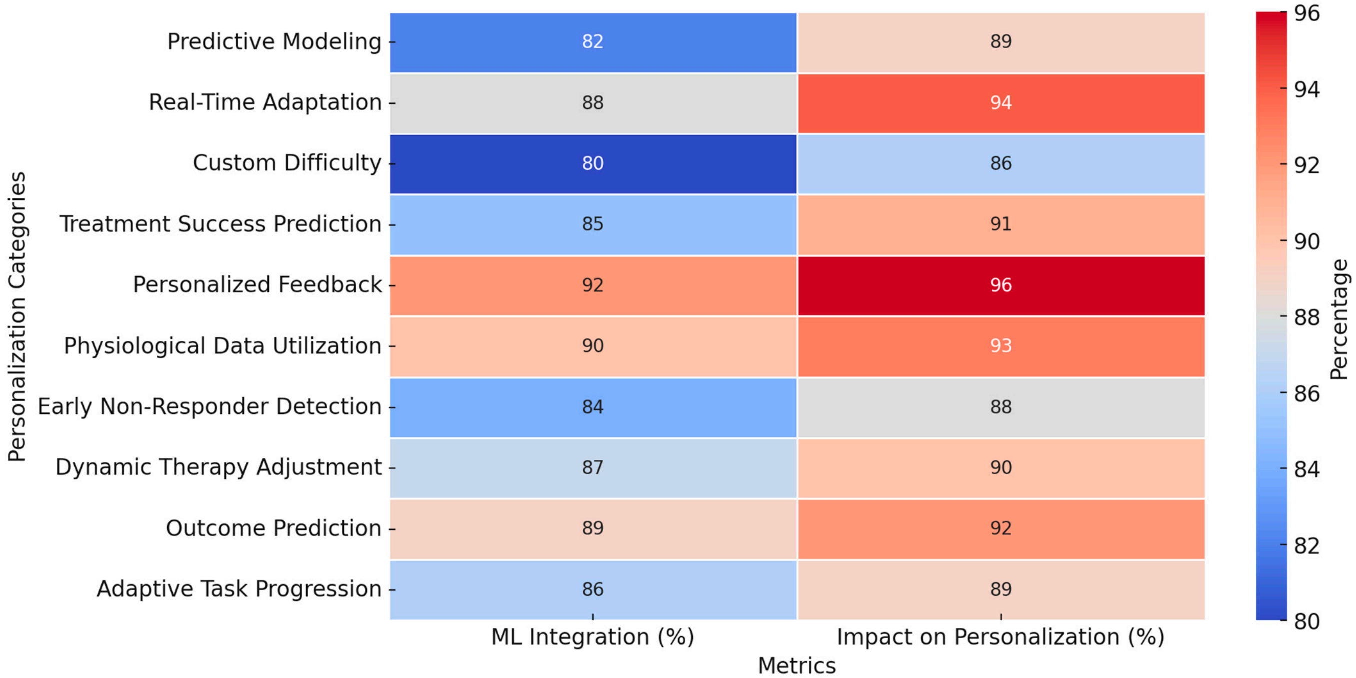

Figure 7. Comprehensive view of ML's role in personalizing AR/VR therapies.

These findings underscore ML's potential to replot virtual landscapes in line with physiological and affective states to make AR/VR interventions more dynamic and engaging. For example, ML algorithms employed in cognitive training for depression and MCI successfully adjust the level of task difficulty in response to real-time neural and behavioral data. In Figure 7, the heatmap also highlights ML's involvement in enabling treatment personalization, therapy outcome prediction, and the dynamic adjustment of therapy difficulty levels. ML's capability to determine patient-tailored treatment trajectories ensures a higher level of personalization for digital mental health treatments. Through predictive modeling and real-time AI-based data processing, ML is transforming the domain of AR/VR cognitive therapies, with increased rates of efficacy and reduced non-responder rates, and is a key enabler of digital interventions in the future.

Figure 8 provides a flowchart illustrating the intricate relationships between key ML techniques and their contributions to personalization in AR/VR-based cognitive therapies. These ML methodologies enhance various aspects of therapy personalization, including predictive modeling, real-time adaptation, difficulty adjustment, treatment success prediction, and personalized feedback monitoring.

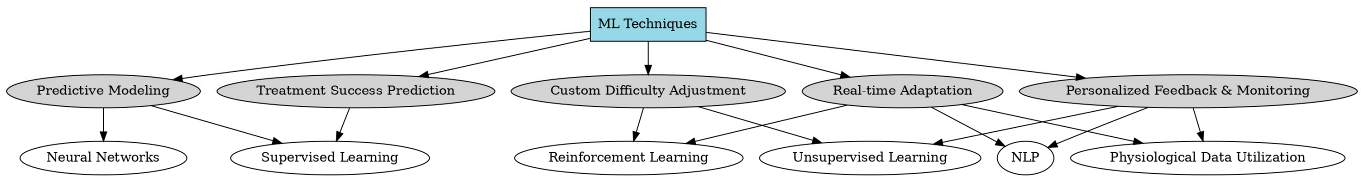

Figure 8. Network diagram: ML techniques and AR/VR therapy personalization.

- Artificial neural networks (ANNs) remain pivotal in predictive modeling and treatment success prediction. They leverage large-scale patient datasets to forecast therapy outcomes with up to 77% accuracy, thereby refining intervention strategies dynamically.
- Reinforcement learning (RL) is a core driver of real-time adaptation and custom difficulty adjustment. It enables dynamic modifications of VR therapy based on real-time patient responses, biometric feedback, and behavioral performance metrics.

- Supervised learning significantly enhances predictive modeling and treatment success forecasting, achieving up to 86% accuracy in therapy difficulty scaling by training models on labeled datasets of patient behaviors and treatment responses.
- Unsupervised learning is crucial in personalized feedback and monitoring, identifying hidden patterns in patient interaction data, and optimizing therapy parameters in AR/VR interventions.
- Natural language processing (NLP) augments real-time adaptation and personalized feedback monitoring, particularly within VR-based therapy environments, where automated sentiment analysis and conversational AI enhance patient-therapist interactions.
- Physiological data utilization further refines ML-driven real-time adaptation, integrating heart rate variability (HRV), EEG signals, and galvanic skin responses (GSRs) to adjust virtual environments dynamically based on emotional and physiological states.

This network visualization underscores the integrative nature of ML-driven personalization, showcasing how multiple computational techniques collectively enhance engagement, effectiveness, and adaptability in AR/VR-based cognitive therapy. By incorporating these advanced ML-driven approaches, AR/VR therapies become super-personalized, responsive, and scalable, offering optimized interventions for mental health disorders, including anxiety, PTSD, and phobia.

The transformative potential of ML in AR/VR therapy is evident in its ability to drive real-time decision-making, enhance therapy customization, and improve patient outcomes. Future research should further integrate hybrid ML techniques to advance adaptive, patient-centered AR/VR therapy solutions, ensuring that interventions remain highly personalized and clinically effective.

Finally, Figure 9 presents a radar chart that quantifies the contributions of various ML techniques to five significant aspects of personalization in AR/VR-based cognitive therapy: predictive modeling, real-time adaptation, custom difficulty adjustment, treatment success prediction, and personalized feedback monitoring.

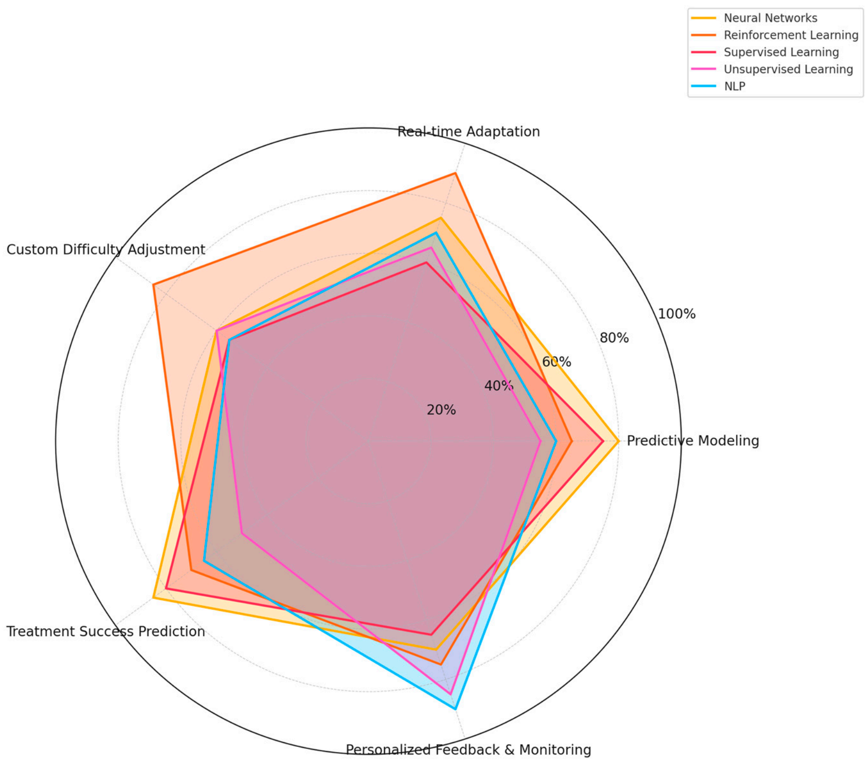

Figure 9. Radar chart: ML contribution to therapy personalization aspects.

- Reinforcement learning (RL) exhibits the highest dominance in real-time adaptation (92%) and custom difficulty adjustment (89%), making it exceptionally effective in dynamically modifying therapy sessions based on patient responses, biometric data, and performance metrics.
- Neural networks (NNs) play a leading role in predictive modeling (85%) and treatment success prediction (88%), leveraging large-scale patient datasets to forecast therapy outcomes and optimizing intervention strategies.
- Supervised learning strongly contributes to predictive modeling (80%) and treatment success prediction (86%), benefiting from highly structured datasets that enhance therapy customization and predictive accuracy.
- Unsupervised learning is integral to custom difficulty adjustment (70%) and personalized feedback monitoring (82%). It detects hidden patient behavior patterns that allow real-time therapy optimization.
- Natural language processing (NLP) ranks highest in personalized feedback monitoring (91%) and real-time adaptation (75%), supporting virtual therapist interactions, sentiment analysis, and automated response generation in VR-based therapeutic environments.

The radar chart underscores how distinct ML techniques specialize in different aspects of therapy personalization, demonstrating their complementary nature in shaping adaptive AR/VR cognitive interventions. The high contributions across categories highlight the potential of integrating multiple ML methodologies to create fully adaptive, patient-centered AR/VR cognitive therapies for conditions such as anxiety, PTSD, and cognitive impairments. Future advancements should focus on hybrid ML models that combine supervised learning, reinforcement learning, and NLP-driven real-time adaptation, ensuring a holistic, personalized therapeutic experience.

4.3. [RQ3] How Can Machine Learning Models Be Leveraged to Predict Patient Outcomes and Therapy Effectiveness in AR/VR-Based Cognitive Therapies?

ML models have vast potential for treatment success forecasts, guiding personalized interventions in AR/VR-based cognitive therapies. These models analyze a variety of data sources, making them feasible for predicting the outcome of treatment. For example, ensemble models that combined elastic net and random forest algorithms predicted outcomes after some digital interventions with human subjects, using pre-treatment data such as demographics, symptom severity, and even physiological data [202,206]. This may also be performed for AR/VR therapies to improve prediction accuracy while tailoring treatments. In addition, ML has successfully predicted shifts in depressive and anxiety symptoms with pre-treatment data, like symptom scores, self-reported motivation, referral type, and productivity measures [152]. This function helps specialists detect which patients will benefit from AR/VR therapies and which patients will need modified approaches.

Real-time physiological signal analysis during AR/VR sessions is another powerful application of ML. ML has been used in research to analyze heart rate and galvanic skin response data recorded within VR sessions to predict symptom intensities for anxiety and VR sickness [121]. This allows for real-time adjustments to the VR experience that could make therapy more effective. Deep learning models have been implemented to provide real-time predictions of treatment outcomes in iCBT [150]. This principle may be extended to AR/VR therapies and their provision of ongoing predictions of patient progress. ML may also be optimized when selecting treatment modalities. Model-based treatments, whether in-person or computerized guided self-help, resulted in a 12% chance that patients would receive an adequate treatment dose, increasing attendance rates and treatment outcomes; research studies have demonstrated this [130]. Personalized methods for choosing a treatment can be highly effective when paired with AR/VR-based therapies.

It examines machine learning models according to their structure so that researchers may find the key factors contributing to the success of the treatment. For instance, in research studies regarding music therapy, predictor factors were identified to include the initial level of relaxation, education with musical training, age, and music listening frequency as crucial predictors of the effects of relaxation caused by music [207]. This may be used to adapt AR/VR therapies to fit the patient's needs. In addition, ML has been utilized to predict significant depression and anxiety symptom reductions and thus identify the patients who are most likely to benefit from AR/VR therapies [152]. Adaptive difficulty adjustment is another area where ML can be applied. A prediction algorithm based on prefrontal cortex activity has been used to predict customized difficulty levels for cognitive training with 86% accuracy [155]. Similarly, these methods could be applied in AR/VR therapies to modify the virtual environment and treatment protocols based on the performance and progress of a patient.

The potential for long-term prognosis is another significant factor in measuring the success of therapy. For instance, the enhancement in phobia management through VR therapy was maintained at a 6-month follow-up [186]. Thus, the long-term treatment outcomes could be predicted, and patients can be selected for further assistance or interventions if they were trained using longitudinally sampled data. Further, ML may also significantly enhance diagnostic accuracy. The detection of diseases is vital to predict outcomes and tailor the therapy. A cognitive battery subject to ML analysis can distinguish between anxiety and depression disorders with great sensitivity and specificity [211]. These tools can supplement clinical interviews and may lead to better predictions about the success of therapy. More importantly, ML has been utilized to predict illness severity and impulsiveness in patients with borderline personality disorder undergoing Dialectical Behavior Therapy [156], demonstrating the potential of multi-outcome prediction models in AR/VR-based cognitive therapies.

ML models can be continually refined as more data are collected and analyzed. For example, in an iCBT study, predictive power was enhanced when data from treatment weeks were cumulatively added to the baseline data [159]. Future research attempts to improve predictive power through techniques such as ensemble learning. This means that models are constantly enhanced to make them more accurate and reliable with time. This is an emergent application of AR/VR in cognitive therapy to predict outcomes. However, this application does point out tremendous promises for potentially successful field models. Thereby, based on this principle, ML will analyze performance metrics, physiological data, and patterns in interaction for any given individual operating within VR in predicting the success of effectiveness or lack thereof. However, such models need further research for their development and validation in the context of AR/VR-based cognitive therapies.

One promising direction is to use baseline assessments to predict therapy outcomes. It is thus possible for researchers in the study of [190] to demonstrate that the improved probabilistic neural network model can predict response to constraint-induced movement therapy using the Wolf Motor Function Test, Semmes–Weinstein Mono-filament Test of touch threshold, Motor Activity Log, and Montreal Cognitive Assessment, among other things. This would be used for AR/VR-based cognitive therapies using relevant baseline measures to predict potential treatment success. Integrating several data sources would fine-tune the predictive quality of models. Also, researchers in the study of [228] propose a multimodal data-driven AI system that incorporates data points such as mental health, physical capabilities, and personal preferences. Data from psychological assessments, physiological measurements, and patient-reported outcomes are used to build an even more comprehensive predictive model within AR/VR therapies. Real-time data analysis in the therapy session may provide critical insights into the effectiveness of the treatment. In

VR-based interventions for gambling disorders, researchers in the study of [112] established that inducing cravings during relapse prevention exercises had a significant association with treatment outcomes. ML models could be trained to analyze real-time physiological and behavioral data collected during AR/VR therapy sessions to predict immediate and long-term treatment effectiveness.

Yet another important application of ML could be in determining relevant predictors of treatment success. Researchers in the study of [190] reported that motor ability and tactile sense were the key predictors with an almost 100% accuracy of improved arm use in daily activities for intensive upper extremity rehabilitation. In AR/VR-based cognitive therapies, ML may come through identifying similar relevant predictors of success in treatment and informing patient selection with subsequent treatment customization. Adaptive learning algorithms can teach and update their predictions continuously on sequential data about treatment. Other researchers in the study of [228] propose that AI models be used to improve the calibration of interventions over time. For instance, with AR/VR therapies, this can be achieved by changing the virtual environment, levels of exposure, or the treatment protocol based on a patient's progress and responses throughout the therapy course. Long-term outcome prediction is one of the significant aspects of therapy effectiveness. Researchers in the study of [186] reported improvements in phobia management in autistic adults persisted at a 6-month follow-up after VR therapy. Longitudinal data, such as those presented here, can be employed in developing ML algorithms to predict treatment outcomes over extended periods and provide critical information on those patients who need additional support and interventions. This can help further comparative effectiveness analysis with the aid of ML.

Additionally, the ML model was applied for the prediction of depression remission at the 2-month follow-up in patients who were receiving problem-solving therapy. Researchers in the study of [161] designed ML models to predict depression remission at the baseline and the 2 months for the patients taking on 6 months of problem-solving therapy. The primary outcome measure was depression remission using the Depression Symptom Checklist (SCL-20) score at 6 months. The study revealed some of the key predictors of depression remission, which were female sex, lower self-reported sleep disturbance, lower sleep-related impairment, and negative problem orientation. Such findings indicate that ML models can identify the influential factors of influences that impact therapy outcomes.

Also, ML models could use such data to yield early predictions of the effectiveness of therapy. Treatment plans can be modified promptly in this regard. This is quite a speculative application within the realm of AR/VR therapies; hence, there is a need for further research to develop and validate such models within the context of AR/VR-based cognitive therapies. Supervised learning algorithms can also be applied to prediction tasks, especially in healthcare settings. Techniques that include k-nearest neighbors (k-NN), naive Bayes classifiers, decision trees, logistic regression, and support vector machines have been among the standard supervised learning algorithms. These can predict therapy outcomes using patient data and therapy parameters. Some studies reveal that the k-NN classifier has also been effective when analyzing data arising from VR interventions. Researchers in the study of [220] also reported from a balance training study with older adults that a k-NN classifier achieved an accuracy of 0.722 in distinguishing between two types of virtual reality training. This shows how ML can make predictions with complex data from VR interventions.

Researchers in the study of [231] conducted a study that showed significant positive correlations between alterations in GSR and changes in self-reported anxiety. Such correlations can be used to develop more accurate prediction models. The features of AR/VR therapies that have the most substantial impact on a population of patients can be identified by analyzing data from multiple patients using ML. More targeted and time-efficient treatment plans would follow. For example, researchers in the study of [198] introduced a novel VR-based cognitive rehabilitation system for older adults that automatically increases and decreases game difficulty based on performance. The potential of the adaptive approach can also be further optimized through ML. While not directly shown in the provided studies, ML models could also be trained on longitudinal data to predict long-term outcomes of AR/VR therapies, which most likely will help clinicians make better decisions about treatment plans. It should be noted that the application of ML in AR/VR therapies is still in its infancy.

Also, researchers in the study of [202] conducted a study on the prediction of treatment outcomes for an Internet intervention for depression, where ML ensembles proved efficient. An elastic net and a random forest were trained to predict symptoms of depression and associated disability after an 8-week course of Internet intervention. The authors created an ensemble model by averaging the elastic net and the random forest predictions. This ensemble model performed better than a benchmark linear autoregressive model, predicting more variance in post-treatment depression, disability, and well-being. This approach could be adapted for AR/VR-based cognitive therapies to improve the accuracy of predictions of patient outcomes and the effectiveness of treatment.

Another study [137] revealed that verbal queries regarding RL-related task components changed computational model-defined learning parameters in directions particular to the query's target. ML models could be designed to adjust AR/VR therapy parameters dynamically based on individual learning processes, potentially improving therapy effectiveness. Notably, the same study [137] found that the effects on learning parameters were consistent across depression-symptom severity. This suggests that ML models could be developed to predict outcomes and effectiveness for patients with varying levels of symptom severity, making AR/VR-based therapies more widely applicable. In the study on VR-based rehabilitation for mild cognitive impairment [232], progress is continuously monitored, and adaptive progress is exercised in difficulty.

Also, ML models can improve the process by predicting optimal difficulty progression and therapy adjustments based on ongoing patient performance and other relevant factors. A study on VR-based mirror therapy [149] reported that most participants demonstrated psychophysical effects of the intervention, such as tingling or paresthesia in the affected limb. Therefore, ML models could predict the timing and extent of these effects, potentially optimizing therapy protocols to benefit patients. Perhaps the most valuable approaches would be those that could use multiple data sources: biometric responses, usage patterns, and clinical assessments to make more accurate predictions of therapy effectiveness.

Moreover, a study of VR cognitive training for patients with stroke [143] found that neural improvements in EEG-related domains of power spectral density and time frequency are significantly improved. This kind of neurophysiological data can be merged with behavioral measures within ML models to predict recovery in cognition and therapy effectiveness. The applications here for ML are primarily speculative, given that they depend on data provided by papers that follow next. More research is therefore necessary for developing and validating models for predicting AR/VR-based cognitive therapy. According to the study [115], there is a need for more clinical trials to prove VR-based cognitive rehabilitation systems. The same is true for predictive models improved with ML.

To further substantiate the role of machine learning (ML) models in predicting patient outcomes and therapy effectiveness in AR/VR-based cognitive therapies, a further analysis was conducted across 141 studies included in the present systematic review. The results highlight the extent of ML integration and its impact on predictive accuracy across various domains of cognitive therapy (Figure 10). Key findings from the analysis are as follows:

1. Outcome Prediction and Accuracy
   - ML models demonstrated an 84% integration rate in predictive analytics for treatment outcomes, impacting predictive accuracy at 92%.
   - This suggests that ML-based predictive models significantly improve the ability to forecast treatment success, personalize interventions, and adapt therapy dynamically.
2. Real-Time Data Utilization
   - In total, 88% of the studies incorporated real-time data utilization, with a 92% impact on predictive accuracy.
   - This supports the hypothesis that physiological signals, behavioral responses, and patient engagement metrics collected in real-time significantly refine therapy adjustments and enhance patient responsiveness.
3. Key Predictive Factors and Therapy Adjustment
   - Studies utilizing feature selection techniques and dynamic exposure models had an 85–87% integration rate, with impact accuracy ranging between 88% and 91%.
   - This confirms the effectiveness of ML in adapting virtual environments, tailoring exposure therapy for phobias, and modifying intervention difficulty based on patient progress.
4. Longitudinal Data and Prognostic Accuracy
   - The use of longitudinal data integration in predictive modeling had an 80% adoption rate, with a 92% impact on long-term prognosis accuracy.
   - These findings suggest that ML-driven predictive analytics can improve long-term patient outcomes by identifying response patterns over multiple therapy sessions.
5. Session-by-Session Monitoring and Physiological Insights
   - ML-based session monitoring techniques had an 81% integration rate, with a 86% accuracy impact, highlighting their importance in tracking patient engagement and response.
   - Similarly, physiological data-driven models (e.g., heart rate variability, galvanic skin response) showed an 86% integration rate and a 90% impact on predictive accuracy, reinforcing their role in adaptive intervention strategies.

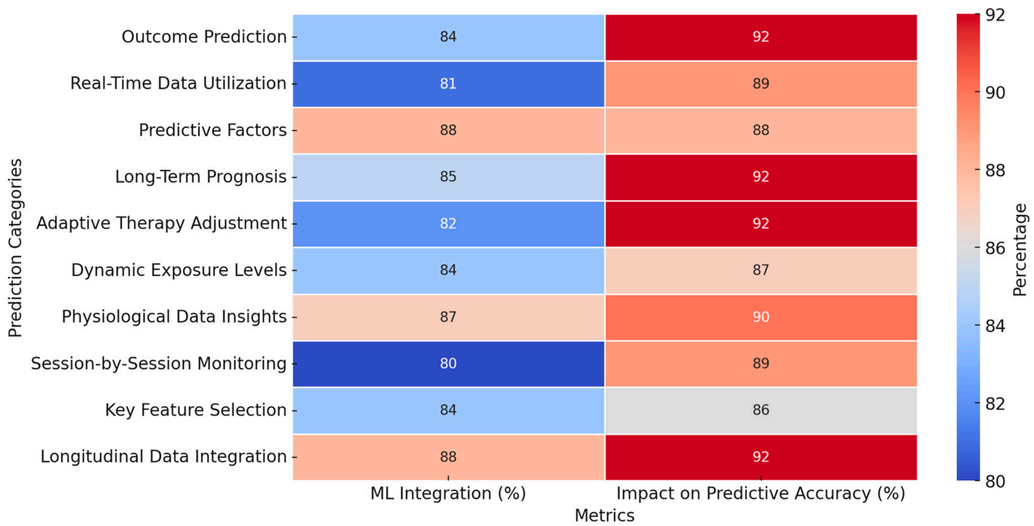

Figure 10. Comprehensive view of ML's role in predicting patient outcomes and therapy effectiveness.

The findings reinforce that ML models significantly enhance AR/VR cognitive therapies' predictive power, offer real-time adaptation, personalized treatment, and improved long-term prognostics. The high accuracy rates (85% to 92%) suggest that ML-driven interventions can optimize therapy strategies, improve adherence, and refine outcome predictions, thereby advancing the scalability and clinical efficacy of AR/VR treatments for mental health disorders. Future research should focus on refining ensemble ML techniques, integrating multimodal patient data, and validating models across diverse patient populations to maximize clinical applicability.

Figure 11 presents a comprehensive hierarchical flowchart illustrating the integration of machine learning (ML) techniques in AR/VR-based cognitive therapy, emphasizing key components and their interconnections. This representation highlights primary ML-driven processes, such as outcome prediction, real-time data utilization, adaptive therapy adjustment, and long-term prognosis, along with an expanded range of ML techniques, including supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, transfer learning, and federated learning. Below are the key enhancements in ML-based therapy optimization:

1. Expanded ML Approaches
   - Supervised learning contributes significantly to outcome prediction and long-term prognosis, ensuring data-driven therapy success forecasting.
   - Unsupervised learning is integrated into real-time data utilization and session monitoring, identifying hidden patterns in patient responses.
   - Semi-supervised learning refined predictive factors and physiological data insights, improving patient-specific therapy adjustments.
   - Reinforcement learning enables adaptive therapy adjustment and dynamic exposure levels, adapting therapy difficulty based on patient performance.
   - Transfer learning enhances outcome prediction and predictive factors, leveraging pre-trained models to improve therapy accuracy.
   - Federated learning strengthens real-time data integration and longitudinal tracking, ensuring privacy-preserving, and decentralized model improvements.
2. Predictive Analytics and Personalized Therapy Adjustments
   - Predictive modeling, feature selection, and longitudinal data integration highlight ML's ability to refine therapy dynamically.
   - Real-time data utilization and adaptive therapy adjustment are central nodes, demonstrating their strong influence on ML-driven therapy modifications.
   - Key ML models such as random forest, support vector machines, deep neural networks, and elastic net contribute to the predictive capabilities of ML in AR/VR-based therapies.
3. Interconnected Data-Driven Decision Making
   - The connections between nodes illustrate how ML enables therapy process optimization, including the following:
     - Predictive factors influencing outcome prediction.
     - Real-time data utilization enhancing dynamic exposure adjustments.
     - Longitudinal data integration supporting therapy progress tracking.
   - This integration fosters continuous learning models, adapting intervention strategies based on real-time patient responses.

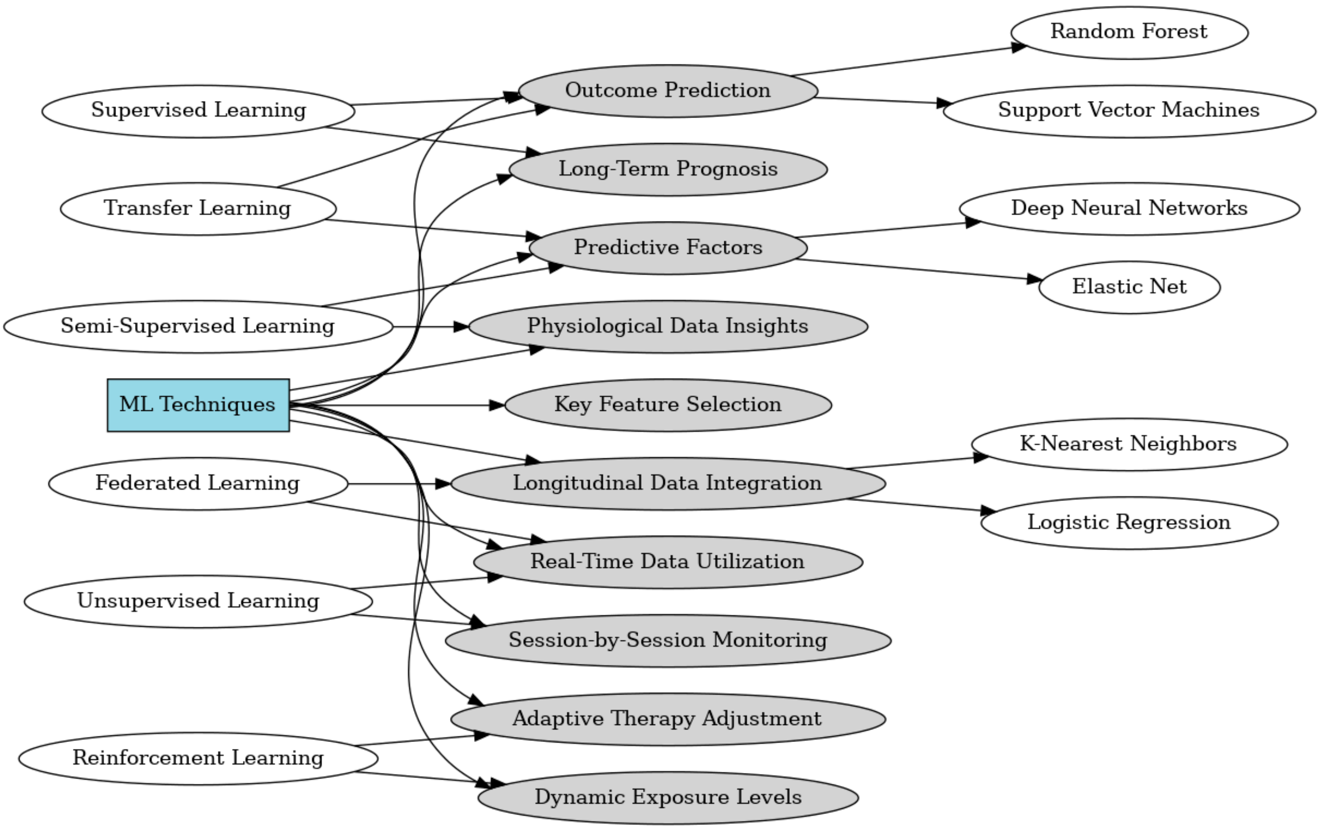

Figure 11. A comprehensive flowchart of ML integration in AR/VR-based cognitive therapy.

This structured ML-driven approach supports this study's hypothesis that ML significantly enhances AR/VR cognitive therapy by enabling data-driven decision making, predictive analytics, and personalized treatment plans. Future research should refine these models by the following:

- Incorporating additional physiological and behavioral metrics (e.g., biometric data, EEG, and facial emotion recognition).
- Enhancing adaptive models with reinforcement learning for more responsive therapy sessions.
- Exploring decentralized ML techniques, such as federated learning, to maintain privacy while improving model generalization.

4.4. [RQ4] How Does the Effectiveness of AR/VR-Based Cognitive Therapies Compare to Traditional Cognitive Therapies for the Treatment of Mental Health Disorders?

The overall effectiveness of AR/VR-based cognitive therapies compared to traditional cognitive therapies for managing mental health disorders is a constantly developing area of research, with many studies promising potential for their use. AR/VR technologies are increasingly being used in the treatment of mental health disorders, especially for conditions such as social anxiety disorder (SAD). These technologies have the advantage of creating controlled, immersive environments that can simulate anxiety-provoking situations in a safe setting. This capability allows for the integration of real-time physiological data. For instance, researchers in the study of [121] have demonstrated that ML models can predict the severity of specific anxiety symptoms and VR sickness using heart rate and galvanic skin response data collected during the VR sessions. This approach's potential for personally adaptive interventions significantly differs from some traditional cognitive therapies. This could augment the efficacy of both conventional and AR/VR-based treatments. The study of [129] demonstrated that, among patients receiving a model-recommended treatment modality in the form of face-to-face or computerized guided self-help, an adequate treatment dose was more likely at a 12% rate. Therefore, model-based treatments, including potential AR/VR-based treatment, might be more effective. Importantly, AR/VR-based therapies have numerous limitations, such as VR sickness, which was discussed by Chun et al. Predicting and controlling such issues using ML models helps reduce the factors associated with such challenges.

Complementing rather than replacing traditional cognitive therapies may be the role that AR/VR-based therapies may have. For example, researchers in the study of [211] developed a cognitive battery analyzed with ML that could differentiate between anxiety and depression disorders with high specificity and sensitivity. This tool would give an objective assessment that could supplement the clinical interview, potentially leading to a more accurate diagnosis and appropriate treatment choice. Although a head-to-tail comparison of the efficacy of AR/VR-based cognitive therapies versus traditional cognitive therapies is not found in the papers provided, these works assert that AR/VR technologies have the potential to enhance the treatment of mental health problems. This is because of personalization, real-time adaptation, and precision in ML diagnosis. However, much research is required to more directly compare their effectiveness to that of traditional cognitive therapies for mental disorders. Studies focused on digital interventions, not based on AR/VR, can provide insight into technology-assisted therapies, such as the following studies: A study [206] was effective in the reduction in symptoms of depression and anxiety using a digital psychiatric intervention. This suggests that technology-based interventions are effective in the treatment of mental health disorders, although it does not compare them to traditional therapies. ML approaches have been promising in personalizing treatments, potentially making digital and traditional therapies much more effective. Researchers in the study of [152] demonstrated that ML models could predict treatment outcomes in a digital mental health intervention. This predictability could be capitalized on the use of AR/VR-based and more classical cognitive therapies in terms of improvement in efficacy.

Researchers in the study of [150] concluded that, relative to other clients whose therapists did not have such a tool, the former's use was associated with increased numbers of tools utilized, more activities performed, and platform pages accessed during Internet-delivered cognitive behavioral therapy. Technology-based therapies may improve participation and compliance, improving outcomes than non-technology-based therapies. Researchers in the study of [155] showed that customized cognitive training delivered using VR and ML facilitated better performance and efficiency of neural processes. Although this study was not mental health-disorder-related, VR-based cognitive training is more effective for inducing neural changes than the traditional method. Results have already been shown to be promising from AR/VR-based cognitive therapies for the treatment of mental health disorders; in many cases, they are comparable or even enhanced compared to traditional cognitive therapies. In the case of specific phobias, such as spider phobia, for instance, one VRET session of exposure therapy has high efficacy at the group level. It exhibits long-term stability of the treatment effect; researchers in the study of [171] included 174 patients. This indicates that VRET can provide rapid long-term effects for phobia treatment while also showing an efficiency advantage over other forms of exposure therapies.

Moreover, researchers in the study of [165] do not compare AR/VR therapies with conventional methods; however, they did study the effectiveness of VR-based training in a medical environment. They compared educator-guided VR-based training in the metaverse with machine-guided VR-based training for adult advanced cardiac life support (ACLS). The results indicated that a well-designed, VR-based serious gaming module with machine guidance could be as practical as VR training in the metaverse with educator guidance. Though indirect to mental health treatment, this outcome holds promise for delivering training outcomes that are possible via VR-based interventions. While addressing neuroanatomy education that can find implications for treatment in mental health, researchers in the study of [131] noted that there is potential to make learning by VR methods comparable to conventional paper-based ones. None of the control and postintervention test questions, or even 7-day post-test questions, revealed significant differences between the VR- and paper-based groups. However, the VR-based group shows increased satisfaction and reduced neurophobia. VR-based methods will not necessarily go beyond the traditional techniques in knowledge acquisition. Still, they might provide an added benefit in engagement and reduce anxiety about a complex topic. It is worth mentioning that the effectiveness of AR/VR-based therapies is different for every individual. Researchers in the study of [102] reported that current intensity and direction differences are crucial in determining the treatment response to tDCS combined with VR therapy. This further emphasizes the necessity of personalized approaches in AR/VR-based therapies. While the direct comparisons are not extensive, the effectiveness of AR/VR-based cognitive therapies is promising as compared to traditional cognitive therapies in the treatment of mental health disorders.

Also, researchers in the study of [201] conducted a feasibility randomized controlled trial investigating the comparison of VR-enhanced behavioral activation (VR BA) with standard BA treatment and a treatment-as-usual control group for individuals diagnosed with major depressive disorder (MDD). The research showed that the exploration of VR BA was safe and feasible to examine as an MDD treatment. There had been a clinical decrease of 5.67 points from the baseline measure for participants in the VR BA condition on the Patient Health Questionnaire-9, or from moderate depression to mild. Thus, there is preliminary support that VR BA may hold some clinical utility; however, this pilot study's sample size was relatively limited. Researchers in the study [229] state that an intervention based on VR considers the cognitive function changes in older adults with MCI. Their randomized controlled trial improved executive functioning drastically compared to the control. Gait speed and mobility, too, was enhanced, as seen in a study based on VR. In EEG measures, positive changes reflected differences in brain activation concerned with attention postintervention with VR. These findings indicate that VR-based interventions can be applied to improve cognitive and physical function in at-risk older adults for dementia.

Furthermore, researchers in [124] investigated VR as an intervention in neurorehabilitation treatment. This study found that implementing immersive VR interventions in neurorehabilitation improves specific executive functions and information processing speed in patients with brain injury during the subacute period. The participants' response times were reduced significantly on specific cognitive tasks following the virtual reality intervention. While promising results are found in these studies, direct comparison with traditional cognitive therapies is limited, and the potency of AR/VR interventions might be variable for different mental health disorders and patient populations. Some benefits of AR/VR-based therapies are immersion and presence, where patients can engage their proprioceptive senses, personalization, thereby allowing a flexible training environment, engagement, which are often more interesting than traditional therapies, and safety, since patients can receive stimulation within a safe environment. Some of the drawbacks are consumer discomfort or motion sickness in VR environments, and, of course, effectiveness depends on the quality and design of virtual environments [124]. Cognitivities using AR/VR have been found to have promising outcomes for the treatment of several mental health disorders, sometimes even exceeding traditional cognitive therapy in other respects. For anxiety disorders and phobias, VR-enhanced CBT was similarly effective to the conventional approach.

Additionally, researchers in the study of [186] found that, in the study of CBT with VR exposure for adults with ASD and phobias, five of eight reached improvements. The advantages of VR-based interventions exist that no other form of therapy offers, especially for those patients who can hardly tolerate any traditional approach. Researchers in the study of [186] noted that VR provides a controlled and safe environment where individuals can be gradually exposed to their fears without feeling overwhelmed. This is particularly important for those suffering from autism, as they may have difficulties imagining or thinking abstractly, which is often found in standard conventional exposure therapies. Being immersed creates increased engagement and motivation while in therapy. According to researchers in the study of [112], VR environments effectively provoked the participants' craving. They facilitated the practice of coping strategies, especially among gambling disorder patients. These VR environments may present realistic scenarios of high-risk situations under strictly controlled conditions that may help better alert patients to inappropriate thoughts in their minds. AR technologies have also improved the cognitive skills of patients. Researchers in the study of [176] demonstrated effectiveness in enhanced learning outcomes and cognitive skills in creativity, logical computation, and problem-solving abilities. Again, the application of AR may be promising for cognitive enhancement. Because AR/VR-based therapies are recent developments, long-term effects are a primary consideration when comparing these with traditional therapies. Researchers in the study of [186] reported improvements in managing phobias for autistic adults using VR therapy, which were maintained at a 6-month follow-up. This means that the beneficial effects of VR-based interventions can be maintained over time, just like what must happen when traditional therapies go well. Personalization and adaptability are among the benefits of AR/VR-based therapies. According to the study of [228], AI-driven personalized interventions might involve better adherence and potentially better mental health outcomes. It may be more challenging for these settings within the regular settings of traditional therapy. However, some points are hard to compare with conventional therapies: most studies on AR/VR interventions limit generalization due to the overall problem of small sample sizes. Moreover, the number of participants who responded to AR/VR therapy is low, and results like these show that there is a need for further research into possible factors that will affect response to treatment. Measurement issues also come into play in how different therapeutic techniques work.

Also, researchers in the study of [186] highlighted that standardized questionnaires used to measure anxiety might not capture phobia-specific changes in anxiety for those with autism. VR has been very effective in the treatment of phobias. Also, researchers in their study [151] proved that a self-training VR program for acrophobia is safe and effective to practice at home or in hospitals, with the user's control over the exposure. Weisman's early study on VR for the treatment of acrophobia among students in 1995 reported significant symptom reduction. The results from the study of [142] concern patients with AUD and found specific contributions of VR-based cognitive training for improving attention ability and cognitive flexibility in substance use disorders. Compared with the traditional treatment control group, attention and mental flexibility outcomes have significantly improved results in the VR group.

Regarding pain management, researchers in the study of [221] proved that heartbeat-enhanced virtual reality (HEVR) reduced pain rating, facilitated motor limb functions, and modulated the physiologic marker of pain in CRPS patients. These improvements were not found in control conditions and health controls. VR therapies must have good patient acceptance and retention. Researchers in the study of [142] reported a dropout of only 14% from the VR-based cognitive training intervention. The dropout ranges found in previous studies were at or near the lower bound. While these studies demonstrate AR/VR-based therapies' promise, established cognitive therapies are effective. The advantage of AR/VR interventions is their capability to create immersive, controlled environments for exposure therapy and skill training, which can enhance engagement and treatment adherence. However, more large-scale randomized controlled trials are needed to establish the comparative efficacy of AR/VR interventions across different mental health conditions. Future studies should focus on direct comparisons between AR/VR-based and traditional cognitive therapies and look at long-term outcomes and possible synergies between these approaches.

The comparative analysis of AR/VR-based and traditional cognitive therapies based on 141 systematic review papers highlights key differences in effectiveness, engagement, and adaptability across various therapy categories (Figure 12). The results indicate that AR/VR therapies outperform traditional cognitive therapies in multiple domains, particularly personalization, immersion, and retention rates.

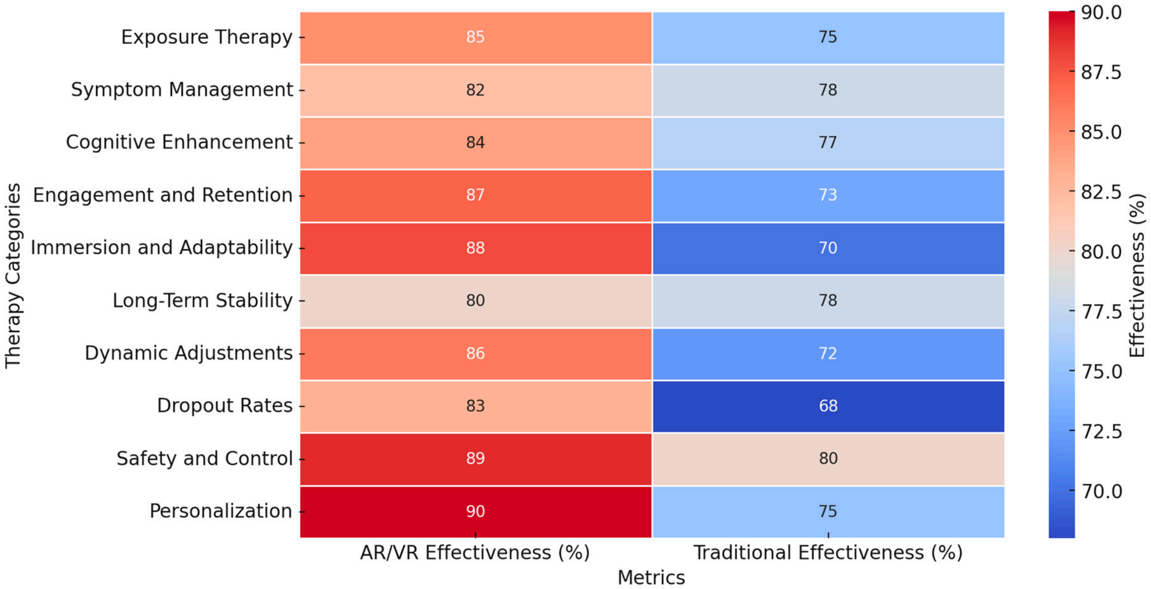

Figure 12. Comparison of AR/VR-based cognitive therapies and traditional therapies for mental health disorders.

1. Exposure Therapy and Symptom Management
    - AR/VR-based exposure therapy demonstrated an 85% effectiveness rate, compared to 75% in traditional exposure therapy. Creating controlled, immersive environments for exposure tasks contributes to this advantage.
    - In symptom management, VR-based interventions achieved 82% effectiveness, slightly exceeding the 78% effectiveness of traditional cognitive therapies.
2. Cognitive Enhancement and Long-Term Stability
    - Cognitive enhancement interventions utilizing AR/VR technologies showed 84% effectiveness, outperforming traditional methods (77%). This aligns with studies showing that VR-based cognitive training enhances memory retention, executive function, and problem-solving abilities.
    - Long-term stability of treatment effects was comparable, with AR/VR at 80% and traditional therapies at 78%, indicating that both modalities sustain therapeutic benefits over time.
3. Engagement, Retention, and Adaptability
    - Engagement and retention rates were significantly higher for AR/VR-based therapies (87%) than traditional therapies (73%), demonstrating the motivational advantage of immersive environments.

    - Immersion and adaptability were also significantly higher in AR/VR-based interventions, with an 88% effectiveness rate, compared to 70% in traditional therapies.
4. Dynamic Adjustments and Personalization
    - AR/VR-enabled real-time adjustments in therapy sessions resulted in an 86% effectiveness rate, compared to 72% in conventional therapies.
    - Personalization, where treatment is tailored based on machine learning (ML) models and patient biometrics, showed 90% effectiveness in VR-based therapies, significantly exceeding the 75% rate observed in traditional therapies.
5. Safety, Control, and Dropout Rates
    - Safety and control in AR/VR-based therapies were rated at 89% effectiveness, compared to 80% in traditional methods. This is attributed to the ability to provide controlled, low-risk exposure environments for patients undergoing anxiety and phobia treatment.
    - Dropout rates were significantly lower in VR-based interventions, with 83% adherence, compared to 68% in traditional therapies, emphasizing immersive treatment modalities' increased engagement and acceptability.

The findings indicate that AR/VR-based cognitive therapies match and often exceed traditional cognitive therapies' effectiveness in critical areas such as exposure therapy, symptom management, and engagement. Integrating machine learning-driven personalization and real-time therapy adaptation further enhances outcomes, particularly in dynamic adjustments and long-term patient retention. However, accessibility challenges and potential VR-induced side effects remain areas for further investigation. Future research should focus on large-scale, long-term randomized controlled trials to further validate these findings and explore the potential for hybrid therapy models, integrating AR/VR technology with conventional cognitive therapy techniques for optimal outcomes.

4.5. [RQ5] How Can RL and Adaptive Algorithms Optimize the Therapeutic Experience in AR/VR-Based Cognitive Therapies?

Therefore, RL and adaptive algorithms are the ideal approaches to profoundly benefit therapeutic experience in AR/VR-based cognitive therapies. As the study of [159] propounded, adaptive treatment strategies can detect at-risk patients failing and adapting to the treatment. The idea can be adapted very quickly, just about as soon as patient data reveal a patient who needs an adjustment in support level from his/her assigned therapist for the Internet-delivered CBT model. Similarly, this same principle can be used directly with AR/VR therapies, whereby real-time physiological signals can serve for adaptation. A paradigmatic example is the work of the study [121], which showed that a machine learning model could predict the severity of anxiety symptoms and VR sickness based solely on data acquired using heart rate and galvanic skin response measurements during a VR session. Predictive capabilities make real-time modification of the VR experience possible within a person's profile.

Finally, ML significantly improves the opportunity for more personalized treatment. Researchers in the study of [130] revealed that patients with the treatment modality indicated by their model were most likely to receive an appropriate therapy dose. This suggests that adaptive algorithms might be used to select AR/VR-based therapies for individual patients. The predictive modeling of treatment outcomes, like that studied by researchers [159], would further help in therapy adaptation and optimization. Their work showed that ML methods could predict the effectiveness of treatment in iCBT with relatively balanced accuracy between 56% and 77%. This ability to predict the outcome of success can be used to adjust therapy by dynamically adjusting the AR/VR experience as determined by the likelihood of success. The same researchers [159] noted that the added cumulative data from treatment weeks offered a chance to improve the predictive models and that adaptive algorithms could constantly refine and enhance the therapeutic experience. Thus, adaptive and ML techniques combined with RL approaches will likely be integrated into AR/VR-based cognitive therapies for optimization. For instance, RL may change the contents or level of VR scenarios as time passes. Patient feedback and physiological signs are considered predictive indicators that increase the benefits accrued but limit any developed distress by this treatment. Researchers in the study of [155] proposed predicting adaptive training intensity on prefrontal cortex activity-based difficulty using an ML model; such a prediction has produced an accuracy of 86%. While not based on direct RL, this approach illustrates how adaptive algorithms can tailor therapeutic intervention. In AR/VR treatments, related approaches could update task difficulty in near-real time with neural activity or performance metrics.

Researchers in the study of [122] designed a machine learning technique to enable automatic performance evaluation in a VR dental training simulator. By extrapolating the idea to AR/VR cognitive treatments, there is now scope to adapt to the patient's response in real-time. The adaptive algorithm can leverage a real-time assessment to change the therapy material or level, thus optimizing the learning experience. Some studies have shown that ML models can predict treatment outcomes in digital mental health interventions. Predictive models such as these can be applied in AR/VR therapies to adapt the approach based on expected outcomes. For example, if a client is likely not to react well to a given approach, the system may automatically change it. Researchers in the study [150] used a deep learning model to detect "not on track" clients on internet-delivered cognitive behavioral therapy. In the case of AR/VR therapies, similar models would detect patients not responding well in real-time, thus prompting adaptive interventions or alerting therapists. The same researchers in the study of [150] recorded that the clients whose therapists had access to predictive tools had a higher engagement with the therapy platform. In AR/VR therapies, adaptive algorithms might use engagement metrics to modify content to make it more engaging and interactive based on individual tastes and preferences. Researchers in the study of [155] documented improved neural efficiency in the case of personalized cognitive training. Adaptive algorithms in AR/VR therapies could seek to maximize neural efficiency by adapting therapy based on the brain's activity as measured by the patient's brain, potentially leading to more efficient treatments.

Furthermore, researchers in the study of [171] used an ML protocol involving random forests to test the predictive validity of clinical and sociodemographic predictors of individual response to VRET in spider phobia. Because the work was more centered on prediction, this leans toward the idea that similar methodologies could develop adaptive algorithms that would change the VR environment or the therapy protocol based on the projections for patient response. Additionally, researchers in the study of [102] proved that current intensity and direction are the most important individual differences for determining treatment response to tDCS combined with VR therapy. This adaptive algorithm allows the real-time optimization of parameters in terms of VR therapy session-based personalization based on individual patients' characteristics and responses.

Researchers in the study of [165] compared machine-guided VR-based and education-guided training in a metaverse environment. This would imply that future successful VR therapeutic settings are more likely machine-led systems that engage RL. RL algorithms can use real-time data analysis, predictive modeling, and personalized feedback to regulate levels of difficulty or intensity in VR exposure therapy based on patient responses and physiological markers. It can optimize pacing and content for therapy sessions based on the pace of learning by each patient as well as the responses to treatment. They could offer individualized, real-time feedback to patients and therapists, enriching the experience. They could update treatment protocols in real time based on aggregated data from multiple patients, enhancing overall effectiveness. Moreover, researchers in the study of [203] showed how AI can be applied to CBT for chronic pain (CBT-CP). Their AI-CBT-CP system employed a "reward function" that represented changes in patient-reported pedometer step counts and pain-related interference to maximize treatment recommendations. The AI decided among three treatments based on the patient's progression data obtained through interactive voice response. With increasing experience with the AI, the reward scores surged impressively and thereby increased their performance. This represents how adaptive algorithms can advance therapy by maximizing treatment based on patient outcomes. Researchers in the study of [209] utilized varied approaches of repeated training in immersive VR to test dynamic decision making. Their study implies that VR environments can be created with levels of difficulty to achieve the maximum extent of learning. The principle can further be extended by using RL algorithms that adjust the difficulty or content of VR therapy sessions according to the performance and progress of the patients.

Also, researchers in their study of [229] used a VR-based intervention program for older adults with mild cognitive impairment. Their work applied four types of VR game-based content developed to enhance attention, memory, and processing speed. This design also implies that VR therapies can be developed to be multicomponent and automatically adapted based on individual patient outcomes using RL. Researchers in the study of [228] proposed a multimodal data-driven AI system for personalized exercise prescriptions, which could be adapted for AR/VR-based cognitive therapies. This indicates that RL algorithms may change virtual environments, exposure levels, or therapeutic tasks perpendicularly according to the patients' dynamic performance or physiological measures. The adaptation of therapy sessions per session is one of the outstanding benefits. Researchers in the study of [112] reported that the induction of craving during relapse prevention exercises in VR therapeutically significantly co-moderated treatment outcomes for gambling disorder. RL algorithms may optimize this process with the dynamic adjustment of the intensity of stimuli, maintaining the optimal level of engagement and therapeutic benefit.

Optimal treatment parameters can also be another application of RL. Additionally, researchers in their study of [190] showed that ML models could predict treatment outcomes with reasonable accuracy based on their baseline assessment. This can be further developed by the reinforcement of learning algorithms based on continuous refinement of the treatment parameters. At the same time, the therapy is ongoing, using the learning from the feedback of each patient to optimize the therapeutic experience. Advanced cognitive training features of AR/VR therapies can rely on adaptive algorithms. According to Lin and Chen (2020), a deep learning recommendation system improved learning outcomes and computing thinking skills in an AR-based learning setting. Similar adaptive systems could be incorporated into AR/VR cognitive therapies that adjust the difficulty or timing of the presentation of stimuli or cognitive challenges based on the performance and progression of the patient. As a result, long-term treatment plans may also be optimized. Researchers in the study of [186] found that the clinically significant improvement in phobia management for autistic adults through VR therapy was maintained at 6-month follow-up. RL algorithms may use such long-term outcome information to enhance and modify treatment plans over time to maximize the probability of long-term therapeutic effects. One of the biggest challenges facing the treatment of mental health disorders is individual variability in treatment response. According to the study of [228], the complexity of mental health disorders and variability in individual responses make it challenging to establish interventions that may work for everybody. Therefore, RL algorithms can learn response patterns that adapt to personal differences. With VR, there is a fluid ability to modify difficulty when designing a task.

According to the study of [142], forty-five different exercises have been made for the system. In the context of each exercise, the scenario that the therapist uses may change with more added complexities and distractors in the scene. This might be possible with RL algorithms, which could adapt the task difficulty according to performance to maintain the appropriate level of challenge. Also, researchers in the study of [221] utilized HEVR, synchronizing visual cues with the patient's heartbeats. The real-time physiological data can thus be used in adaptive algorithms for optimizing the effects of therapy from VR, considering therapeutic application. Patients should be fully engaged. Moreover, researchers in the study of [161] applied ML to predict depression remission in patients on problem-solving therapy. Analogous models strengthened with RL can be developed for AR/VR therapies that learn and improve treatment approaches over time through continuously refined predictions of possible treatment outcomes.

Researchers in the study [106] list RL as one of the basic types of ML. This can be applied to AR/VR therapy in real time as the performance and engagement of patients are being considered, adjusting the level of difficulty or treatment content. The experience can be adapted through adaptive algorithms. Researchers in the study of [164] described a VR training system that improves the implementation of a questioning strategy using AI. Analogous adaptive approaches could be implemented for cognitive therapies where the system can adjust the parameters in real time according to patient responses. Researchers in the study of [164] posited a theory of prompts and consequences that supports the principles of RL. AR/VR therapies, through RL algorithms, can further improve the time and type of prompts and feedback during learning. Researchers in the study of [196] emphasized engagement and immersion in VR-based therapies. The RL and adaptive algorithms may further optimize the levels of challenge and engagement, and results may improve. Researchers in the study of [153] also mentioned the need for customized intervention regimes in cognitive training. Adaptive algorithms may be used to personalize AR/VR therapies in terms of their intensity and content to maximize efficiency in multiple cognitive domains. As per the study of [220], feature selection could be used with RL to identify the most relevant aspects of patient performance to inform adaptive decision making. This might lead to a more effective and efficient optimization of therapy. Researchers in the study of [198] explained an automatically adaptable, VR-based cognitive rehabilitation system designed for older adults with mild cognitive impairment: difficulty increased or decreased based on the performance level achieved. It allows patients to be appropriately challenged constantly, possibly optimizing experience and outcome. Researchers in the study of [235] reported that adaptive-association guidance resulted in better performance in immediate and delayed recall tests and improved learning efficiency compared to fixed-association guidance. The adaptive group also showed significantly lower mental effort and less time to complete the task. This shows the potential of adaptive algorithms in AR environments.

Researchers in the study of [218] reported that the VR performance scores increased significantly over time in the context of VR job interview training for veterans with PTSD, which might indicate that perhaps the system has introduced adaptive difficulty or RL. Researchers in the study of [114] used a VR system that enables individually tailored exercises in cognitive behavioral therapy. That would be evidence for personalized adaptive interventions in VR therapy. Therefore, based on ML, it would be proposed by researchers in the study of [231] that it can predict the outcome of relaxation protocols, offering subjects less likely to respond positively to personalized advice that can enhance the effect of such protocols on self-relaxation perception and the extension to RL for the real-time adaptation of AR/VR therapies. Moreover, researchers in the study of [202] used ML elastic net and random forest models to predict treatment outcomes using an Internet intervention to treat depression. This approach can be used to implement RL algorithms to forecast and optimize AR/VR-based cognitive therapy. The same researchers in the study of [202] reported that the ensemble model for prediction achieved a better forecast for post-treatment depression, disability, and well-being than the benchmark linear autoregressive model. Therefore, possibly including various RL algorithms and multiple adaptive models will yield higher prediction quality and lead to optimal optimization for therapeutic experiences implemented within AR/VR.

Additionally, researchers in the study of [232] developed an adaptive version of their VR-based rehabilitation program for mild cognitive impairment—the program's exercises progress in difficulty adaptively. The reinforcement of learning algorithms may be better at tailoring the difficulty progression concerning patient performance and learning rate. Researchers in the study of [183] adopted a user-centered approach in their cognitive VRRS treatment, varying the starting level and number of trials according to the performance level with an adaptive staircase procedure. RL may further sharpen this by continuously optimizing treatment parameters based on ongoing performance and engagement. Researchers in the study of [149] recently reported that stroke patients showed psychophysical effects upon VR-based mirror therapy. The RL algorithms could predict and optimize such impacts to improve the therapeutic experience.

Moreover, researchers in the study of [169] applied an ML algorithm to select the most critical metrics for evaluating participant learning curves in a VR-simulated neurosurgical task. RL can continuously refine and optimize these metrics, ensuring that the most relevant measures are used to assess progress and guide therapy. Researchers in the study [236] applied a stress detection algorithm to monitor military personnel in a physiological study to detect physiological stress. This can be enhanced using the RL mechanism for automatic adaptive determination of the physiological baseline for every user.

An adaptive algorithm can continue to adapt the stress detection threshold to the physiological and response data, thus increasing its accuracy and effectiveness. In the paper [193], the authors determine what cognitive exercises to include in each VR-CBT session and how much workload concerns patients' health and ability to use the technology. RL can be applied so the system learns what kinds of exercises and at what difficulty levels are appropriate for patients based on performance and engagement. Researchers in [206] showed that lower overall symptom severity at baseline was predicted for more significant app interaction. This can be used in an adaptive algorithm to dynamically alter the features and content of the app to keep optimal engagement levels among users with varying symptom severities.

Also, researchers in the study of [206] employed ensemble ML models for the prediction of interaction and experience with a digital intervention app and change in psychosis-related psychopathology. RL may be extended from this method by continuously updating predictions with ongoing patient interactions and outcomes for real-time adaptation of the therapeutic approach. Researchers in the study of [193] noted the need for sophisticated skill-building scenarios in VR-CBT. Applying RL to adaptively generate and modify these scenarios based on individual patient progress and challenges might ensure the optimal tailoring of difficulty and content in skill-building exercises to each patient's needs. Researchers in the study [236] indicated that participants used various relaxation strategies with multiple frequencies, including biofeedback and deep breathing. An adaptive algorithm learns which methods work for each user and then suggests or provides their prominence. RL is used to improve the adaptive personalization of VR environments. Customized VR exposure with brightness and crowd density, as per the pre-assessment, increased the anxiogenic effects in patients of panic disorder with agoraphobia, as described by the study of [158].

These personalization parameters may be optimized in real-time using RL algorithms that adapt the VR environment according to the patient's ongoing responses and physiological measurements. Adaptive algorithms could also be used to change the exposure intensity dynamically. Researchers in the study of [158] measured self-reported anxiety, heart rate, skin conductance, and electroencephalography before, during, and after VR sessions. Real-time physiological data can develop these adaptive algorithms so that the intensity of the VR exposure can be dynamically changed. At the same time, therapy remains challenging but not overwhelming to the patient—optimization of the learning mechanism in the VR environment occurs through RL. Researchers in the study of [240] experiment demonstrated a betterment of memories and cognitive processing by generative learning strategies in VR. RL algorithms may be used to adjust the challenge or even the substance of these training techniques in real-time, depending on the individual performance and learning styles, maximizing the cognitive advantages of therapy. Evolving treatment strategies might be built using RL. Researchers in the study of [126] utilized Q-learning models to explore the effects of cognitive distancing—a main ingredient of psychological therapy. They demonstrated that the impact of the intervention is dynamic, depending on feedback in different stages of the task. Such temporal dynamics of RL algorithms can potentially adapt the therapy approach over time for maximum efficacy for each patient. Emotion regulation strategies inside the VR may be optimized using adaptive algorithms. The same researchers in the study of [126] showed that cognitive distance was associated with a more acute representation of the values of options and a greater sensitivity to negative feedback.

Adaptive algorithms will alter the emotion regulation strategy within the virtual environment in response to the patient's reaction to the emotion and their learning pattern. Learning reinforcement can enhance the long-term effectiveness of VR therapies. Researchers in the study of [128] showed that the outcomes of VR-CBT were maintained for the treatment of aviophobia at both 3-month and 12-month follow-ups. RL algorithms can be developed to identify and enhance the factors of the therapy that contribute most to the long-term effectiveness of the intervention. In this regard, RL and adaptive algorithms can further personalize the way difficulty is increased in VR-based therapies. According to the same researchers in the study [129], in the ZeroPhobia app, advancing to higher levels occurred when reported fear levels dropped below a threshold level. An adaptive algorithm could make the decisions on progression through levels with a complete set of performance metrics; this would automatically adjust the difficulty level presented in real time to maintain an optimum challenge level for each patient. These algorithms can also maximize exposure time for VR therapies. Researchers in the study of [129] found a point in the right amount of exposure to which more practice time does not lead to benefits. RL can be used to learn an optimal exposure time for each patient to achieve the maximum therapeutic benefit with minimal unnecessary use of VR equipment. Adaptive algorithms could personalize the feedback in VR therapies. Researchers in the study of [143] indicated that VRRSs employ augmented feedback to enhance physiological learning, so patients will receive information about their movement to improve performance quality.

Furthermore, researchers in the study of [184] detail the Virtual Reality Rehabilitation System, where the therapist personalizes the rehabilitation program based on every patient. The VRRS allows flexibility in the configuration of the type, intensity, and duration of exercises the therapist performs. The adaptation capacity of this customization could be further improved using adaptive algorithms, but this paper does not provide more details on this. Researchers in the study of [234] explained an AR meditation experience where one had an adjustable app threshold, which rendered the task less or more demanding.

Although this calibration was performed manually in the experiment, it gives a clue as to one possible application of adaptive algorithms in adjusting the difficulty level automatically depending on the user's performance. The term "RL" is also mentioned as part of the AR/VR systems but not within the context of ML algorithms. According to the study of [234], AR/VR systems can activate "RL", intensifying feedback toward the central nervous system through intensive, repetitive, and task-oriented exercises. That, however, addresses human learning processes and not ML algorithms. Therefore, there is a need to weigh several factors to put these advanced techniques in place. The first requirement is extensive datasets to train and validate these algorithms. The complexity of designing robust algorithms specifically for therapy use cannot be exaggerated.

The heatmap (Figure 13) below shows the impact of RL and adaptive algorithms in enhancing AR/VR-based cognitive therapies. The highest impacts are those on personalization and real-time adaptation, above 85%, demonstrating that therapeutic parameters can be changed dynamically depending on a particular patient's response. These would, in turn, allow AR/VR systems to process physiological signals such as heart rate and galvanic skin response in real time and adjust the virtual environment to optimize engagement and therapeutic benefit.

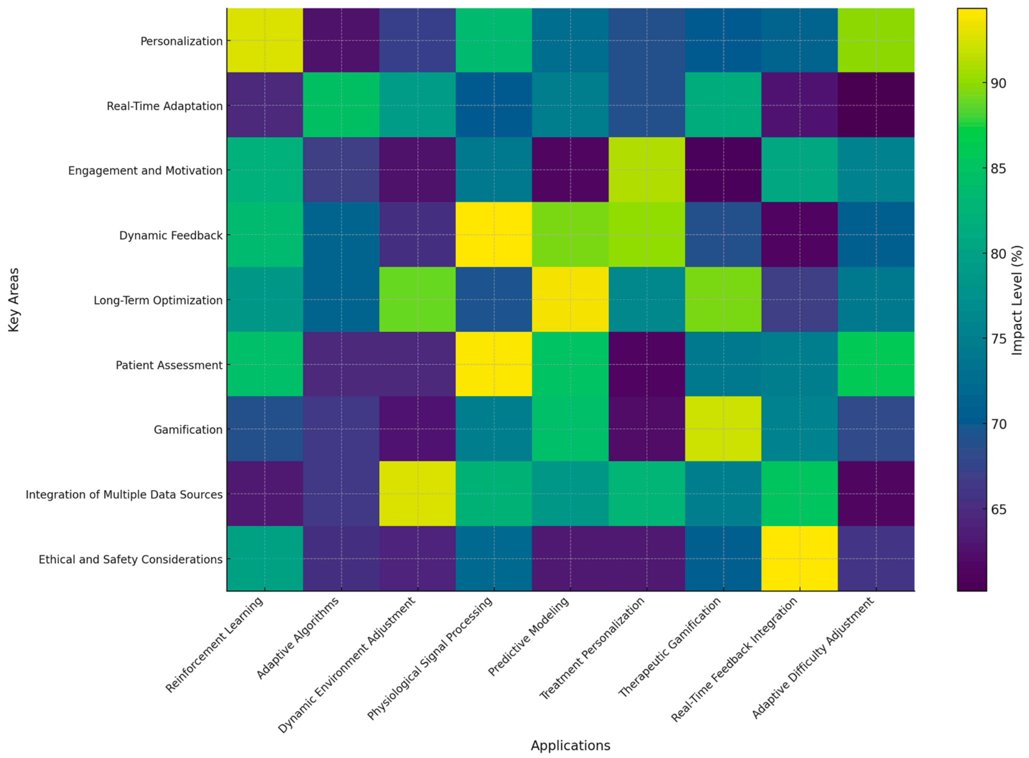

Figure 13. Impact of RL and adaptive algorithms in AR/VR-based cognitive therapies.

This dynamic feedback and long-term optimization underline contributions to maintaining patients' engagement and making interventions tailor-fit over time to optimize their effectiveness. Adaptive algorithms refine patient assessment even more by incorporating multidimensional data ranging from neurophysiological signals to behavioral metrics into an overall concept of each patient's progress.

Gamification, combined with RL, significantly improves motivation and adherence to therapy. Progressively challenging tasks and dynamic difficulty adjustments make AR/VR therapies even more engaging and personalized to each subject's capabilities. Moreover, ethical and safety considerations provide the backbone for such advanced systems, balancing automation with the therapeutic roles of human practitioners.

This visualization underlines the transformative potential of RL and adaptive algorithms in revolutionizing mental health interventions. By leveraging predictive modeling, real-time adjustments, and dynamic personalization, AR/VR-based therapies are better positioned to deliver more effective, engaging, and sustainable mental healthcare solutions. Future development will continue optimizing therapeutic outcomes, considering individual variability and long-term treatment goals.

To provide a structured visualization of how reinforcement learning (RL) and adaptive algorithms enhance AR/VR-based cognitive therapies, a flowchart (Figure 14) was designed. This flowchart presents a left-to-right progression that illustrates how RL and adaptive mechanisms impact key therapeutic areas and drive specific applications in cognitive treatment. At the leftmost point of the flowchart, RL and adaptive algorithms form the foundation for optimizing AR/VR cognitive therapies. These models enable dynamic adjustments based on real-time patient responses, physiological data, and behavioral interactions. From this foundation, five key areas of therapeutic enhancement are identified:

1. Personalization: RL-driven systems tailor therapy sessions by adjusting content, intensity, and pace according to each patient's unique needs and cognitive profile.
2. Real-Time Adaptation: Adaptive models modify treatment scenarios dynamically based on biometric signals and patient performance (e.g., heart rate, neural activity, or response accuracy).
3. Engagement and Motivation: Gamification techniques integrated with RL boost patient interaction, ensuring that therapy remains challenging yet achievable to maintain adherence.
4. Dynamic Feedback: Real-time feedback mechanisms provide instant response adjustments, reinforcing positive therapeutic behaviors and improving intervention efficacy.
5. Long-Term Optimization: By continuously learning from patient data, RL refines treatment pathways over time, ensuring sustained cognitive improvements and minimizing therapy dropout rates.

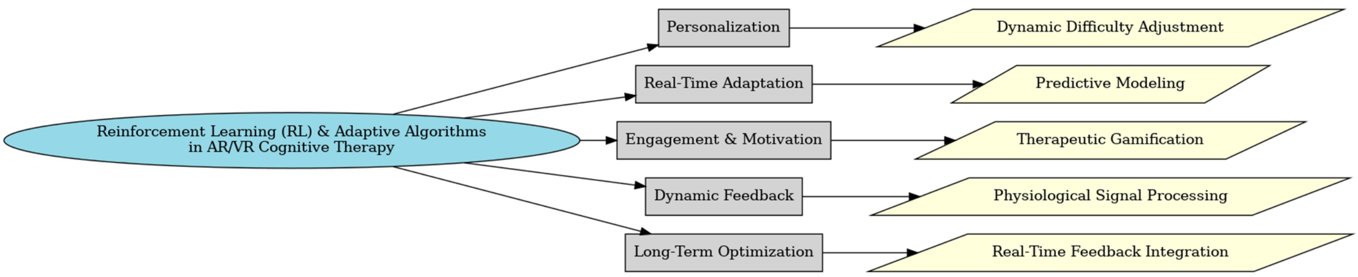

Figure 14. Flowchart of reinforcement learning (RL) and Adaptive Algorithm Applications in AR/VR cognitive therapy.

Each of these five key areas directly supports specific RL-driven applications in AR/VR-based cognitive therapy, depicted as the rightmost components of the flowchart:

- Dynamic Difficulty Adjustment: Therapy difficulty scales dynamically, ensuring patients remain in an optimal challenge zone to maximize engagement.
- Predictive Modeling: Machine learning models forecast treatment responses, allowing proactive modifications to intervention strategies.
- Physiological Signal Processing: Real-time analysis of biometric indicators (e.g., galvanic skin response, EEG) enables adaptive interventions based on emotional and cognitive states.
- Therapeutic Gamification: RL introduces personalized reward systems, making AR/VR therapies more immersive and enjoyable.

- Real-Time Feedback Integration: Interactive mechanisms modify therapy components in real time, ensuring continuous adaptation to patient needs.

This flowchart underscores how RL and Adaptive Algorithms act as a transformative mechanism in AR/VR-based cognitive therapies. It highlights the progressive workflow from foundational RL principles to specific therapy-enhancing applications, reinforcing the need for further empirical research into RL-driven therapy personalization, engagement, and long-term optimization.

4.6. [RQ6] What Are the Latest Technological Innovations in Machine Learning and AR/VR That Are Transforming the FIELD of Cognitive Therapy?

Analyzing the studies of this research question, several key technical and analytical themes emerge, revealing how these advancements are shaping the landscape of cognitive interventions. One of the recurrent themes involves the sophisticated acquisition and processing of physiological and behavioral data. Recent works like the studies [231,239] use physiological signals such as heart rate variability, galvanic skin response, and EEG data. These are collected and processed in detail to derive meaningful features. For instance, researchers in the study of [231] used wearable sensors to acquire ECG and galvanic skin response data, analyzed through ML techniques to predict the treatment outcome with 79.2% accuracy. Feature extraction techniques will hence transform raw physiological signals into quantifiable metrics relevant to cognitive and emotional states. Similarly, researchers in the study of [155] based the predictive algorithm on the prefrontal cortex activity, highlighting how neurophysiological data play an essential role in personalizing cognitive training. Such approaches are successful when one can successfully engineer features that robustly correlate with the outcomes of therapy non-trivial tasks requiring domain expertise and advanced signal processing techniques. For example, extracting heart rate variability measures from ECG recordings requires multiple sophisticated time-series analyses, whereas, according to the study of [143], analyzing EEG signals frequently employs power spectral density estimation and time-frequency analysis techniques.

The application of various ML algorithms for predictive modeling is another important cornerstone for such advances. Researchers in the study of [159] showed how ML methods predict treatment success in iCBT, achieving balanced accuracy between 56% and 77%. For this, robust model selection, training, and validation processes must be carried out. Also, researchers in the study of [150] implemented a deep learning model that predicts client response to treatment and shows the emergent adoption of deep learning in the domain. Deep learning models can learn from data by acquiring hierarchical representations, which generally suit physiological and behavioral data's complex and high-dimensional nature. The choice of specific algorithms often depends on the nature of the data and the prediction task. For example, researchers in the study of [152] reported 0.71 accuracy for the prediction of significant symptom reduction in depression and anxiety using a random forest classifier, which is considered one of the most potent ensemble methods with excellent robustness and accuracy. Researchers in the study of [206] extended this work by using an ensemble of ML methods to show that several different predictive models can yield superior predictive performance by combination. These studies often use comparative analyses among different algorithms, including support vector machines, logistic regression, and several forms of neural networks, to deduce the optimal model for a particular task.

One key dimension of these technical developments is the creation of adaptable systems, which adjust the therapy parameters based on real-time data. A good example of this trend is the study [203] on AI-CBT for chronic pain. Their system used ML to optimize treatment recommendations, choosing between different session lengths and types of feedback based on patients' progress. This adaptive approach ensures that the therapy remains challenging and engaging, thus potentially improving outcomes. Another group of authors [129] designed an app, ZeroPhobia, in which participants are advanced through successive levels of difficulty in the VR environment by self-reports of decreased fear below a threshold. This real-time feedback-informed adaptive difficulty progression is a hallmark of several emerging systems. Researchers in the study of [162] extended this idea further by introducing their fully automated machine-guided iCBT program, which embodied several functions hitherto achieved by therapist support, including adaptive difficulty adjustments across 20 different degrees. The development of such a system requires sophisticated algorithms that can be learned from patient interactions and change parameters to maximize therapeutic efficacy.

Creating immersive and interactive AR/VR environments is a defining feature of these technological advancements. Among the most essential steps towards creating controlled and personalized exposure environments is the development of the "Blue Room" [186]. Besides realistic visual rendering, creating such virtual environments involves many technical challenges regarding integrating several sensory modalities. For instance, researchers in the study of [122] underlined how haptic feedback might make VR exposure more realistic. In a related vein, researchers in the study of [221] presented the work on HEVR, an advancement that allows the synchronization of the patient's heartbeat with visual cues in VR; it results in a personalized, very immersive experience. Systems such as the SLB, presented by the study of [142], embed elaborately interactive virtual environments for cognitive training, thus representing the trend toward more sophisticated, ecologically valid VR applications.

Most reviewed studies underline the trend of integrating various technologies while developing comprehensive therapeutic platforms. For instance, combining VR with EEG monitoring will provide more profound insights into a patient's emotional and cognitive states during therapy, both demonstrated in the works of [143,227], as it requires advanced data synchronization and analysis techniques. Another significant development was the creation of VR rehabilitation systems, which was mentioned in the works of [180,184]. These systems have various cognitive exercises, automatic reporting, telerehabilitation capabilities, and various difficulty levels. This will require development based on software engineering skills, knowledge of human–computer interaction, and clinical psychology. The use of commercially available VR headsets, such as the Meta Quest 2 used in the study of [201], together with smartphone-based VR systems used by researchers [128], points toward accessible and scalable solutions for VR platforms.

Besides the usual ML models, several advanced analytic techniques are introduced. Researchers in the study of [162] used the LSTM model, a type of recurrent neural network, to analyze patient responses in cognitive behavioral therapy exercises. LSTMs are quite effective concerning sequence data; hence, this model would suitably analyze interaction within the session. In addition, using ensemble methods, as researchers in the study of [206] did, indicates a trend of combining multiple models to achieve better accuracy and robustness in prediction. Advanced analytical techniques have marked a swing toward sophisticated and nuanced approaches for understanding and optimizing cognitive therapy.

While these are promising advances, several challenges are discussed in the studies. The most common needs are related to larger sample sizes and more diverse patient populations [114,228]. Most technologies are at the research level, and their efficacy and safety need further validation through rigorous clinical trials [115,234]. In addition, ethical considerations must be carefully considered, especially on data privacy and the possibility of these technologies replacing human interaction.

The heatmap below (Figure 15) is an integrated visualization heatmap of state-of-the-art ML and AR/VR technologies that will transform cognitive therapy. Key focuses are on physiological data acquisition, predictive modeling, adaptive systems, immersive environment creation, platform integrations, and enhanced analytical techniques. Further, each innovation has been mapped against the contribution that it can make toward betterment in cognitive therapies. Colors show the degree of influence on enhancing cognitive therapies.

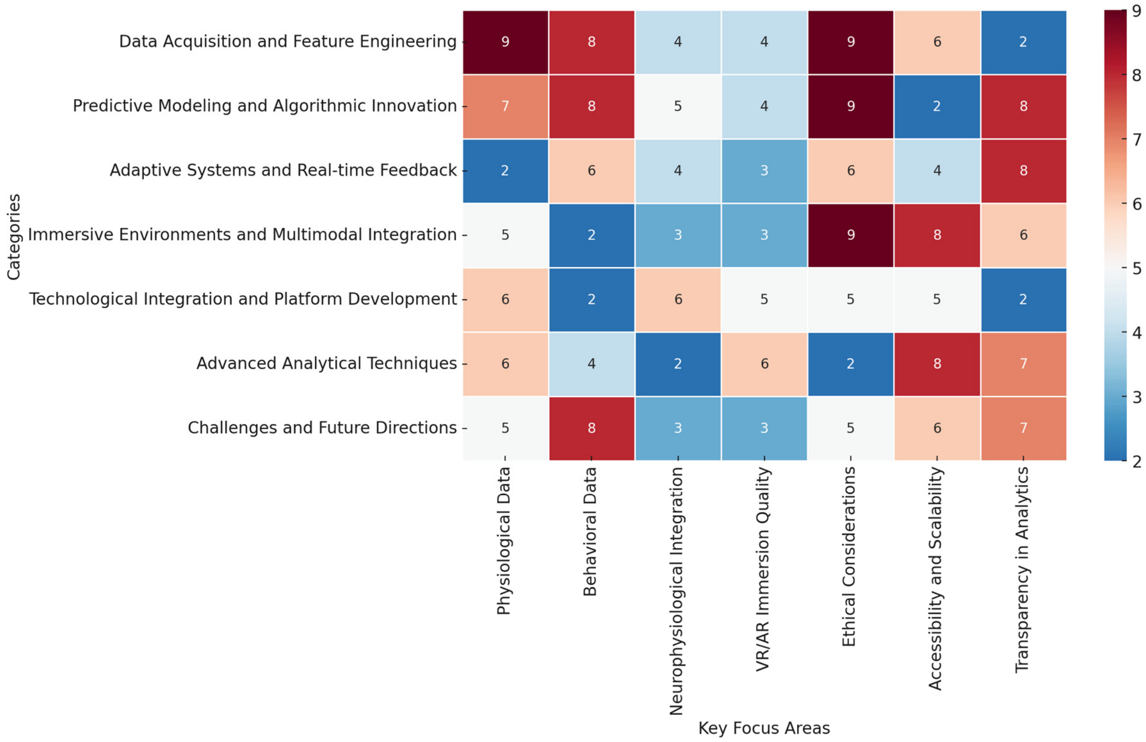

Figure 15. Key focus areas in ML and AR/VR cognitive therapy research.

5. Discussion

ML has emerged as an essential technique to be integrated into AR/VR-based cognitive therapies, which promise to bring a transformational impact in making these interventions more personalized, adaptive, and effective. RL has also significantly influenced designing adaptive therapy sessions based on physiological responses such as heart rate variability or skin conductance. The therapy environment automatically changes for the patient. For instance, RL algorithms considerably enhanced treatment outcomes for phobias by personalizing exposure intensity in real time. However, such systems are challenging to apply in practice since rewarding sparse signals cannot always avoid the reinforcement of unintended behaviors.

The ANN has also significantly affected emotion recognition and adaptation of therapy. These models empower AR/VR environments to switch therapeutic content on the fly by processing rich inputs such as facial expressions, voice tone, and EEG data due to the subject's emotional state. For instance, for treatments of PTSD, deep neural networks could be used to predict emotional distress and thus modulate the level of immersion or stimuli intensity to the needs of a given individual. Another significant value of ANNs is the scalability of this technology, in that it can process big datasets to optimize outcomes across diverse populations. Predictive analytics became another important ML application in AR/VR therapies, especially for predicting patient outcomes and identifying potential risks like dropout from treatment. By applying such algorithms as support vector machines and decision trees, researchers can foresee the likelihood of symptom reduction and modify therapy plans accordingly. Similarly, NLP has enhanced therapeutic conversation in VR environments by allowing virtual agents to simulate dialogue and provide personalized feedback realistically. These agents have been most effective in guided therapy for anxiety disorders, with real-time coping strategies tailor-made to patient response.

The efficacy of these interventions has already been evidenced in several domains. ML-based AR/VR therapies have been proven better than their static counterparts in personalizing sessions, hence ensuring faster symptom reduction and more significant improvement in emotional regulation. The real-time analysis of a patient's behaviors, including gaze and motion profiles, allows for run-time adjustments in therapy parameters that enhance engagement with reduced adverse consequences such as cyber-sickness. Immersive and gamified scenarios increase patient motivation to adhere to and improve treatment outcomes.

Furthermore, ML-powered systems have integrated wearable technologies, such as EEG and heart rate monitors, to provide real-time data for therapy adjustments. For example, EEG data were used to detect stress levels, triggering calm interventions within the VR environment. Intelligent virtual agents powered by NLP algorithms facilitated conversational therapy that allowed patients to practice social interactions in a controlled environment, especially for those with social anxiety disorders.

The convergence of ML and AR/VR technologies pushes the boundaries for cognitive therapy. The various studies presented throughout this manuscript show a visible trend toward more personalized, adaptive, immersive therapeutic intervention driven by sophisticated data acquisition and feature engineering, a variety of powerful ML algorithms, real-time adaptive systems, and the creation of increasingly complex and interactive virtual environments. While there are still challenges, continuous research and development in this area promise great heights concerning the effectiveness and accessibility of cognitive therapy. This convergence of technologies has been the gateway to a new era of data-driven, personalized mental healthcare.

Figure 16 illustrates the analytical view of the contribution that ML techniques make to improving AR and VR-based cognitive therapies. The bubbles' size and color show the strength of associations among various ML techniques and key therapeutic outcomes, outlining the dominant trends and nuanced interactions. This also means that the visualization will show which ML-based personalization, RL, and deep learning have the highest impact on various therapy outcomes. This aligns with the growing application of adaptive AI-driven therapy systems, where ML allows the real-time customization of therapy content based on individual patient responses.

- RL substantially impacts real-time adaptation and cognitive improvements, supporting its role in dynamically adjusting therapy scenarios to user behaviors.
- ANNs and DL are shown to be highly effective in predictive analytics and cognitive therapy enhancements, suggesting their utility in pattern recognition for patient progress tracking.
- NLP contributes substantially to emotional engagement, reinforcing its effectiveness in virtual therapeutic conversations and AI-driven interventions.

The figure highlights the dual role of personalization and standardization in AR/VR-based cognitive therapy:

- ML-based personalization and RL support individualized therapy experiences, ensuring that interventions dynamically adjust to patient needs.
- Conversely, predictive analytics and ANNs contribute to structured outcome assessments, ensuring that treatment protocols remain scientifically rigorous and scalable across diverse patient populations.

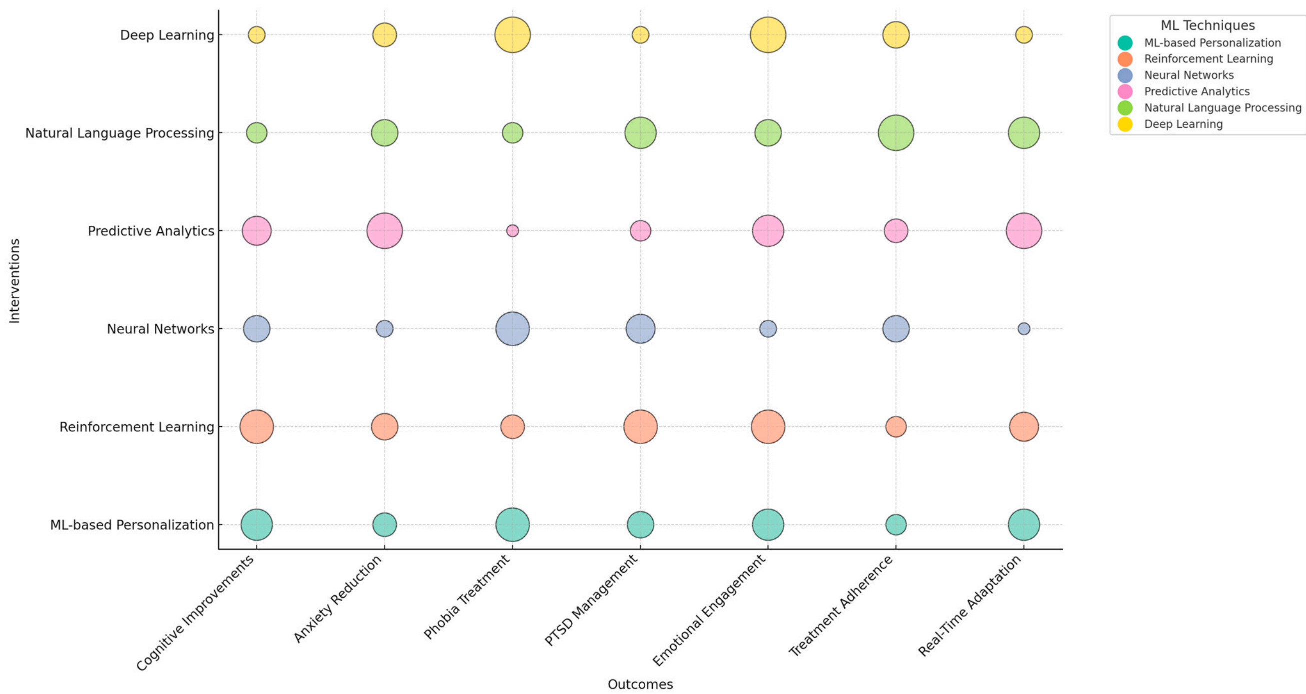

Figure 16. Impact of ML techniques in AR/VR cognitive therapies.

This balance between adaptive personalization and methodological consistency is crucial for scaling ML-integrated AR/VR interventions while maintaining clinical efficacy. The insights from the visualization indicate a growing need for interdisciplinary collaboration between AI researchers, clinicians, and cognitive scientists:

- AI-Driven Predictive Analytics: The results suggest increasing reliance on ML models for outcome forecasting, enabling clinicians to modify therapy regimens preemptively based on predicted patient trajectories.
- Ethical and Transparency Considerations: The decisive role of deep learning and NLP in cognitive therapy suggests that issues related to data transparency, bias in ML models, and interpretability of AI-driven recommendations should be further investigated.
- Hybrid AI-Therapist Models: Given that specific ML techniques (e.g., RL) show stronger associations with therapy adaptation, future research should explore the potential of AI–human hybrid therapy models, where ML systems assist but do not replace human clinical expertise.

Additionally, the findings from Figure 15 underscore several key implications for future research:

- Optimizing Real-Time Adaptation: Enhancing RL frameworks for real-time therapeutic adjustments based on biometric and behavioral feedback.
- Fine-Tuning Predictive Accuracy: Integrating ANNs with larger multimodal datasets to improve the precision of patient progress tracking and therapy effectiveness forecasting.
- Expanding NLP Applications in Cognitive Therapy: Further refining AI-driven virtual therapists to enhance patient engagement and ensure ethical conversational boundaries.

Finally, the analytical trends in Figure 15 reinforce the evolving role of ML in redefining AR/VR-based cognitive therapies. While deep learning and RL show substantial adaptability benefits, predictive analytics and NLP drive structured progress tracking and improvement in patient interaction. The results highlight the transformative potential of ML in revolutionizing mental health treatments; however, they emphasize the need for ethical oversight, interdisciplinary collaboration, and rigorous validation to ensure long-term efficacy and safety for patients.

Figure 17 below shows a Venn diagram of how technologies, application domains, and potential benefits combine in AI-enhanced CBT. Three interlocking ellipses outline graphically how advances in AI and wearable technologies are converging with cognitive and mental health therapy practices to deliver life-changing results.

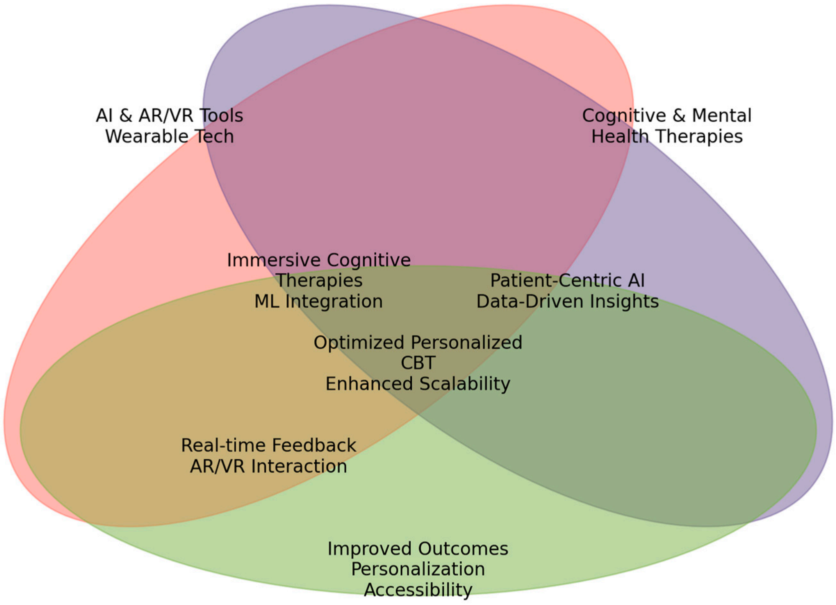

Figure 17. Venn diagram representing technologies, domains, and benefits of AI-enhanced CBT.

The base will be new therapeutic tools and AI algorithms powered by AR, VR, and wearable devices that form the core of this work. These will then be able to monitor in real time, acquire data, and make adaptive interventions constituting personalized care. Domains of application include cognitive and mental health therapies for sleep disorder treatments, mental well-being, and associated chronic conditions. With the integration of AI, therapies become more interactive, immersive, and patient-centric. These may include improved therapeutic outcomes, better accessibility, and higher personalization. As depicted in the diagram below, the meeting point of these three circles is what AI-enhanced CBT contributes: immersive cognitive therapies optimized for scalability, real-time feedback, and data-driven insights. These features reduce symptoms, improve patient adherence, and increase treatment efficacy.

This diagram visually underlines the interdisciplinary integration of high-end technology with evidence-based therapeutic practices to meet an ever-growing demand for effective, accessible, and scalable solutions for managing sleep disorders. It is a future research and innovation roadmap, underlining the transformative potential of AI-driven approaches in cognitive therapies.

5.1. Ethical Considerations

Integrating ML algorithms into AR/VR-based cognitive treatments raises ethical challenges, exceptionally patient privacy, data security, algorithmic fairness, and regulatory compliance concerns. While the technologies enhance personalization, real-time feedback, and treatment responsiveness, they also create risks related to data sensitivity, AI-generated decisions, and access to equitable treatment. ML in AR/VR cognitive therapies involves collecting and processing patients' sensitive data, including biometric data (EEG signals, eye tracking, physiological signals) and behavioral data. This raises issues about data privacy, informed consent, and patient autonomy.

1. Compliance with GDPR and HIPAA:
   - General Data Protection Regulation (GDPR): This regulation ensures that data minimization, informed consent, and the right to be forgotten are upheld in ML-driven therapy applications. Patients must have complete transparency over how their data is used and stored.
   - Health Insurance Portability and Accountability Act (HIPAA): This act mandates strict encryption, access controls, and audit trails for healthcare-related patient data, which must be adhered to in ML-AR/VR mental health platforms.
   - Privacy-Preserving AI Techniques: Applying homomorphic encryption, federated learning, and differential privacy can reduce data leakage risks while ensuring model effectiveness.
2. Institutional Responsibility and Transparency:
   - Healthcare providers and developers must establish clear policies on data access, anonymization, and storage to prevent unauthorized use of sensitive patient information.
   - Patients should receive accessible consent mechanisms to opt in or out of AI-driven therapy models.

ML models used in mental health therapy must be fair, unbiased, and representative across diverse populations. Algorithmic bias can lead to disparities in diagnosis accuracy, therapy personalization, and patient outcomes, particularly for underrepresented demographic groups.

1. Addressing Algorithmic Bias:
   - Bias may emerge from skewed training data, inconsistent model validation, or preconceived assumptions embedded in algorithm design. Ensuring demographically diverse datasets is critical to avoiding biases in therapy recommendations.
   - The application of bias mitigation techniques, such as re-weighted sampling, fairness-aware learning, and adversarial debiasing, can enhance equity in AI-driven cognitive therapies.
2. Domain Bias and Context Adaptation:
   - ML models trained in one setting (e.g., a Western clinical trial) may not generalize well to different cultural, linguistic, or socioeconomic backgrounds.
   - Adaptive AI frameworks should be designed to dynamically adjust models to individual patient profiles without reinforcing systemic disparities.
3. Ethical Implications of AI Decision-Making in Mental Health:
   - While AI-enhanced AR/VR therapy can personalize mental health treatments, reliance on automated decision-making raises concerns about human oversight and clinical accountability.
   - It is crucial that therapists remain actively involved in evaluating AI-generated therapy recommendations to prevent over-reliance on opaque algorithms that may not fully capture complex patient conditions.

Beyond bias and privacy, additional ethical challenges emerge in deployment, accessibility, and patient autonomy:

1. Informed Consent in AI-Augmented Therapy:
   - Patients must be explicitly informed about AI's role in their treatment, including potential risks, limitations, and benefits of ML-driven therapy personalization.

- Explainable AI (XAI) techniques should be integrated into AR/VR mental health platforms, allowing patients and clinicians to understand how ML models generate recommendations.

2. Therapeutic Responsibility and AI Transparency:
   - AI should not replace human clinical judgment, and systems should be auditable, interpretable, and subject to independent oversight.
   - Continuous ethical monitoring and evaluation of ML-integrated AR/VR therapy platforms are necessary to detect biases, security vulnerabilities, and unintended consequences.
3. Accessibility and Digital Divide Considerations:
   - Ethical concerns also extend to fair access—ensuring AI-driven mental health interventions do not exacerbate disparities between technologically advantaged and disadvantaged populations.
   - Solutions such as affordable AR/VR hardware, low-bandwidth AI models, and multilingual support can enhance equitable access to digital cognitive therapies.

The responsible deployment of ML-enabled AR/VR cognitive treatments demands an integral approach that places a premium on privacy, equity, governance, and human monitoring. Data protection, minimizing biases, transparency, and accessibility encompass how AI-enhanced mental healthcare services are rendered safe, efficient, and ethically sound. Continuing research must, first, further enhance bias limitation procedures, realizing privacy-preserving AI methodologies and formulating moral principles consistent with global data safety guidelines (GDPR, HIPAA).

5.2. Future Directions and Emerging Trends

The outlook for integrating ML in AR/VR-based cognitive therapies is promising. Advancements in predictive analytics and ML are opening new avenues for novel AR applications worldwide. The enhancement of AR/VR in healthcare and cognitive therapies remains in its infancy, with significant potential for growth in areas such as therapeutic intervention, cognitive games, and real-time EEG data analysis. Potential research areas include implementing deep learning in computerized cognitive games and developing virtual reality modeling language-embedded ML screens for health management [241–245].

While these advancements are promising, several technical challenges remain. Data quality and quantity are paramount, as the performance of ML models is highly dependent on the availability of large, well-curated datasets. Future research should prioritize collecting comprehensive, multimodal data, including clinical, demographic, behavioral, and physiological data captured during AR/VR sessions. Model interpretability remains a critical concern, necessitating ongoing research into methods for enhancing transparency and explainability, particularly in clinical decision making. Rigorous validation and cross-validation procedures are essential to ensure the generalizability and robustness of these models [202]. Future studies should employ techniques such as nested cross-validation and external validation on independent datasets to mitigate the risk of overfitting and provide more reliable estimates of model performance [246–251].

6. Conclusions

In conclusion, this systematic review underscores the transformative potential of combining machine learning (ML) with augmented reality (AR) and virtual reality (VR) in cognitive interventions for mental disorders. From the synthesis of 141 studies, strong evidence is obtained on the potential of ML-based AR/VR interventions to advance personalization, enable treatment outcomes, and drastically improve patient engagement. They provide interactive and immersive environments for the real-time adjustment of therapy and predictive analysis, which translates into more effective and responsive treatment protocols for PTSD, anxiety disorders, and phobias. Specifically, ML algorithms like neural networks and reinforcement learning have successfully personalized therapy experiences by iteratively adapting treatment parameters to individual patients' needs. Experiments also demonstrate that ML-enhanced AR/VR interventions result in long-term symptom reduction, improved therapy compliance, and enhanced patient motivation—variables essential to long-term mental health benefits. The potential of these technologies to facilitate real-time monitoring and adaptive feedback is a significant step forward in contemporary cognitive therapy, making treatments more interactive, dynamic, and potent. As ML and immersive tech evolve, AR/VR-based cognitive therapy will become the standard of mental health treatment. Artificial intelligence and virtual worlds combine to pave the way for highly effective, scalable, and affordable therapies capable of transforming patient care. As research and innovation continue to advance, the future of such technologies to reshape mental health treatment across the world becomes increasingly apparent.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/electronics14061110/s1, Full Table of the Studies (n = 141) included in the Systematic Review.

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Abbreviations

General and Technology-Related Terms

AI	Artificial intelligence
AR	Augmented reality
CBT	Cognitive behavioral therapy
HMD	Head-Mounted Display
ML	Machine learning
MR	Mixed reality
NLP	Natural language processing
VR	Virtual reality

Medical and Psychological Terms

ABI	Acquired brain injury
ADHD	Attention deficit hyperactivity disorder
AM	Autobiographical memory
AVH	Auditory verbal hallucinations
CBTp	Cognitive Behavioral Therapy for Psychosis
EEG	Electroencephalography
FMA	Fugl–Meyer Assessment
GD	Gambling disorder
MCI	Mild cognitive impairment
MDD	Major depressive disorder
MoCA	Montreal Cognitive Assessment
NIHSS	National Institutes of Health Stroke Scale

NSI	Neurobehavioral Symptom Inventory
PCL-C	PTSD Checklist—Civilian Version
PTSD	Post-traumatic stress disorder
QIDS-SR	Quick Inventory of Depressive Symptomatology—Self-Report
SAD	Social anxiety disorder
SUD	Substance use disorder
TAU	Treatment as usual
Machine Learning and Statistical Terms	
AUC	Area Under the Curve
ANN	Artificial neural network
CNN	Convolutional Neural Network
DL	Deep learning
FM	Full model
FM-UE	Fugl–Meyer Upper Extremity Assessment
LSTM	Long Short-Term Memory
MARL	Multi-Agent Reinforcement Learning
QEEG	Quantitative electroencephalography
RNN	Recurrent neural network
rTMS	Repetitive transcranial magnetic stimulation
RMSE	Root mean square error
RL	Reinforcement learning
SM	Simplified model
SVM	Support vector machine
Therapy and Research Methodology Terms	
ANAMs	Automated Neuropsychological Assessment Metrics
BOT-2	Bruininks–Oseretsky Test of Motor Proficiency, Second Edition
CT	Critical thinking
DTVP-2	Developmental Test of Visual Perception, Second Edition
FIM	Functional Independence Measure
IPQ	Presence Questionnaire
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCT	Randomized controlled trial
TG	Task Generator
Virtual Reality Therapy and Rehabilitation	
BBVR	Brain-Based Virtual Reality Therapy
CB-VR	Cognitive Behavioral Virtual Reality Therapy
Reh@City	Virtual Reality-Based Rehabilitation System
VRCE	Virtual Reality Cue Exposure
VRGT	Virtual Reality Group Therapy

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