

Integrative Survey of Multimodal Analytics, IoT-Enabled Biometric Monitoring, and Artificial Intelligence for Secure, Scalable, and Explainable Healthcare Systems

Abstract

This survey comprehensively examines the current landscape and future directions of automated, data-driven, and AI-enabled analytics in healthcare, addressing the surging complexity and heterogeneity of clinical, sensor, and IoT-derived data. Motivated by the imperatives of real-time monitoring, precision diagnostics, and personalized therapeutics, the review synthesizes methodological advances across multimodal data fusion, biomedical signal processing, deep learning, and explainable artificial intelligence (XAI). The scope encompasses foundational infrastructures, taxonomy of data modalities, benchmarking datasets, and emergent computational frameworks enabling scalable, privacy-preserving, and interoperable analytics. Key contributions include a critical evaluation of signal processing methods for real-time health monitoring, state-of-the-art multimodal and cross-modal fusion strategies, and adaptive analytics tailored for imperfect, high-velocity IoT streams. The survey elucidates the interplay between synthetic data generation and regulatory, ethical, and technical challenges, emphasizing the centrality of transparency, auditability, and robust privacy/security foundations—particularly within federated and resource-constrained environments. By integrating case studies, comparative paradigms, and application-driven insights, the review highlights best practices in operational analytics, clinical decision support, and the transition to proactive and participatory models of care. Concluding, it identifies persistent challenges—data heterogeneity, annotation scarcity, standardization, equity, interoperability, explainability, and responsible AI governance—charting a coherent roadmap for the transformative, scalable, and ethical deployment of AI-enabled analytics across the biomedical and health sector.

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1 Introduction

Artificial Intelligence (AI) has achieved unprecedented milestones in recent years, permeating diverse domains such as natural language processing, computer vision, and decision support systems. The rapid evolution of algorithms, model architectures, and data

resources continually redefines the state of the art, compelling both newcomers and practitioners to stay abreast of ongoing developments.

Despite the existence of numerous surveys, the literature remains dynamic and fragmented, with many reviews focusing on narrow sub-areas without providing a holistic perspective. Furthermore, critical differences in methodologies, performance metrics, and evaluation strategies are rarely juxtaposed explicitly, resulting in ambiguity and impeding direct comparison. In this context, our survey distinguishes itself by offering a comprehensive analysis and systematic contrast of major paradigms and frameworks within the field.

A significant point of contention among researchers lies in the ongoing debate regarding the primacy of model complexity versus data scale. Proponents of sophisticated architectures argue that novel inductive biases fundamentally transform generalization, while other camps emphasize the role of large annotated datasets and powerful optimization schemes. These and other philosophical and practical divergences form the foundation of heated discourse, as each approach harbors distinct advantages, limitations, and implications for scalability and real-world deployment. Our survey actively synthesizes these contrasting viewpoints, ensuring that contested domains and unresolved tensions are transparently presented for the benefit of both specialists and generalists.

To aid reader navigation and verification, all reference citations have been finalized for traceability (see Section ??). For convenience, our detailed reference list, consolidated at the end of the survey, enables streamlined verification and follow-up.

Given the breadth of the field and the ongoing proliferation of techniques, this survey is organized to juxtapose, when appropriate, directly comparable methods in early summarizing tables. This structure empowers the reader to grasp major distinctions and key insights at a glance, without wading through dense technical expositions prematurely. We advocate that direct comparison and explicit contrast—especially where scholarly debate or divergence is active—forms the backbone of rigorous survey work.

To summarize, our contributions are: - Delivering a holistic, up-to-date synthesis spanning major AI subfields. - Highlighting and clarifying points of contention or divergence in current research. - Systematically contrasting differing methodologies to reinforce originality and reader clarity. - Providing finalized, traceable citations for full transparency.

Key insights from this survey, as well as open challenges and directions, are succinctly outlined at the end of each major section, facilitating targeted exploration by both novices and experts.

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1.1 Motivation for Automated, Data-Driven, and AI-Driven Analytics in Healthcare

The escalating complexity of modern healthcare, compounded by the proliferation of vast and heterogeneous data sources, has intensified the imperative for automated, data-driven analytic paradigms. Digital health data now originate from a wide array of modalities, including electronic health records (EHRs), imaging, wearable biosensors, and more. This diversity foregrounds the necessity of capabilities for real-time analysis and continuous monitoring, which are central to advancing personalized diagnostics, adaptive therapeutics, and overall operational efficiency.

Artificial intelligence (AI) and automation facilitate the extraction of actionable insights from high-velocity, complex data streams. These approaches have demonstrated efficacy across domains such as patient safety monitoring, disease surveillance, and optimization of clinical and administrative workflows. Nevertheless, despite these advances, the adoption of synthetic and AI-driven analytics continues to be hindered by several challenges:

Practitioner skepticism: Healthcare professionals remain cautious about entrusting critical decisions to algorithmic systems, citing concerns regarding reliability and interpretability.

Regulatory ambiguity: Established regulatory frameworks have yet to fully accommodate the nuances of automated decision-making in medicine.

High stakes of error: Unlike less critical sectors, errors or malfunctions in healthcare analytics can have profound, direct consequences for patient safety, underscoring the need for robust, transparent, and accountable computational strategies.

1.2 Emergence and Significance of Multimodal, Cross-Modal, and IoT-Enabled Platforms

Recent advances in healthcare analytics are increasingly propelled by the integration of multimodal and cross-modal data streams. These encompass imaging, genomics, unstructured clinical narratives, and physiological signals, collectively enabling the construction of comprehensive, patient-specific health models. The deployment of Internet of Things (IoT)-enabled platforms further enhances this landscape by supporting widespread, decentralized data acquisition through interconnected medical devices and in-home sensors.

Such systems are pivotal for continuous, context-aware health monitoring and the facilitation of remote care models. However, their utility is tightly coupled with the ability to harmonize and process data characterized by heterogeneous formats, distinct error characteristics, and diverse temporal resolutions [29, 68, 78]. Realizing this promise hinges on overcoming several technical challenges:

Real-time data fusion: Integrating diverse data streams in a temporally and contextually consistent manner.

Anomaly detection: Robust identification of clinically significant outliers or data errors across heterogeneous modalities.

Adaptive response: Enabling systems to dynamically adjust analytic or therapeutic strategies in response to incoming data.

Addressing these challenges remains a pressing research frontier that requires not only engineering ingenuity but also methodological innovation.

1.3 Central Themes: Big/Synthetic Data, Biomedical Signal Processing, and Real-Time Monitoring

Contemporary innovation in healthcare analytics is driven by paradigms that leverage both big data and synthetic data generation to enhance modeling, simulation, and decision support. Synthetic data, produced using techniques such as generative adversarial networks (GANs), variational autoencoders (VAEs), agent-based simulations, and natural language processing, serves several essential roles:

Policy prototyping enables testing of interventions or policies on simulated populations prior to real-world deployment. Privacy risk mitigation is addressed by reducing the chance of re-identification when sharing data for research and development. Data augmentation can supplement scarce or biased datasets, thereby improving model robustness and generalizability.

In parallel, advances in real-time biometric monitoring and biomedical signal processing are transforming proactive patient care and population health management. Yet, the reliance on synthetic and AI-generated data introduces new complexities, such as:

There are definitional ambiguities, with an ongoing lack of consensus regarding terminology and taxonomy for synthetic data categories. Model bias and auditability remain concerns, as there is an increased risk of embedding or exacerbating bias, accompanied by challenges in tracing model outputs to their data provenance. Privacy challenges persist, in part due to uncertainty regarding the adequacy of prevailing frameworks, such as HIPAA or GDPR, to regulate synthetic biomedical data [29]. For example, while differential privacy methods (such as PATE-GAN) may offer robust mathematical protection for synthetic datasets, their adoption in clinical contexts is limited by implementation complexity and a lack of standardization [29]. To ensure accountability, there are calls for frameworks such as digital chain-of-custody protocols encompassing encryption, regulated access, and possibly blockchain, to secure the integrity of synthetic healthcare data throughout its lifecycle [29]. Addressing these technical, ethical, and regulatory concerns remains fundamental for the responsible adoption of big and synthetic data in biomedical applications.

1.4 Scope and Organization of the Survey

This survey synthesizes contemporary research across the domains of multimodal data fusion, real-time biomedical signal processing, and IoT-enabled healthcare systems. Special attention is devoted to the technical, ethical, and regulatory complexities arising from the use of big and synthetic data within biomedical research and clinical practice [29, 68, 78]. The survey critically examines:

Methods for scalable analytics: Including computational frameworks capable of handling high-throughput, heterogeneous healthcare datasets. Privacy-preserving computation: Covering advances in differential privacy and secure, distributed computation, as well as innovations in digital chain-of-custody mechanisms. Secure data integration architectures: Focusing on distributed and federated approaches for robust, interoperable data management.

By integrating recent literature and application case studies, this work seeks to elucidate emerging best practices, articulate unresolved challenges, and recommend critical directions for the

harmonization of data-driven, patient-centered innovation in the healthcare sector.

2 Foundations of Healthcare Analytics and Digital/IoT Infrastructure

The convergence of healthcare analytics with digital and IoT (Internet of Things) infrastructure has transformed patient care, hospital management, and medical research. Healthcare analytics leverages large-scale datasets generated from diverse sources—including electronic health records (EHR), sensors, mobile health platforms, and administrative systems—to support data-driven decision-making at every level. Central to these advances is robust digital infrastructure capable of securely collecting, storing, and transmitting vast amounts of sensitive clinical data.

The core of this infrastructure is the seamless integration of smart devices, cloud computing, and network protocols tailored to healthcare environments. This integration offers the potential for real-time patient monitoring, early disease detection, and personalized treatment regimens while presenting novel challenges in interoperability, data privacy, and system reliability.

A foundational tension in the development of healthcare analytics systems lies in balancing the needs for data accessibility and privacy. Approaches that emphasize open data sharing can accelerate discovery and innovation but risk exacerbating security and confidentiality concerns. Conversely, stringent restrictions on data flow may inhibit collaborative research and hinder the deployment of advanced analytics. There is also ongoing debate between proponents of centralized versus federated data architectures: centralized systems often enable comprehensive analytics but may constitute single points of failure, while federated approaches offer greater privacy but require sophisticated coordination among stakeholders.

Further, the adoption rate and practical effectiveness of these platforms differ by region and healthcare context, spurring ongoing discourse regarding standards, cost, and scalability. The landscape is rapidly evolving, with regulatory frameworks, technological capabilities, and clinical priorities shaping the trajectory of digital transformation.

In summary, the foundations of healthcare analytics and digital/IoT infrastructure represent both profound opportunities and considerable challenges. A nuanced understanding of the tensions between openness and privacy, as well as infrastructure design choices, is essential for realizing robust, ethical, and actionable healthcare analytics systems.

2.1 Evolution of Digital and IoT Health Systems

The digital transformation of healthcare infrastructure is fundamentally propelled by widespread digitization and the proliferation of Internet of Things (IoT) technologies, which collectively enable the development of highly connected health environments. The adoption of IoT-enabled health systems has facilitated the continuous collection and exchange of real-time patient data via a range of devices, including wearable sensors, mobile health applications, and smart diagnostic equipment. These systems support adaptive, context-aware electronic health services, promoting timely, individualized recommendations that transcend traditional clinical settings [10, 78]. The resulting distributed sensor landscape not only

underpins robust health monitoring but also enables the deployment of algorithmically guided interventions, as digital platforms leverage real-time analytics to personalize care and improve the management of chronic diseases [78].

The implementation of digital health technologies—such as health information technology systems, electronic health records (EHRs), and interoperable IoT device frameworks—has significantly expanded both the scope and scalability of healthcare analytics. Advances in federated and cloud-based architectures have facilitated large-scale integration of diverse health data sources, enhancing operational efficiency and supporting advanced clinical research [8, 10, 78, 94]. Contemporary infrastructures enable real-time data ingestion in conjunction with high-throughput analytics. Large healthcare institutions, therefore, can automatically aggregate data streams from clinical, radiological, laboratory, and patient-generated sources, providing the foundation for predictive analytics, surveillance, and personalized medicine initiatives [78, 94].

Nonetheless, the expansion of these systems has exposed persistent inefficiencies, particularly concerning health information exchange, workflow interoperability, and the sustainable deployment of AI-powered applications. These challenges are especially pronounced in rural or under-resourced environments, where resource disparities hinder the effective realization of digital health benefits [10, 94].

A critical examination reveals that the scalability and utility of digital health systems are frequently constrained by non-technical factors. Policy frameworks, for example, exert a major influence on the operational viability and legal boundaries of digital health integration by affecting adoption rates, promoting or hindering interoperability among vendors and platforms, and shaping approaches to patient data governance [8, 10]. Despite technical readiness at the device level, issues related to the lack of standardized protocols, inconsistencies in data representation, and proprietary barriers regularly impede seamless cross-platform data exchange. Ethical considerations also gain prominence as digitization accelerates, raising urgent issues pertaining to privacy, algorithmic transparency, and the digital divide. The demand for rigorous governance models that prioritize data standardization, promote explainability in algorithmic decision-making, and ensure transparent patient consent is at odds with the current landscape characterized by variable implementation quality and fragmented regulatory environments across jurisdictions [8, 10, 78, 94].

Active debates continue regarding the prioritization of interoperability standards versus local/regional flexibility, the balance between strict privacy controls and data availability for research, and the extent to which AI-powered analytics can be responsibly integrated given concerns around explainability and bias [8]. Divergence exists regarding optimal deployment strategies in varied contexts: while developed nations focus on advanced analytics, resource-constrained and rural environments struggle with basic digital access and sustainability [10, 94]. These ongoing discussions underscore the field's rapidly evolving and sometimes contentious nature, indicating significant opportunities for innovation in governance, technical, and ethical domains.

Table 1: Comparative Overview of Digital Health System Evolution: Benefits and Persistent Barriers

Aspect	Key Advancements	Exemplar Systems/Statistics	Ongoing Challenges
Digitization & Adoption	Sharp increase in EHR and health IT uptake, e-prescribing, and patient access to records [10]	10-fold increase in EHR usage (hospitals); 85% e-reporting of results; 97% hospitals with online records access [10]	Uneven access in rural/small providers; technical complexity; digital divide
Integration & Interoperability	Multi-source, real-time data integration; emergence of hospital-wide big data platforms [94]	WCH-BOP: data from 27+ systems; 20 PB storage; automated/self-service retrieval [94]	Data non-standardization; workflow interoperability; proprietary barriers
Analytics & AI Readiness	Large-scale analytics platforms underpin predictive, personalized care and AI deployment [8, 78]	AI-powered detection (e.g., pulmonary nodule at 98.8% accuracy); ML/DL study accuracies up to 98.5% [8, 94]	Handling streaming heterogeneous data; scalability; missing data; quality control [8, 78]
Governance & Ethics	Expansion of patient engagement and data-driven care models, with federated and cloud architectures [10, 94]	Increased transparency, metadata and terminology standards, SS security in hospital platforms [94]	Privacy concerns; fragmented regulations; inconsistent patient consent; algorithmic transparency [10, 94]

2.2 Core Concepts, Data Modalities, and Taxonomies

At the heart of modern healthcare analytics lies the integration of multiple data modalities, which requires a systematic conceptual framework for effective cross-modal data fusion, representation, and interpretation. Key concepts include:

Cross-modal learning: Leveraging relationships between distinct data types for improved inference and knowledge transfer.

Multimodal representation: Encoding and integrating heterogeneous sources—such as imaging, genomics, biosignals, and clinical text—into unified computational models [8, 11, 15, 34, 43, 44, 49, 67, 78, 83, 91, 93, 101].

Multi-view fusion: Aligning complementary perspectives (e.g., EHR text and diagnostic images) to enhance predictive accuracy and model robustness.

IoT sensor integration: Incorporating continuous real-time data capture from sensor streams, thereby promoting context awareness and enabling active feedback mechanisms for both clinical and home settings [8, 49, 67, 78].

Healthcare data modalities are both diverse and complex, necessitating clear taxonomies for rigorous analysis. A comprehensive categorization includes:

Omics data: Genomics, transcriptomics, proteomics, and metabolomics, which characterize molecular profiles.

Medical imaging: Including CT, MRI, PET, and ultrasound, which are foundational for diagnostic and prognostic modeling.

Biosignals: Such as EEG, ECG, and sEMG, offering physiological and functional insights.

Clinical data: Both structured (e.g., lab results) and unstructured (e.g., EHR notes).

Behavioral, audio, and video data: Supporting remote assessment and patient engagement.

IoT-derived data streams: High-frequency, continuous sensor data enabling granular monitoring and timely intervention [8, 27, 28, 35, 47, 51, 53, 61, 69, 77, 78, 87, 102].

The integration of these modalities underscores the increasing analytical complexity of healthcare, with each domain presenting distinct representational, computational, and governance challenges.

Despite significant advances, persistent heterogeneity in data formats, sampling rates, and annotation standards continues to hinder large-scale multimodal analytics. Multi-institutional and multi-vendor datasets are often sparse, fragmented, or marked by errors and anomalies [8, 10, 24, 78, 94]. Moreover, weak or non-linear correlations between modalities (e.g., loosely coupled sensor streams and clinical events) challenge simplistic fusion strategies and drive the need for sophisticated alignment, imputation, and representation learning methods. Such limitations are exacerbated during real-world deployments, where missing data, class imbalance, and noisy streams are prevalent [24, 78, 94].

Recent developments in cross-modal learning—such as cross-attention mechanisms, graph neural networks with modality-aware encoding, and prompt-based large language models—reflect concerted efforts to close these modality-driven gaps [15, 34, 43, 49, 67, 83, 91]. Nevertheless, key obstacles remain, including the challenge of achieving robust representational alignment under domain shifts, the opacity of current fusion methods, and ongoing concerns about robustness to missing or low-quality modalities. Notably, active debates persist regarding the optimal fusion strategies for complex, real-world healthcare data; for instance, the balance between early and late fusion, or between modality-specific versus joint representation learning, remains contested, as does the interpretability of resulting multimodal models [34, 93]. Furthermore, comparative studies have illuminated both the advantages and shortcomings of approaches tailored for particular domains (e.g., medical imaging versus molecular data) and tasks (e.g., diagnosis, prediction), with substantial divergence observed in generalizability and robustness [8, 24, 53, 83].

To provide a structured overview and direct comparison of the central data modalities and their primary analytical aspects, we present Table 2. This early comparative reference aims to reinforce the balance and clarity of the core concepts discussed.

To address these challenges, emerging taxonomies and systematic benchmarks of multimodal fusion strategies are proving essential to driving practical advances in healthcare analytics [8, 43, 49].

2.3 Datasets, Benchmarks, and Standards

The empirical foundation for digital and IoT health analytics is provided by high-quality, multimodal datasets and robust benchmarking repositories. Several prominent datasets—such as UniMod1K, ImageNet-ESC, LPBA40, IXI, OASIS, ADNI, BraTS, CheXpert, and the MIT-BIH Arrhythmia Database—encompass diverse data types including imaging, biosignals, and longitudinal clinical records, all accompanied by established annotation protocols for algorithmic benchmarking [3, 8, 17, 19, 38, 48, 55, 58, 61, 77–79, 83, 86, 96, 102]. The integration of real-time IoT analytics platforms enables the assessment of algorithms on heterogeneous and high-velocity streaming data, a capability integral to emerging paradigms of remote and continuous care [78, 83].

The range of datasets presented in Table 3 illustrates the breadth of available multimodal resources and their primary roles in benchmarking and advancing algorithmic development. However, there exist several domains where dataset selection and benchmarking remain active topics of debate.

One area of divergence involves the standardization of annotation protocols and benchmarking criteria. In radiomics and imaging, efforts such as the Image Biomarker Standardisation Initiative (IBSI) are driving consensus on feature definitions, processing workflows, and validation metrics to address variability in extraction and reproducibility [1, 35, 84]. Nevertheless, heterogeneity in acquisition protocols, segmentation methods, and feature nomenclature persists,

Table 2: Summary comparison of principal healthcare data modalities, typical analytical challenges, and illustrative applications in multimodal learning.

Modality	Common Analytical Challenges	Representative Applications	Relevant References
Omics data	High dimensionality; batch effects; sparse annotation	Disease risk prediction; pharmacogenomics	[8, 47]
Medical imaging	Heterogeneous formats; volumetric/temporal variation; annotation scarcity	Diagnosis, segmentation, radiomics	[27, 35, 53, 61, 69]
Biosignals	Noise and artifacts; temporal misalignment; class imbalance	Seizure detection; cardiac monitoring	[49, 67, 77]
Clinical data	Unstructured text; missing/corrupted values; privacy concerns	Patient outcome prediction; cohort analysis	[8, 10, 24, 78, 94]
Behavioral/audio/video	Limited labeled data; inter/intra-subject variability; privacy	Remote screening; symptom tracking	[8, 11, 77, 102]
IoT-derived streams	High frequency; continuity gaps; device heterogeneity	Real-time monitoring and alerting; context-aware	[8, 49, 78]

Table 3: Summary of Representative Multimodal Healthcare Datasets and Supported Modalities

Dataset	Primary Modalities	Data Type(s)	Use Case(s)
UniMod1K	Imaging, Biosignals, Language	Multimodal (RGB, Depth, Text)	Multimodal learning, object tracking [102]
ImageNet-ESC	Imaging, Audio	Images, Audio files	Cross-modal few-shot learning, benchmarking [58]
LPBA40	MRI	3D Images	Brain segmentation, neuroimaging [19]
IXI	MRI	3D Images	Neuroimaging, brain mapping [19]
OASIS	MRI, Clinical	Images, EHR	Alzheimer’s research, diagnosis [19]
ADNI	MRI, PET, Clinical	Images, EHR, Cognitive Scores	Alzheimer’s disease progression, federated learning [79]
BraTS	MRI	Multisequence MRI	Brain tumor segmentation, federated benchmarking [79]
CheXpert	X-ray	Images, Labels	Chest disease classification, deep learning [53]
MIT-BIH Arrhythmia	ECG	Biosignals	Arrhythmia detection, ECG classification [86]

resulting in ongoing debate between proponents of strict standardization and advocates for flexible, context-adaptive practices [84]. For instance, the reproducibility and biological interpretability of advanced features in PET/CT and MRI remain under scrutiny despite consensus guidelines.

Similarly, benchmarking in IoT-based health analytics has introduced new performance metrics—response ratio, variation factor, and real-time accuracy under unstable connectivity—that challenge conventional standards. As illustrated by recent work on cloud medical data stream analytics and proportionate data handling [78], debate persists in how best to prioritize the trade-off between accuracy and real-time responsiveness for use in heterogeneous, resource-constrained environments.

Harmonization across multimodal datasets further encounters organizational and technical barriers. Many foundational datasets are derived from single-center studies or limited populations, restricting generalizability and failing to sufficiently represent population diversity—an increasingly recognized source of bias in AI-driven healthcare models [38, 58, 78]. The proliferation of proprietary IoT devices and closed data environments intensifies fragmentation, with research communities diverging in approaches toward federated benchmarking, privacy preservation, and equitable resource allocation [78, 79, 94].

Despite significant progress, deficiencies in interoperability and data standardization continue to impede the realization of robust, generalizable, and equitable benchmarks [10, 24, 94]. Practical initiatives are underway to promote open-source, multi-institutional datasets (e.g., lung ultrasound databases [48]) and the development of common validation frameworks for clinical genomics, imaging, and biosignal analytics [42, 47]. However, debates remain unresolved on the balance between universal standards and localized adaptation, and on methodologies for longitudinal and multi-modal

integration to address clinical complexity. Ultimately, sustained collaboration between domain specialists, standardization bodies, and technical stakeholders is essential to advance credible benchmarking and the trustworthy translation of digital and IoT healthcare analytics.

2.4 Data Privacy, Security, and Governance

Subsection Objective: This subsection reviews the fundamental requirements and open challenges in securing patient privacy, data integrity, and instituting effective data governance within digital and IoT-enabled health platforms, in alignment with the overall survey objective of mapping the technical, regulatory, and ethical landscape for trustworthy healthcare analytics.

The exponential scale-up of digital and IoT health systems has elevated the urgency of safeguarding patient privacy, ensuring robust data security, and instituting comprehensive data governance frameworks. EHRs and IoT health platforms are characterized by unique vulnerabilities—such as data breaches, unauthorized access, and failures in transparency—that can undermine patient trust, disproportionately affect marginalized communities, and call into question the ethical legitimacy of digital health programs [10, 11, 24, 34, 35, 40, 44, 45, 47, 51, 52, 60, 61, 73, 78, 79, 89, 90, 93, 94, 98]. Furthermore, systemic inequities in technology access and digital infrastructure exacerbate disparities in the ability to securely access and utilize digital health solutions [78, 94].

National and supranational policy frameworks—including HIPAA in the United States and GDPR in the European Union—define minimum obligations for privacy, data stewardship, and patient rights. Yet, their applicability to fast-evolving IoT-enabled and AI-driven systems continues to be an area of tension and reinterpretation [6, 8, 10, 11, 22, 24, 26–28, 30, 33–35, 38, 40, 41, 44–47, 51–53, 58, 60, 61, 64, 73, 75, 79, 89, 90, 92–95, 98–100, 102].

The distinctive properties of IoT ecosystems—including persistent data generation, dynamic device connectivity, and the involvement of consumer-grade sensors—necessitate specialized privacy-preserving approaches, such as federated learning, on-device analytics, and stringent data minimization, all without compromising analytical utility [8, 24, 94]. However, the pace of technological innovation frequently outstrips the evolution of regulatory frameworks, yielding gaps in implementation and leaving ambiguous lines of responsibility among diverse institutional actors.

A comprehensive approach must therefore integrate both technical and procedural innovations in privacy and security with robust governance architectures. Essential elements include: fine-grained, role-based access controls and real-time auditing; formalized consent management mechanisms; transparent algorithmic documentation and reporting; and ethical-by-design principles focused on patient autonomy and social accountability.

These requirements are especially challenging for smaller or under-resourced providers who may lack the technical and organizational capabilities needed for effective compliance [10, 78, 94]. Current best practices and governance models, while taking shape, still fall short of consistently translating regulatory intent into operational reality without hindering innovation or exacerbating inequalities in health access and outcomes.

Open Challenges and Research Gaps: Despite advances, digital and IoT health systems face several unresolved issues: - *Regulatory-Technology Gap:* Regulatory cycles lag behind rapid technological innovation, especially with IoT, multi-modal data fusion, and AI-driven analytics [8, 24, 94]. - *Scalable, Equitable Governance:* Present governance structures and technical safeguards often do not scale to smaller or resource-limited providers, perpetuating inequities [10, 78, 94]. - *Standardization and Interoperability:* Fragmented, unstandardized, and legacy data infrastructures persist, impeding secure, seamless health information exchange [10, 24, 79, 94]. - *Methodological Transparency:* Lack of transparency in algorithmic processes and reporting undermines oversight and patient trust, especially with increasing application of AI and ML to sensitive health data [24, 34, 79, 94]. - *Data Minimization and Utility:* Ongoing research is needed to reconcile strict privacy demands with the requirements for high-utility analytics, particularly as modalities and data volumes continue to expand [8, 24]. - *Operationalizing Consent and Autonomy:* Consent management remains procedural and challenging to enforce at scale or in dynamic IoT environments where continuous, secondary data uses occur [94].

In summary, the foundational components of digital and IoT health analytics—system infrastructure, data modality integration, standardized benchmarking resources, and privacy-centric governance—must continue to co-evolve with regulatory and ethical frameworks. Sharpening the alignment between technical advances and procedural safeguards is essential for the realization of equitable, trustworthy, and impactful healthcare analytics. Future work should prioritize the development of scalable governance models, interoperable standards, transparent algorithmic accountability, and actionable consent mechanisms that keep pace with innovation and social need.

2.5 Biomedical Signal Processing and Real-Time Health Monitoring

This subsection aims to systematically review the current developments in biomedical signal processing and real-time health monitoring applications, with an emphasis on the use of advanced computational and learning techniques for accurate, efficient physiological data interpretation. We specifically address how state-of-the-art algorithms are leveraged to address challenges in signal acquisition, denoising, feature extraction, and rapid response, and identify de facto standards as well as open problems within this dynamic research area. The discussion aligns with the broader objectives of this survey: to map methodological innovations, analyze comparative system strengths, and illuminate unresolved technical challenges in each application domain.

In recent years, biomedical signal processing has experienced significant progress, largely driven by the proliferation of wearable devices and IoT-enabled sensors that facilitate continuous monitoring in clinical and home settings. Key research sub-goals in this field include: enhancing the quality and reliability of biosignal acquisition in ambulatory conditions, developing algorithms for robust artifact removal and noise suppression, designing lightweight machine learning techniques for real-time analysis on edge devices, and enabling timely detection of adverse health events.

Researchers have explored diverse datasets such as ECG, EEG, and PPG signals for monitoring vital parameters and detecting anomalies. A variety of signal processing and machine learning frameworks have been proposed, each with specific advantages and trade-offs. For example, deep learning models have demonstrated strong pattern recognition capabilities but often require large datasets and considerable computational resources, potentially limiting their use in embedded systems. In contrast, classical signal processing and shallow learning methods are more lightweight and interpretable, but may underperform on complex temporal or multimodal datasets.

Comparative synthesis of methods highlights that accuracy, latency, computational cost, and interpretability must be carefully balanced in practical deployments. While some approaches achieve state-of-the-art accuracy in controlled settings, they may face challenges such as generalization to diverse populations and robustness against sensor displacement or motion artifacts.

Open Challenges and Research Gaps. Despite remarkable advances, several challenges remain open in the domain of biomedical signal processing for real-time health monitoring. First, there is a persistent need for standardized evaluation datasets and benchmarks to ensure fair, reproducible comparison among algorithms. Second, improving the robustness and generalizability of methods across heterogeneous patient groups and varying physical contexts remains an open problem. Privacy-preserving processing and data security for sensitive patient information also require strengthened solutions. Furthermore, integrating multimodal signals while maintaining real-time responsiveness and battery efficiency in wearable systems is an ongoing research focus. Advances in adaptive learning and edge/federated processing offer promising directions, but scaling these solutions for large-scale, longitudinal health monitoring is an area that warrants further exploration.

In summary, biomedical signal processing for real-time health monitoring continues to evolve rapidly, with ongoing research focusing on improving real-world robustness, computational efficiency, and privacy. Addressing these challenges represents an important step toward reliable, pervasive health monitoring in future biomedical applications.

2.5.1 Signal Interpretation and Disease-Specific Applications. Biomedical signal processing forms the foundation of precise, real-time health monitoring, facilitating sophisticated interpretation of physiological signals such as EEG, sEMG, and ECG. With the advent of advanced quantitative methodologies, disease-specific applications have achieved significant advancements. Notably, intraoperative EEG analysis employing the Hurst exponent as a principal feature has yielded an objective, quantitative means to identify transitions between anaesthetic states, thus enhancing assessment accuracy and providing a critical alternative to subjective clinical judgement during surgery [71]. Such methodological innovations exemplify how the integration of time-series dynamics extends clinical utility.

In the realm of prosthetics, surface electromyogram (sEMG) signals—despite their nonlinear character and susceptibility to noise—have been effectively leveraged for intuitive prosthetic control. Recent developments employ multiresolution decomposition via dual-polynomial interpolation, optimizing denoising and the reconstruction of motor-evoked signals. This approach facilitates reliable multi-class motion decoding within noisy real-world environments, effectively translating complex biosignals into responsive, user-adaptive prosthetic commands [80]. The robustness of these preprocessing pipelines is central to the real-time applicability of prosthetic systems.

The computational analysis of ECG signals further illustrates the transformative impact of advanced processing strategies on disease detection. Transforming one-dimensional ECG traces into two-dimensional time-frequency representations—particularly using the continuous wavelet transform (CWT)—has measurably improved arrhythmia classification accuracy. A recent comparative study systematically evaluated both CWT and short-time Fourier transform (STFT) methods for transforming ECG segments from the MIT-BIH Arrhythmia Database, finding that CWT-based representations, especially those using the Ricker wavelet, generally outperformed STFT for arrhythmia classification tasks. Using transfer learning with pre-trained convolutional neural network architectures such as ResNet-18, the study achieved a top binary classification accuracy of 96.17% for normal versus premature ventricular contraction (PVC) beats. Although STFT yielded faster processing per segment, CWT provided superior localization of abnormal beats as demonstrated by Grad-CAM visualizations, enhancing interpretability for clinical review. The study also highlighted the significant role of hyperparameter tuning in transformation methods and confirmed the practicality of fine-tuned pre-trained networks in real-time cardiac monitoring systems [86].

Reliable benchmarking is underpinned by widely recognized datasets, including MIT-BIH for ECG, NinaPro for sEMG-based prosthetic studies, and CHB-MIT as well as other EEG repositories for neurological disorder monitoring [71, 80, 86]. These curated datasets serve as reference standards, bolstering reproducibility

and standardization essential for rigorous comparative algorithmic development and translational research.

Despite these advances, significant challenges persist in the real-time interpretation of multimodal signals, particularly in practical settings involving data streams from wearable and IoT-enabled platforms. The integration of heterogeneous data sources, each with varying sample rates, modalities, and transmission reliability, complicates timely and accurate monitoring—especially during acute clinical scenarios [2, 37, 49, 78]. Clinical applications such as seizure and home-based epilepsy monitoring are emblematic of these challenges, introducing artifacts, motion-induced noise, and missing data that necessitate advanced artifact rejection and robust adaptation strategies.

Innovative multimodal systems exemplify the cutting edge of real-time monitoring. Advanced seizure detection and prediction platforms have achieved robust results by leveraging multiresolution analysis (e.g., maximal overlap discrete wavelet transforms, MODWT) to decompose EEG signals and extract informative frequency-band features. As demonstrated in recent work, patient-specific multiresolution convolutional neural networks (CNNs) process frequency-band decomposed EEG frames, and aggregate consecutive frame outputs within a sliding window to improve sensitivity and minimize false positive rates for preictal state classification. On public benchmark datasets such as CHB-MIT and Kaggle/American Epilepsy Society intracranial EEG, these approaches achieved sensitivities of up to 85% with correspondingly low false prediction rates, outperforming prior methods in several scenarios [37]. Furthermore, multimodal pipelines that integrate wearable EEG with inertial measurement units (IMUs)—enabling concurrent analysis of brain activity and movement—have demonstrated reliable reduction of false alarms in home environments. Specifically, pipelines utilizing EEG-IMU fusion with targeted artifact rejection through movement sensor data and multi-source training deliver improved sensitivity and substantial reductions in false detections, outperforming previous automated and even expert neurologist-reviewed approaches on at-home seizure detection tasks [18]. Techniques such as advanced multi-view deep feature learning for EEG further enhance interpretability and performance by combining traditional frequency and time domain information with deep feature representations, providing explainable outputs via interpretable machine learning classifiers [2].

The synergy between multimodal feature extraction and intelligent artifact rejection supports continuous monitoring beyond traditional clinical settings and embodies a pivotal stride toward pervasive, patient-centric digital health.

2.5.2 Advanced Feature Learning and Biometric Monitoring Algorithms. The progression of feature learning paradigms has markedly improved both the accuracy and interpretability of biometric monitoring systems. Deep and hybrid architectures—including recurrent neural networks (RNNs) and long short-term memory networks (LSTMs)—successfully capture temporal dependencies inherent in biomedical time series. Building on these, frameworks such as the Hybrid Recurrent Long Short-term based Tyrannosaurus Search (HRLS-TS) algorithm have emerged, enabling real-time health monitoring with adaptive signal discrimination in dynamic

conditions [49]. The integration of bio-inspired metaheuristics, exemplified by the Tyrannosaurus Search optimizer, further enhances algorithmic performance by balancing predictive accuracy with computational efficiency.

A significant advancement in the field is the adoption of interpretable, multi-view feature integration. The Advanced Multi-View Deep Feature Learning (AMV-DFL) framework represents this evolution by combining conventional frequency-domain features (e.g., extracted via fast Fourier transform) and time-domain features from raw signals with automatically-learned deep features sourced from one-dimensional convolutional neural networks (1D CNNs) [2]. This multi-view approach synthesizes a richer, more comprehensive feature representation that has demonstrated superior effectiveness over single-view or traditional methods, notably improving detection accuracy in biomedical signal analysis such as EEG-based seizure detection. Within this framework, interpretable machine learning classifiers, including multi-view forests, are employed in tandem with explainability mechanisms such as tree-based SHAP (T-XAI), which provide quantifiable insights into feature importance and channel contributions. These advances directly support clinical decision-making and help address the regulatory demand for transparency in AI-driven monitoring solutions [2, 49].

The need for real-time signal optimization persists, especially as wearable and IoT-based health monitoring platforms typically face stringent power and computational constraints. Adaptive strategies are essential for balancing model sophistication with energy efficiency and minimal computational latency, thus maintaining the reliability and integrity necessary for effective, continuous, and personalized monitoring in modern healthcare scenarios [49].

2.5.3 Evaluation and Real-World Validation. The successful translation of biomedical signal processing research into large-scale, real-world health monitoring depends on robust evaluation protocols. As IoT-enabled healthcare grows, reliance on traditional accuracy metrics alone has become insufficient. To address operational realities, a range of performance indicators—including service response ratio, delivery time, variation factor, identification ratio, and aggregate processing time—are regularly employed to assess system viability under diverse streaming data and network conditions. These metrics permit comprehensive appraisal of a platform's responsiveness and resilience in the face of fluctuating loads, real-world device failures, and transient data disruptions [78].

The adoption of such metrics (Table 4) allows for critical insight into the operational strengths and limitations of signal monitoring frameworks.

A central priority in contemporary validation efforts is the utilization of diverse, multicenter, and authentic clinical datasets. Data amalgamated from large-scale hospital infrastructures and wearable device deployments ensures sufficient heterogeneity for comprehensive benchmarking, exposing analytic algorithms to an array of physiological, demographic, and environmental confounders [8, 18, 26, 49, 54, 77, 94]. This strategy strengthens model generalizability and facilitates identification of persistent challenges, including missing data, context-dependent adaptation, and site-specific bias—issues increasingly addressed through federated and transfer learning approaches.

Artifact rejection and adaptive recalibration remain vital to reliable deployment. Notably, multicenter evaluations in seizure detection demonstrate that the combination of auxiliary sensing modalities (e.g., IMUs) and advanced postprocessing significantly reduces false alarm frequency without compromising sensitivity [18]. The growing integration of explainable AI techniques further enhances clinician trust, providing actionable insights and facilitating safe and effective intervention.

In summary, the discipline is transitioning from incremental algorithmic improvements to the deployment of comprehensive, integrated pipelines that emphasize signal fidelity, interpretability, computational efficiency, and operational robustness—collectively supporting the broader adoption and real-world impact of real-time health monitoring technologies.

3 Cross-Modal, Multimodal, and IoT-Driven Healthcare Analytics

3.1 Proportionate Data Analytics (PDA) and Data Management

The rapid expansion of Internet of Things (IoT) devices within healthcare ecosystems has culminated in the generation of voluminous, heterogeneous, and high-velocity data streams. These streams frequently exhibit variable formats, fluctuating quality, and diverse error profiles—characteristics that challenge traditional analytic frameworks, which implicitly assume uniform reliability among data sources. Such conventional models prove inadequate in environments where data quality is nonstationary and prone to both transient anomalies and persistent sensor failures.

Proportionate Data Analytics (PDA) offers a principled paradigm for addressing these complexities. By employing statistical techniques—for example, linear regression applied to temporally disjoint intervals—PDA frameworks can discriminate between routine signal variability and substantive anomalies, thus enabling the rapid identification and isolation of compromised data streams without excessively impacting system responsiveness or service continuity [78]. This context-sensitive approach allows healthcare systems to dynamically tailor data processing pipelines: streams exhibiting anomalous behavior, incomplete information, or degraded quality are proportionately de-emphasized or routed for secondary verification, while reliable signals maintain their operational priority. In practice, this strategy enhances overall analytic robustness and ensures that clinical decision-support systems remain well-calibrated, even in the face of environmental noise and transient uncertainty.

The imperative for PDA in healthcare stems from two principal motivations:

- **Mitigating Downstream Analytic Risk:** To ensure that decision-support mechanisms are governed by the most reliable data, thereby minimizing the possibility of error amplification and unintended clinical consequences.
- **Autonomous Adaptive Resource Allocation:** To empower monitoring platforms and autonomous diagnostic systems with the capacity to allocate analytic resources dynamically, guided by real-time assessments of data quality and provenance.

Table 4: Representative Metrics for Evaluating Real-Time Health Monitoring Systems

Metric	Description
Service Response Ratio	Measures the fraction of health events correctly recognized and responded to within a defined period
Delivery Time	Quantifies time taken from signal acquisition to response generation
Variation Factor	Assesses system performance stability under changing network or signal conditions
Identification Ratio	Evaluates correct identification of target events relative to all system outputs
Aggregate Processing Time	Captures total computational time for processing and classification tasks

Crucially, PDA frameworks embed anomaly detection, quality scoring, and error flagging directly into the data ingestion and management layers, thereby maximizing operational transparency. By systematically documenting points of error, correction, and exclusion throughout the analytic workflow, PDA not only serves technical robustness but also aligns with regulatory mandates for traceable data lineage and auditability in clinical contexts.

3.2 Multimodal and Multisource Data Fusion

Subsection Objectives: This subsection provides a focused overview of how multimodal and multisource data fusion is shaping healthcare analytics. It restates the broader survey goal of mapping the landscape of integrative AI methodologies in healthcare and highlights the specific aims to (1) clarify core data fusion paradigms, (2) comparatively synthesize the benefits and limitations of each, and (3) identify pressing open challenges and future research needs in this domain.

The confluence and synthesis of diverse biosignals, medical images, behavioral metrics, and IoT-derived contextual data have revolutionized the scope and depth of healthcare analytics. Integrative multimodal and multisource fusion methodologies are indispensable for leveraging the distinctive yet complementary informational content inherent to each modality, whether in continuous physiological monitoring, static or temporal imaging, longitudinal behavioral profiling, or the incorporation of structured electronic health records [8, 27, 28, 30, 31, 33–35, 42, 47, 49, 51, 53, 56, 61, 77, 78, 87, 94]. Key application areas include:

Radiomics. This encompasses the extraction and fusion of high-dimensional features from CT, MRI, or PET imaging with omic datasets and clinical histories, thereby supporting enhanced biomarker discovery and risk stratification [35, 53, 56, 61]. Despite the promise, radiomic approaches face open challenges in reproducibility, big data management, integration of multimodal and temporal data, and explaining models for clinical trust.

Cardiometabolic Monitoring. Integrating wearable biosensors with behavioral and environmental data enables robust, longitudinal risk assessment [8, 31, 77]. Nevertheless, systems must address missingness and variability in real-world data streams, as well as the need for models generalized to diverse populations.

Intelligent Hospital Platforms. Cohesive synthesis of laboratory results, procedural logs, and real-time monitoring supports advanced analytics, AI-driven triage, and operational optimization [78, 94]. While real-time data integration systems have shown scalable impact, further work is needed for structural standardization, privacy governance, and multicenter interoperability.

To effectively harness multimodal data, several distinctive fusion paradigms have emerged, summarized below:

Systems frequently require dynamic selection among these paradigms, dictated by the evolving data landscape, operational constraints, and analytic objectives (see Table 5). Each fusion approach has context-specific strengths and limitations. For instance, early fusion readily models short-range interactions but is challenging with high-dimensional or partially missing data, while late fusion is flexible but may sacrifice synergistic interpretation; hybrid methods strike a balance but increase computational complexity and design choices [8, 26, 30, 87, 94].

A central technical challenge in this context remains the quantification and propagation of uncertainty, which is vital for trustworthy diagnostic inference and risk management in clinical settings [25, 34, 35, 61]. Methods such as Dempster-Shafer theory have been adapted to healthcare data fusion to aggregate evidential support, capturing both the strength of belief and the degree of conflict among modalities [25]. Probabilistic and evidential frameworks facilitate a nuanced response to incomplete or contradictory data. Technical strategies for handling missingness and partial observation include:

Domain-Informed Statistical Imputation. Leveraging clinical expertise enables plausible data reconstruction but may be limited by evolving datasets and domain drift.

Representation Learning with Variable-Length Sequences. Models robust to interrupted or incomplete input streams are emerging as critical, especially in IoT-intensive and event-driven contexts [6, 8, 26, 77, 94].

Comparative Synthesis. In addition to the above, fusion methods differ in their computational requirements, explainability, sensitivity to heterogeneous data quality, and ability to leverage structured versus unstructured inputs; the choice of paradigm is application-dependent and drives downstream effectiveness [34, 53, 61, 94].

Open Challenges and Future Directions. (1) *Robustness and Generalizability:* Improving resilience to missing, noisy, or inconsistent modalities remains an urgent research gap, as highlighted by persistent limitations in real-world medical image and biosignal analysis [8, 35, 53, 56]. (2) *Standardization and Interoperability:* There is a pronounced need for data curation, harmonization, quality assurance, and common protocols to support reliable fusion, especially in multi-institutional and cross-national contexts [35, 42, 47, 51, 94]. (3) *Explainability and Transparency:* Ensuring trustworthy, explainable fusion models is a key open challenge identified throughout the literature [8, 28, 34, 35, 53], particularly as AI tools are integrated into decision-making pipelines.

Table 5: Comparison of Multimodal Data Fusion Paradigms

Paradigm	Characteristics	Advantages and Limitations
Early Fusion	Merges raw features from all modalities before modeling; enables low-level cross-modal interactions	Captures direct synergies; prone to dimensionality issues, may require large datasets
Late Fusion	Combines outputs from modality-specific models (decision-level)	Robust to missing modalities; may overlook deep synergistic structure
Joint/Hybrid Fusion	Interleaves intermediate representations, often with attention mechanisms or layered interactions	Balances representation richness with tractable modeling; excels in streaming and heterogeneous IoT environments

(4) *Computational Scalability*: Efficient real-time analytics for massive, heterogeneous multimodal data streams highlight unresolved issues in distributed and edge-computing scenarios [78, 94]. (5) *Ethical and Privacy Considerations*: Multisource fusion heightens ethical complexity, reinforcing the critical need for privacy protection, secure governance, and responsible AI deployment [34, 94].

Collectively, these innovations and open questions constitute the methodological backbone and forward research agenda for developing highly resilient, data-rich analytics in real-world healthcare systems. This focus is essential to fulfill the overarching survey objective of charting trustworthy, effective, and scalable AI/Machine Learning integration across multimodal medical contexts.

3.3 Emerging Adaptive and Cross-Modal Processing

This subsection aims to synthesize and critically assess recent advances in adaptive and cross-modal learning paradigms for healthcare-related data, with an explicit focus on adaptive, distributed, and semi-supervised strategies that address challenges unique to multi-institutional, privacy-sensitive, and weakly supervised data scenarios.

The dynamic, often multi-institutional, and privacy-sensitive character of contemporary healthcare data ecosystems has driven the advancement of learning paradigms that are adaptive, distributed, and effective under limited annotation. In distributed IoT healthcare, adaptive, semi-supervised, and federated multi-source fusion strategies have demonstrated substantial promise: enabling analytics at scale even when labeled data is scarce, privacy regulations are restrictive, and data distributions drift over time [49, 63, 78].

Self-supervised learning facilitates the extraction of generalized data representations from large unlabeled corpora, thus supporting efficient transfer to downstream clinical tasks. Continual learning methods aim to prevent catastrophic forgetting by permitting analytic models to adapt to new data streams; this property is essential for long-term monitoring and responding to the evolution of disease profiles. Semi-supervised cross-modal frameworks such as SPamCo employ co-training, regularization, and pseudo-labeling across multiple data views, allowing labeled and unlabeled examples from different perspectives to be effectively leveraged for improved model generalization [36, 63]. These advancements are directly relevant for healthcare settings characterized by pervasive sparsity and noise in labeled data, as well as substantial underlying heterogeneity.

Nevertheless, important methodological limitations and research gaps remain. Current adaptive fusion models still demonstrate vulnerability to performance declines under extreme distributional shifts produced by temporal changes, contextual factors, or institutional heterogeneity within incoming clinical or IoT data [78].

While federated learning mitigates privacy and localization barriers, it poses new problems—such as difficulty in aligning learned representations across non-i.i.d. datasets, as well as challenges in ensuring the consistency and stability of distributed model updates. Methods like the Robust Cross-modal Learning (RCL) framework highlight the importance of handling partially mismatched pairs in cross-modal retrieval scenarios by emphasizing negative pair information and risk minimization [36], but the integration of these techniques under dynamic, real-world healthcare conditions requires substantial further study.

Another significant gap concerns the lack of unified frameworks that harmonize adaptive and privacy-preserving cross-modal learning with robust uncertainty quantification and flexible, scalable fusion architectures. While several approaches address individual aspects (e.g., error segregation in IoT data streams [78], self-paced co-training [63]), a synthesized perspective that coordinates these developments remains underexplored compared to prior reviews.

Balancing these strengths and weaknesses, the unique framework explored in this survey is its emphasis on integrating emerging cross-modal retrieval robustness (as demonstrated by advances like RCL [36]) and practical distributed data handling (PDA from [78]), alongside the latest in adaptive co-training and federated learning, to chart a comprehensive path for next-generation healthcare analytics.

Future research should address: (1) developing adaptive fusion schemes resilient to severe distributional drift and out-of-distribution data, (2) constructing privacy-aware cross-modal architectures that ensure consistency across federated updates and heterogeneous sources, and (3) advancing unified theoretical and practical frameworks that bridge self-supervised, semi-supervised, and continual learning for healthcare’s diverse modalities. These directions are prerequisite for realizing the transformational promise of multimodal and IoT-driven analytics in next-generation healthcare systems [36, 49, 63, 78].

In summary, this subsection has critically reviewed the objectives, strengths, and limitations of current adaptive and cross-modal learning paradigms, outlined unique integrative opportunities suggested by recent literature, and posed concrete future research directions to guide the evolution of robust, scalable, and privacy-preserving AI in healthcare.

4 Machine Learning, Deep Learning, and Explainable AI in Healthcare

This section aims to systematically review the applications, progress, and challenges of machine learning (ML), deep learning (DL), and explainable AI (XAI) within the healthcare domain. The objectives are: to critically survey major methodologies, synthesize distinguishing frameworks proposed in the field, highlight contrasts with prior works, and outline future research priorities.

Machine learning and deep learning have catalyzed significant advancements in healthcare, providing robust capabilities for large-scale data analysis, predictive analytics, and personalized medicine. There is a growing deployment of ML/DL approaches for diagnosis, prognosis, and treatment recommendation; however, widespread clinical integration remains hindered by several methodological and practical limitations. A major barrier is the opacity of many state-of-the-art deep models, resulting in limited trust and interpretability for end users.

Explainable AI (XAI) methodologies seek to bridge the interpretability gap, augmenting transparency for clinicians and stakeholders. While various explanation frameworks and post-hoc interpretability techniques have emerged, their adoption is not universal. Many approaches are tailored to specific tasks or data modalities, and there is no consensus on standardized evaluation metrics for explainability in clinical settings.

Despite considerable progress, several critical research gaps persist. First, the majority of clinical ML/DL models are developed and assessed on limited or homogeneous datasets, raising concerns about generalizability. Second, bias and fairness issues, stemming from non-representative data or unaccounted confounders, are seldom systematically addressed. Third, the predominant paradigm favors accuracy-centric evaluation over comprehensive assessments of safety, robustness, and real-world impact. Fourth, while this survey synthesizes distinct frameworks for integrating XAI into clinical workflows, there remains a need for universal benchmarks and guidelines to harmonize evaluation of interpretability methodologies across healthcare domains.

Unlike previous reviews, this survey uniquely emphasizes the intersection of ML/DL methodologies with context-aware explainable frameworks, comparing the strengths and limitations of popular model architectures and explanation algorithms in heterogeneous clinical applications. In doing so, we synthesize comparative criteria that facilitate a more rigorous assessment of clinical AI solutions beyond traditional performance metrics.

To further advance the state of the art, future research should prioritize: (1) the development and validation of models with improved transparency, generalizability, and fairness; (2) the creation of standardized benchmarks and reporting guidelines for clinical XAI; (3) deeper investigation into the integration of end-user feedback within explanation frameworks; and (4) rigorous evaluation of methods across diverse, real-world clinical environments.

In summary, this section provides a critical and balanced overview of ML, DL, and XAI in healthcare, explicitly highlighting both the transformative potential and the prevailing challenges. By foregrounding open research questions and emphasizing concrete future directions, we seek to clarify priorities for researchers and clinicians seeking to responsibly deploy AI-driven solutions in healthcare.

4.1 Model Architectures and Learning Methods

4.1.1 Traditional ML and Deep Learning Architectures in Healthcare. The landscape of machine learning (ML) and deep learning (DL) architectures in healthcare has evolved considerably, shaped by the increasing diversity and complexity of biomedical data, alongside escalating demands for diagnostic accuracy, scalability, and

robustness. Traditional ML algorithms—specifically, Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Decision Trees—have long provided robust baselines for structured data analyses. These algorithms possess notable strengths in settings emphasizing interpretability and computational efficiency, often yielding competitive performance in classification and regression tasks where datasets are moderate in size and efficient feature engineering is feasible [44, 91].

The advent of high-dimensional and heterogeneous biomedical data modalities—including medical imaging, multi-channel physiological signals, and structured electronic health records (EHRs)—has made deep neural architectures indispensable. Among these, Convolutional Neural Networks (CNNs) have become the predominant choice for medical image analysis, excelling at complex feature extraction and hierarchical representation learning in imaging modalities such as X-ray, MRI, and CT [3, 8, 22, 33, 34, 38, 41, 44, 49, 61, 69]. Furthermore, architecture variants such as U-Net and 3D CNNs are tailored for biomedical image segmentation and volumetric delineation, effectively handling spatial complexities inherent in such data [55, 56, 59, 61].

For sequential clinical data, particularly physiological time-series (e.g., ECG, EEG) and EHR data, Recurrent Neural Networks (RNNs)—notably, Long Short-Term Memory (LSTM) networks—have demonstrated substantial efficacy in capturing temporal dependencies [58, 69, 87, 101]. The emergence of Transformer architectures has further augmented the modeling of long-range temporal and contextual dependencies in both time-series and textual modalities. The incorporation of multi-head self-attention within Transformers enables robust performance and flexibility, particularly in complex multimodal fusion scenarios [6, 8, 19, 26, 28, 41, 44, 53, 55, 102].

Emerging models such as Graph Neural Networks (GNNs) are increasingly leveraged to analyze data with intrinsic graph structures, enabling significant advancements in tasks ranging from molecular property prediction in drug discovery to the modeling of population or knowledge networks in epidemiology [76, 92, 102]. Integrative frameworks combining GNNs and large language models (LLMs) within multi-modal architectures have shown marked improvements in property prediction and knowledge extraction across complex scientific domains [92].

Despite these advances, several persistent challenges limit the full realization of deep learning's promise in healthcare: Data annotation scarcity, impeding the training of data-hungry models; High inter-class variability, which complicates generalization; Limited generalizability to rare or outlier cases; Insufficient transparency and interpretability, hindering clinical acceptance. These obstacles remain focal points for ongoing research and methodological innovation [28, 30, 33, 53, 55, 56, 59, 93].

4.1.2 Transfer, Hybrid/Ensemble, Annotation-Efficient, and Self-Supervised Learning for Multimodal and IoT Healthcare Data. To address challenges relating to data scarcity and annotation, the field has advanced a variety of methodological strategies, including transfer learning, hybrid/ensemble modeling, annotation-efficient approaches, and self-/semi-supervised learning. Collectively, these methods enhance performance and utility for both unimodal and multimodal healthcare data.

Transfer learning exploits pre-trained models—often established on large, generic, or related datasets—which are subsequently fine-tuned on smaller, domain-specific biomedical datasets. This approach enhances model performance when labeled data is limited or expensive to produce [6, 8, 28, 41, 53, 69, 92]. Frameworks such as COMET use RNNs pre-trained on extensive EHR cohorts and employ early/late fusion of omics and clinical data, achieving improved predictive modeling and deeper biological insight, especially in small-sample contexts [55].

Hybrid and ensemble methods, encompassing strategies like model stacking and combining traditional ML classifiers with contemporary DL architectures, bolster resilience against overfitting and elevate generalizability—an asset in disease diagnosis for oral cancer, cardiovascular disease, and rare event prediction [8, 27, 33, 53, 56, 61, 91]. This integrative approach allows for adaptive model selection driven by contextual priorities, such as balancing accuracy and interpretability.

Annotation-efficient paradigms, such as semi-supervised and self-supervised learning, are critical in environments with limited labeled data. Semi-supervised learning, deploying techniques like pseudo-labeling or consistency regularization, empowers models to exploit vast unlabeled datasets effectively—for example, in prostate MRI segmentation tasks where performance nears that of fully supervised baselines [6, 26, 47].

Self-supervised learning employs pretext tasks or contrastive objectives to extract meaningful representations from unlabeled data. Notably prevalent in transformer-based and contrastive learning frameworks, these strategies drive superior feature learning for downstream biomedical tasks [6, 30, 51, 69, 78]. In complex settings (e.g., multi-sensor IoT healthcare), self-supervised transformer models and robust pseudo-annotation pipelines, augmented by knowledge distillation, achieve heightened performance and annotation efficiency [6, 8, 26, 28, 53, 55, 78, 79].

Multimodal learning, integrating signals from text, images, structured data, and physiological waveforms, presents considerable promise for health informatics. Multi-modal large language models (MLLMs), equipped with sophisticated fusion and alignment mechanisms such as joint attention networks, have enabled integrated contextual analysis and superior clinical prediction [6, 8, 17, 28, 41, 47, 53, 55, 58, 61, 78]. When combined with transfer learning and self-supervision, these models demonstrate further enhanced capability. However, challenges related to interpretability, computational overhead, and the need for well-aligned multimodal representations persist.

The approaches summarized in Table 6 collectively address major bottlenecks in data efficiency, generalizability, and multimodal integration in healthcare AI.

4.2 Explainability, Transparency, and Clinical Trust

4.2.1 The Imperative for Explainable AI (XAI) Methods and Clinical Applications. Realizing the transformative potential of ML/DL in healthcare depends critically not only on predictive accuracy but also on model explainability, transparency, and ultimately, the establishment of clinical trust. The imperative for explainable AI (XAI) is pronounced in medical decision-making, where clinicians

and regulatory stakeholders require machine learning models to provide not only reliable outputs but also cogent justifications for those outputs [28, 32, 54, 61, 82].

Post-hoc XAI techniques—such as SHAP, LIME, and ELI5—have emerged as standard approaches to quantifying feature contributions and clarifying model decision pathways [28, 44, 61, 64, 82]. For example, recent diagnostic models for diseases like diabetes, monkeypox, and cardiac arrest apply these methods to highlight the influence of specific clinical or physiological features, offering granular, patient-level interpretability. In the case of monkeypox, SHAP, LIME, and ELI5 were deployed to identify fever, oral/genital ulcers, swollen lymph nodes, and fatigue as the most significant predictors in a transparent, interpretable risk model, directly supporting real-world clinical adoption and fostering trust [82]. Similarly, time-series models for cardiac arrest prediction in ICU settings used SHAP to reveal the contributions of ECG-derived heart rate variability measures, like the baseline width of the RR interval histogram, towards risk estimation, making deep models more actionable and understandable for clinicians [54]. These explainability tools are thus foundational in bridging algorithmic outputs and clinical reasoning, facilitating integration into practice and supporting regulatory and operational transparency [2, 28, 32, 44, 61, 62, 64, 82].

Advanced domains of XAI are seeing increased demand in clinical research and practice. One area is event-level causal reasoning, where models such as those deploying causal interventions can uncover and disentangle spurious correlations among features or modalities, enabling more robust and clinically meaningful insights into the temporal and causal relationships underpinning diagnostic decisions [32, 62, 64]. Another crucial domain is the interpretability of signal-level data: models analyzing biomedical signals (EEG, ECG) via SHAP, counterfactuals, and event-level causal modeling not only distinguish relevant temporal features but also ground their explanations in established physiological phenomena. For example, methods for cardiac arrhythmia detection attribute model predictions to signal properties like R-R interval regularity; meanwhile, advanced deep feature learning frameworks for EEG signals leverage post-hoc explainability to connect deep features to recognizable electroclinical markers, supporting not only prediction accuracy but also the discovery of new potential biomarkers [2, 39, 67]. Despite these advances, translating deep model features into physiologically or pathologically explicit entities remains a significant open challenge. This underscores the dynamic, evolving landscape of XAI in healthcare, where continuous refinement is needed to align data-driven intelligence with real-world clinical knowledge and workflow requirements [2, 39].

4.2.2 User-Centric Analytic Interfaces and Transparency in IoT Healthcare. Enhancing explainability further, recent progress emphasizes user-centric analytic interfaces that advance beyond algorithmic transparency to foster real-time, patient- or case-specific interpretability and direct clinician engagement. Modern analytic platforms now deliver self-explanatory interfaces that blend predictive modeling with intuitive explanation layers, frequently leveraging techniques such as SHAP for transparent insights and designed for both expert and non-expert audiences [20, 39, 77, 78].

Table 6: Overview of Learning Methods and Their Key Contributions in Healthcare

Method	Main Contribution	Key Applications/Examples
Transfer Learning	Leverages pre-trained models to improve performance, especially with limited labeled data	Fine-tuning CNNs for medical imaging [8, 41, 53], RNNs on EHRs (COMET) [55]
Hybrid/Ensemble	Combines diverse models to boost generalizability and reduce overfitting	Disease diagnosis (oral cancer, CVD) [8, 33, 56]
Semi-supervised Learning	Utilizes both labeled and unlabeled data, improving learning efficiency	MRI segmentation [26, 47], pseudo-labeling [6]
Self-supervised Learning	Learns representations via pretext tasks, requiring no labeled data	Transformer-based feature extraction [30, 69, 78]
Multimodal Learning	Fuses diverse data types for richer predictions and context integration	MLLMs with joint attention for clinical text, images, and waveforms [6, 41, 55, 78]

In IoT-augmented healthcare environments, system transparency and the capacity for rapid, real-time analytics are pivotal for regulatory compliance and widespread adoption [8, 78]. Deploying transparent analytic layers and dynamic visualization tools supports both trust and clinical uptake, while also allowing for continuous anomaly detection, real-time feedback, and responsive adaptation as IoT data streams and clinical situations evolve [20, 39]. For instance, recent work demonstrates that integrating SHAP explanations within diagnostic interfaces enables users—including clinicians and patients—to better understand the rationale underpinning predictions, thus enhancing user confidence and actionable decision-making [20, 39]. Additionally, the capability to differentiate between variations and errors in heterogeneous data streams, as seen in proportionate data analytics systems, strengthens real-time performance and compliance by dynamically responding to anomalies and delivering timely feedback [78]. Collectively, these advancements establish a groundwork for explainable, trustworthy analytics capable of supporting continuous, patient-centric care in complex IoT healthcare systems.

4.2.3 Clinical and Real-World Validation of AI and IoT-Augmented Systems. The definitive measure of ML/DL and XAI systems’ value lies in their rigorous clinical and real-world validation. This process requires continual evaluation across heterogeneous patient populations, diverse clinical workflows, and variable operating environments. Multicenter studies evaluating AI-augmented radiological segmentation or real-time risk monitoring substantiate that models integrating explainability and user-centric design are more readily adopted and trusted in clinical settings [2, 26, 39, 49, 54, 94].

Despite these successes, robust generalizability remains a pervasive challenge, especially when models confront shifts in data distributions, patient demographics, imaging and scanning protocols, or rare and emergent disease presentations. Key strategies to overcome these limitations include: external validation with independent datasets; prospective and multicenter studies; and continuous adaptation and refinement integrated with user feedback. These practices underpin long-term model robustness and ensure ongoing clinical relevance [26, 39, 49].

In summary, the synergy of advanced learning algorithms, annotation-efficient and transfer learning strategies, and the imperative for explainability and transparency encapsulates both the promise and enduring challenges for AI-driven healthcare. The thoughtful and principled integration of these components is essential to realize trustworthy, effective, and equitable machine intelligence in clinical practice.

5 Medical Imaging, Multimodal, and Cross-Modal Analytics

5.1 Automated Segmentation, Registration, and Imaging Diagnostics

This section aims to synthesize recent advances and ongoing challenges in the field of automated medical image analysis, focusing on segmentation, registration, and diagnostic support. Our primary objective is to distill state-of-the-art methodologies, highlight limitations of current paradigms, and articulate open research questions for future exploration within neuroimaging, oncology, and cardiology applications.

Advances in automated medical image analysis have substantially enhanced both the scale and accuracy of diagnostic workflows across domains such as neuroimaging, oncology, and cardiology. Central to this progress are deep learning architectures—including DenseNet and 3D-UNet—that demonstrate state-of-the-art performance in complex segmentation tasks by effectively capturing hierarchical and contextual features from high-dimensional imaging data. For example, a recent approach utilizes a two-stage network architecture, employing a 2D DenseNet for filtering followed by a 3D-UNet with integrated dense and residual blocks, to achieve robust coronary artery segmentation from CCTA images. This setup not only yields high Dice Similarity Coefficients but also streamlines preprocessing and computational demands. Additionally, the integration of a Gaussian-weighted merging process improves segmentation reliability by reducing block-boundary artifacts, emphasizing the importance of architectural innovations that propagate both local and global contextual information for precise delineation of anatomical structures [57, 85].

In parallel, digital pathology, particularly the registration of whole slide images (WSIs), has witnessed rapid methodological evolution due to the challenges posed by gigapixel-scale data and staining heterogeneity. Recent techniques, such as multi-scale ring encoders, enable efficient matching of multi-stained serial WSIs, reducing spatial uncertainties to sub-200 μm levels and significantly accelerating processing compared to manual methods. These innovations facilitate tumor heterogeneity quantification and support the optimization of biomarkers like Ki-67, exemplifying the clinical value of methodological advances in enabling personalized cancer diagnosis and treatment [57].

However, despite these technical achievements, the field faces unresolved challenges that impede reproducibility and scalable benchmarking. Large-scale deployment remains constrained by factors including annotation scarcity, pronounced class imbalance, and heterogeneity across imaging protocols and patient populations.

Moreover, current dominant approaches—while powerful—are often data-hungry and can exhibit sensitivity to domain shifts, illustrating their limitations when generalizing to real-world settings or rare pathological presentations. Critics have highlighted the need for more robust, data-efficient learning strategies, and for methods better attuned to dataset heterogeneity.

To mitigate these challenges, ongoing efforts include establishing rigorous multi-center collaborations, introducing well-characterized reference controls, and expanding annotated public datasets, all of which are incrementally improving the generalizability of automated diagnostic systems. Nonetheless, further research is warranted in several directions: (1) development of domain-adaptive and semi-supervised methods that can thrive under scarcity of labeled data; (2) robust procedures for quantifying and addressing inter-center heterogeneity; and (3) the creation and adoption of standardized, transparent evaluation benchmarks to facilitate fair comparison and reproducibility.

In summary, automated segmentation, registration, and diagnostic systems are reshaping clinical workflows, yet significant research gaps persist. Future work should prioritize enhancing data efficiency, model robustness, and generalizability, with explicit focus on bridging the gaps between algorithmic advances and practical, large-scale clinical deployment.

5.2 Imaging Data Fusion and Cross-Modal Analysis

The primary objective of this section is to critically survey modern approaches for imaging data fusion and cross-modal analysis, highlighting both the technical innovations and the distinct operational and ethical challenges inherent in integrating heterogeneous imaging modalities. The intent is to provide readers with a coherent understanding of state-of-the-art fusion architectures, real-world deployment scenarios, associated limitations, and persisting open research problems within this domain.

Imaging data fusion involves the integration of information from multiple imaging sensors or modalities—such as visible spectrum, infrared, hyperspectral, and radar—that differ in spatial, temporal, and spectral characteristics. Cross-modal analysis aims to extract complementary features from these sources, thereby enabling more accurate, robust, and context-aware downstream applications.

A wide spectrum of fusion strategies exists, ranging from early (data-level), intermediate (feature-level), to late (decision-level) fusion. Early fusion typically focuses on raw data alignment challenges, while feature- and decision-level approaches leverage advances in deep learning for representation learning and multimodal reasoning. However, despite technical progress, the selection and optimization of fusion architectures remain contingent on the specific application and operational context, with no consensus on a universally optimal methodology.

Transitioning from technical innovation to operational deployment, practitioners face complex tradeoffs among computational efficiency, information gain, and system robustness. Several real-world deployments underscore these tradeoffs, revealing unforeseen issues such as sensor miscalibration, unexpected environmental effects on data quality, and difficulties in harmonizing temporal resolutions. Furthermore, large-scale fusion systems often

expose new vulnerabilities—both technical, like error propagation across modalities, and systemic, such as user bias and trust calibration—requiring multidisciplinary mitigation strategies.

From an ethical and regulatory standpoint, integrating cross-modal imaging data introduces additional layers of complexity. For example, fusing biometric and contextual imagery may trigger privacy concerns regulated differently across jurisdictions, and the potential for covert surveillance exacerbates risks for misuse or unintended consequences. Concrete case studies from healthcare and public safety illustrate the real-world legal ambiguities and failures that have prompted regulatory responses, highlighting the urgent need for domain-specific guidelines.

Despite significant advancements, several unresolved research challenges persist. Open questions include: determining principled criteria for modality selection under resource or privacy constraints; designing explainable fusion architectures that support transparency and auditability; and developing standard benchmarks for evaluating the real-world generalization and robustness of fused models. Debates continue regarding the tradeoffs between end-to-end deep fusion—where representations may be less interpretable—and modular approaches that promote explainability but may sacrifice some performance.

In summary, imaging data fusion and cross-modal analysis represent a rapidly evolving but unsettled area, with ongoing disagreements about best practices, regulatory responses, and the balance between competing technical and ethical priorities. Further research is needed to establish domain-agnostic design principles, scalable operational workflows, and actionable standards for safe and effective cross-modal imaging system deployment.

5.2.1 Fusion of Imaging, Biosignals, Laboratory, and IoT/Behavioral Data. The promise of medical AI increasingly rests upon its ability to synthesize multimodal data, a necessity arising from the multifactorial nature of disease and the heterogeneity of inputs in real-world healthcare systems. Fusion approaches incorporate data from diverse domains such as imaging modalities (CT, MRI, PET), biosignals (ECG, EEG), laboratory results, patient-reported outcomes, and IoT or behavioral sensor data streams [33, 35, 56, 83].

Multimodal integration consistently demonstrates improvements in diagnostic and prognostic performance, particularly when radiomics features derived from medical images are combined with complementary clinical, laboratory, and sensor-based information [35, 56, 83]. For example, radiomics allows the extraction of high-dimensional, quantitative features from CT, MRI, or PET images that, when integrated with clinical or genomic data, enable more accurate risk stratification and personalized management—such as predicting recurrence in localized clear cell renal cell carcinoma [56]. At the system level, modern hospital-wide big data platforms, designed for integration of clinical, radiological, laboratory, and administrative data in real time, have enabled operational efficiencies, improved data retrieval and governance, and supported the routine deployment of AI-based clinical decision support [78, 94]. These platforms not only ingest but also structurally harmonize vast, heterogeneous datasets and provide scalable analytics and automated processing essential for translational research.

Importantly, fusion methodologies developed within medical AI exhibit broad applicability across sectors. Their adaptation in fields

ranging from industrial prognosis to urban monitoring and energy management has led to the development of modular data architectures and robust data governance that inform best practices in medical multimodal analytics [22, 33, 34, 38, 67, 83, 94, 96]. Common themes identified across these sectors include the need for standardized protocols, automated orchestration of heterogeneous data streams, dynamic error handling, interoperability, data security, and explainable analytical workflows. Collectively, these experiences reinforce the critical role of modular platforms, governance frameworks, and high-performance computing as prerequisites for translating multimodal analytics from research into standard clinical use.

5.2.2 Uncertainty Management, Missing/Correlated Data Handling, and Integrated Diagnostics. Effective integration of multimodal data streams requires advanced strategies for uncertainty management, addressing missing values, and understanding correlations between modalities—challenges that are especially pronounced in real-world healthcare environments where data is frequently incomplete, heterogeneous, and subject to errors. Recent methodological advancements addressing these issues include:

Application of Dempster-Shafer theory to quantitatively manage evidence conflicts and derive comprehensive global uncertainty measures [25]. This approach enables explicit quantification of uncertainty and conflict among heterogeneous sources, with fusion rules tailored to complex data environments.

Development of custom loss functions and probabilistic data fusion frameworks that directly incorporate the probabilistic structure of measurement errors and missing data [6, 25, 26, 94]. For instance, diffusion-based probabilistic models can reconstruct full-range responses from sparse, noisy, or heterogeneous sensor measurements with high accuracy and flexibility, demonstrating resilience to typical data limitations in clinical and sensing settings [26]. Hospital-scale data platforms now implement metadata management, data standardization, and automated self-service retrieval to support robust large-scale integration of multisource clinical, laboratory, radiology, and management data, while maintaining scalability and consistency [94].

Utilization of data fusion techniques, such as combining molecular embeddings from various single-task models, to enhance prediction in settings defined by data sparsity or weak inter-modality correlation [6]. These approaches can outperform conventional multi-task learning models under conditions of missing or weakly related data sources, thereby improving analytical performance and clinical applicability. Additionally, systematic evaluations of machine learning models for diagnostic tasks, such as early autism spectrum disorder identification, emphasize careful handling of missing data through imputation, normalization, and feature selection, ensuring robust model performance and generalizability in heterogeneous datasets [77].

Within the context of patient monitoring and IoT-assisted healthcare, approaches such as Proportionate Data Analytics (PDA) enable dynamic classification and adaptive responses to anomalous or incomplete data streams by disentangling measurement errors from natural physiological variation. This leads to improved service response ratios and analytic robustness [8]. Integrated diagnostic frameworks—ranging from machine learning-driven risk

models to prognostic solutions that combine radiomics and clinical data—demonstrate that explicit uncertainty quantification and mitigation strategies not only bolster analytical trustworthiness but also enhance the practical clinical value of predictive systems.

5.2.3 Diverse Fusion Strategies (Joint, Late, Early) and Applications. Operationalizing data fusion in medical domains encompasses a spectrum of strategic models, generally classified into early, joint, or late fusion. The principal characteristics and typical advantages of these strategies are summarized in Table 7.

In healthcare contexts, the decision between early, late, and hybrid fusion depends on data characteristics, the extent and nature of missingness or misalignment, and computational constraints. For example, cross-modal learning frameworks that utilize unbiased retrieval risk estimators and complementary contrastive learning approaches demonstrate strong performance even with noisy or partially mismatched modality pairings, such as those arising in image-text datasets. Techniques that emphasize negative sample regularization are particularly effective at reducing overfitting to noisy, incorrectly labeled positive pairs, while harnessing all available negative pairs to mitigate underfitting in weakly supervised contexts [36, 47, 51]. Furthermore, self-paced multi-view co-training strategies, which incorporate distributed optimization and allow for scalable, PAC-learnable integration across multiple heterogeneous views, provide an extension of classical semi-supervised learning to address the complexity and scale of contemporary medical and IoT scenarios. These frameworks offer robust mechanisms for data selection and co-regularization, improving both generalization and learning efficiency [27, 42, 53, 63].

Across these diverse applications, multimodal data fusion is propelling significant advances in patient monitoring, precision diagnostics, and rapid medical multimedia search—catalyzing a broader transition toward holistic, data-driven clinical decision support [8, 28, 30, 31, 33, 34, 36, 47, 61, 63, 77, 87]. Despite ongoing challenges related to generalizability, interpretability, and standardization, continuous methodological innovations are charting a path toward more robust, trustworthy, and fully integrated medical AI. The confluence of advanced segmentation, multimodal data integration, and uncertainty-aware analytics is ultimately shaping the future landscape of precision medicine.

6 Operational Analytics, Population Health, and Clinical Deployment

This section aims to analyze the real-world implementation of multimodal AI systems in healthcare, focusing specifically on operational analytics, the impact on population health, and challenges associated with clinical deployment. Building on the technical innovations discussed in preceding sections, we shift focus here to the translation of these advances into practical, scalable, and ethically responsible healthcare solutions. The section further clarifies open research questions, unresolved challenges, and competing considerations in regulatory, ethical, and technical domains.

Operational analytics encompasses methods for harnessing multimodal data to monitor, evaluate, and optimize healthcare workflows and outcomes. The section examines the modalities and architectures deployed in current practice, contrasting their integration strategies and practical trade-offs. Critical comparative analysis

Table 7: Comparison of Fusion Strategies in Multimodal Medical Analytics

Strategy	Integration Stage	Key Advantages	Typical Applications
Early Fusion	Raw data or low-level features combined prior to algorithmic modeling	Enables learning of shared modality representations from the outset; high potential information synergy	Deep neural network training with joint feature embedding
Joint Fusion	Intermediate layers form shared representations during modeling; cross-modal learning possible	Balances cross-modal synergy and robustness; adaptable attention and feature selection	Cross-modal learning (RNNs, Transformers, NetVLAD); video categorization; multimedia retrieval
Late Fusion	Decision outputs of separate models are combined post-modeling	Enhances robustness to missing or noisy modalities; modular adaptation	Ensemble learning; multi-system decision aggregation

highlights how fusion approaches affect downstream analytics and decision-making, emphasizing consensus gaps and areas of methodological divergence. The narrative then extends to population health applications, identifying the unique challenges in synthesizing structured and unstructured datasets across diverse patient cohorts. Discussions highlight both the advances and the persistent limitations in achieving robust, generalizable insights at scale.

Clinical deployment introduces an additional layer of regulatory, ethical, and technical complexity. Real-world deployments often expose unanticipated fragilities, including data privacy risks, cross-population biases, and issues of interpretability and trustworthiness for end users. Notable regulatory frameworks, such as HIPAA in the US and GDPR in the EU, provide concrete legal boundaries but may conflict with the scalability of large-scale data fusion or synthetic data generation. The section examines exemplar deployment failures and unresolved debates—such as the balance between accuracy and explainability or the ongoing lack of consensus in synthetic data validation standards—that continue to shape health AI adoption.

Despite significant progress, open problems remain in building robust, reproducible, and defensible multimodal systems for health operations and population management. These include: reconciling competing stakeholder priorities when designing analytics pipelines; configuring federated or privacy-preserving fusion architectures to satisfy regulatory demands; and developing systematic evaluation frameworks for synthetic data reliability in clinical settings. In particular, there is no established consensus on optimal cross-modal fusion strategies or on metric selection for validating real-world impact, with differing methodologies yielding tradeoffs in scalability, interpretability, and generalizability.

To summarize, this section articulates key operational opportunities and deployment risks in multimodal health analytics. It underscores the need for further research into unified evaluation standards, comparative benchmarking across fusion methods, and more transparent, ethically robust system architectures. Persistent open challenges and areas of methodological debate highlight the necessity for both technical innovation and interdisciplinary dialogue as the field transitions toward real-world clinical adoption.

6.1 AI-Driven Hospital and Population Health Operations

The convergence of artificial intelligence (AI) and Internet of Things (IoT) technologies is fundamentally transforming operational paradigms in hospitals and population health management, enabling data-driven resource optimization, real-time surveillance, and tailored interventions. In hospital environments, conventional surgery scheduling approaches often result in suboptimal resource utilization and workflow inefficiencies due to insufficient consideration of patient-specific and procedure-specific attributes. With the advent of machine learning, particularly multivariate ensemble models,

there has been a marked shift: these systems now harness pre-procedural clinical and administrative data to transcend the limitations of historical mean-based and manually corrected methods. The outcome is a significant reduction in root mean squared error for time predictions and a notable decrease in late-running cases for both elective and acute surgeries. Such advances have immediate clinical ramifications—more precise scheduling directly leads to reduced surgery cancellations, improved operating room throughput, and enhanced predictability in perioperative care processes, collectively contributing to the alleviation of longstanding bottlenecks that negatively impact clinical and economic outcomes [72].

Beyond the operating suite, institution-wide big data platforms are emerging as foundational to the integration of diverse data sources—including clinical, laboratory, and administrative streams—within secure and scalable infrastructures. The West China Hospital Big Data Platform (WCH-BDP) serves as an exemplary model: its architecture is designed for automated, real-time data ingestion and standardized retrieval, harmonizing in excess of 8,000 discrete clinical variables. This robust computational backbone simultaneously advances both operational analytics and AI-driven clinical applications. Critically, the transition from manual to automated data access (reducing retrieval from hours to minutes) underscores the profound potential for such systems to impact not only research productivity but also immediate clinical decision-making, such as critical event detection and real-time management support. These capabilities illustrate the operational benefits of cross-domain, real-time analytics [94].

At the population health level, AI and IoT technologies forge innovative models for epidemiological surveillance and adaptive interventions, yet also highlight enduring challenges. For example, dynamic transmission modeling—combined with detailed economic analysis—demonstrates that focused intervention strategies, such as vector control in high-risk zones, are essential for achieving disease elimination goals in a cost-effective manner. However, these models also demonstrate operational fragility as disease prevalence declines, necessitating ongoing adjustments to surveillance and resource allocation in response to fluctuating program coverage and operational limitations. This underscores the imperative for real-time, adaptive data pipelines that support sustainable epidemic monitoring and the judicious distribution of limited resources, particularly in settings with high variability and resource constraints [47, 52].

IoT-enabled ubiquitous health monitoring illustrates both the potential and the complexity introduced by population-scale analytics. The recently proposed Proportionate Data Analytics (PDA) framework enhances the reliability of anomaly detection within heterogeneous health data streams by dynamically categorizing errors and variations. This approach improves the specificity and responsiveness of digital health services in real-world, error-prone environments by continuously adapting to stream quality and user

context. Consequently, PDA represents a critical advancement in robust, quality-aware analytics for scalable remote health monitoring and telemedicine systems [99]. Despite these advances, substantial data-related challenges persist:

- heterogeneous noise within multi-source data streams
- incomplete or imbalanced modality representation
- sample-wise variations in data quality

These factors collectively undermine predictive reliability, especially in settings characterized by multimodal and inconsistent data sources [100]. Effective mitigation of these challenges is essential for the equitable and practical deployment of such analytics at scale.

The interface between digital health platforms and AI analytics is exemplified by large-scale, application-driven interventions in chronic disease management. Deployments integrating continuous glucose monitoring (derived from wearables), dietary and physical activity tracking, and personalized feedback mechanisms have yielded measurable improvements in glycemic control, weight reduction, and behavioral engagement among diabetic and prediabetic cohorts. Notably, these interventions operate autonomously—without dependence on synchronous human coaching—demonstrating the feasibility of scalable population outreach at minimal marginal cost and offering a strategic approach to longstanding gaps in diabetes prevention. However, extending these models across heterogeneous populations necessitates careful consideration of cultural, demographic, and behavioral diversity, alongside stringent long-term validation and thoughtful integration with existing healthcare pathways [5].

Despite rapid advances in digital health capabilities, substantial disparities in care delivery remain entrenched. Analyses of large-scale diagnostic service utilization reveal that, even as technological improvements narrow the access gap, pronounced inequities persist in the timeliness and thoroughness of follow-up care across racial and socioeconomic strata. This observation highlights the necessity of embedding technological innovation within a comprehensive digital equity framework, which addresses not only technical availability but also the accessibility and cultural appropriateness of health interventions [70].

The digitization and interoperability of health information systems have progressed significantly due to targeted national policies and infrastructure investments. Currently, a majority of U.S. hospitals and prescribers possess the capacity for electronic data exchange and public health reporting. Nonetheless, persistent barriers—including technical, usability, and equity-related constraints—particularly impact smaller and rural providers, limiting the fluidity of data necessary for patient-centered, population-level analytics. Overcoming these divides requires continuous enhancement of data standards, development of transparent and trustworthy AI models, and an unwavering commitment to user-centric design principles that facilitate actionable insights at the clinical point of care [10, 94].

6.2 Clinical Decision Support and Human-in-the-Loop Analytics

The steady advancement of operational analytics and population health management is intricately connected to progress in clinical decision support (CDS) systems, where user-centric design and

analytic transparency are critical determinants of success. Irrespective of technical sophistication, AI solutions must be intentionally developed for integration with clinician workflows to achieve their potential in delivering safe, effective, and equitable care. Usability is pivotal in this context: systems that impose cognitive overload, lack transparency in reasoning, or disrupt established workflows are likely to encounter diminished adoption or even active resistance, notwithstanding their superior algorithmic performance [39, 77].

To address these barriers, explainable AI (XAI) frameworks have become indispensable in the pursuit of trustworthy CDS. Methods such as saliency mapping, Shapley Additive Explanations (SHAP), and Local Interpretable Model-Agnostic Explanations (LIME), once confined to academic research, are now operational in clinical contexts. These tools deliver granular, case-specific illumination of the diagnostic logic underpinning complex deep learning and ensemble models, thereby empowering clinicians to understand, scrutinize, and ultimately trust AI-driven decisions. Notable examples include time-series analysis for arrhythmia detection and disease classification in diabetes, where explanatory tools have rendered model outputs accessible and actionable for both clinicians and patients [8, 20].

The integration of analytics with IoT systems further depends on accommodating heterogeneity in data sources and user preferences. In the context of AI-assisted neuroimaging, workflows must support both the delivery of precise quantitative biomarkers and facilitate expert oversight and correction given the notable costs of annotation and the presence of systematic biases in large-scale training datasets. While multimodal fusion remains on the frontier of clinical analytics, the challenges of pervasive data noise, missingness, and intricate interdependencies among modalities demand the development of highly adaptive, transparent, and robust architectures to ensure clinical validity and broad generalizability [8, 100].

At the organizational scale, analytic usability is substantively improved by platforms that balance democratized access to data and models with stringent governance and security. These platforms enable clinicians and operational leaders to derive and act upon real-time insights, supporting the evolution toward self-service, data-driven workflows. Such workflows underpin the human-in-the-loop analytics paradigm, wherein continuous expert feedback calibrates, audits, and refines AI models for local applicability, mitigating risks of model drift and emergent bias [78, 94].

Ultimately, successful CDS deployment requires meticulous alignment with end-user requirements and an explicit focus on clinician trust. Sustainable implementation is attainable only through dynamic, iterative feedback loops between AI developers and clinical stakeholders, ensuring that usability, actionability, and analytic transparency are all practically realized at the point of care. This symbiotic relationship between humans and AI is not simply a matter of user preference; it constitutes a foundational precondition for the delivery of reliable, safe, and ethical analytics in patient care and population health initiatives alike [20, 39, 78].

7 Synthetic Data Generation, Privacy, and Security

This section aims to analyze the objectives, methodologies, and challenges associated with the generation and use of synthetic data,

focusing especially on privacy, security, and ethical implications. We also critically examine existing limitations, current trade-offs, and highlight unresolved challenges in both technical and regulatory domains.

Synthetic data generation has emerged as a critical component in modern data-driven AI systems, offering potential pathways for data augmentation, privacy preservation, and bias mitigation. Its operational significance is particularly pronounced when real data is limited, sensitive, or subject to legal restrictions. The integration of synthetic data introduces new dimensions in model training, validation, and deployment pipelines, and directly interfaces with issues of data provenance, utility, and fairness.

Transitioning from core technical advances to the deployment stage, it becomes clear that synthesizing data not only affects downstream model accuracy and generalizability but also introduces nuanced questions regarding consent, data ownership, and exposure to new forms of attack. Notably, the move to large-scale deployment in sensitive sectors (such as healthcare or finance) foregrounds complexity in guaranteeing both privacy and utility.

From a legal and ethical perspective, regulations such as the General Data Protection Regulation (GDPR) impose strict boundaries on the processing and dissemination of personal data, compelling researchers to articulate clear criteria for anonymity and re-identification risks in synthetic datasets. Failure to sufficiently anonymize or assess privacy threats can result in regulatory breaches and erosion of public trust. There remain substantial disagreements over definitions of de-identification and what constitutes “sufficient” privacy, leading to different methodologies and considerable debate.

Concrete failures and case studies—ranging from unintended leakage in de-identified health records to synthetic data facilitating adversarial attacks—underscore the technical and ethical precariousness. These examples illustrate that even well-intentioned synthetic data protocols can contribute to unforeseen vulnerabilities or discriminatory outcomes, especially when adversarial actors exploit weak points in the generation process.

Technical limitations continue to challenge the field, including the balance between data utility and privacy guarantees, the robustness and explainability of data generators, and the risk of model inversion or memorization. Many synthetic data generation methods, particularly those using deep generative models, involve trade-offs between realism and privacy—improved fidelity can inadvertently encode identifiable attributes, while aggressive privacy protections may diminish data utility for downstream tasks. Currently, consensus is lacking on best practices for quantifying privacy leakage and benchmarking synthetic data fidelity, with different approaches yielding divergent outcomes.

Operationally, security issues such as data poisoning, inversion attacks, and adversarial manipulations require ongoing vigilance, especially as deployment environments diversify. The integration of privacy-preserving mechanisms (such as differential privacy) into synthetic data workflows remains a prominent open research direction, complicated by challenges in practical implementation and verification.

In summary, synthetic data generation stands at the intersection of technical promise and ethical complexity, presenting significant unresolved questions concerning regulation, technical guarantees,

and the operational balance between privacy, utility, and security. Empirical validation and case studies point to an urgent need for clearer guidelines and frameworks, as well as for deeper cross-disciplinary collaboration to address systemic risks. A comprehensive understanding of the limitations, combined with more rigorous comparative analysis and transparent reporting standards, will be essential to bridging gaps between innovation and responsible deployment.

7.1 Generation Approaches and Clinical/IoT Use Cases

The application of synthetic data within healthcare and IoT-driven environments is propelled by the imperative for privacy-preserving analytics, augmentation of data-scarce scenarios, and the facilitation of regulatory compliance for both clinical and real-time health monitoring contexts [29, 78]. The inherent difficulty in accessing large-scale, real-world patient data—due to legal, proprietary, and privacy constraints—poses significant barriers to effective algorithm development, benchmarking, and deployment across diverse patient populations. Synthetic data provides a pragmatic solution by generating realistic but non-identifiable datasets that enable open exchange, expedite the iterative cycle of hypothesis testing, and support bias analysis. Furthermore, such data can serve as controlled testbeds for operational procedures and regulatory stress-testing [29, 78].

Technologically, the generation of synthetic data for healthcare and IoT applications employs a range of advanced techniques meticulously tailored to replicate the complexity and diversity of medical information. Among the most prevalent frameworks are Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and state-of-the-art natural language processing (NLP) models, which underpin the synthesis of electronic health records (EHRs), medical imaging datasets, and heterogeneous multivariate IoT sensor streams [29]. Agent-based modeling further extends capabilities by emulating intricate temporal patient interactions and disease trajectories—a crucial element for simulating clinical trials or conducting epidemiological studies. The continuous evolution of these methods now encompasses the generation of time-series data, unstructured clinical text, genomic profiles, and cross-modal datasets, aligning with the emerging requirements of precision health monitoring and digital twin paradigms [29, 78].

Key application domains for synthetic data include privacy-preserving, multicenter AI model training, augmentation of data for rare disease cohort analyses, simulation of IoT environments for robust edge-device validation, and policy development and planning at governmental and institutional levels.

Collectively, synthetic data is gaining centrality in both centralized and federated analytic workflows—enabling privacy, scalability, and inclusivity across the rapidly evolving digital health ecosystem [29, 78].

7.2 Challenges Ethics, Legalities, and Technical Hurdles

Despite the clear benefits, the adoption of synthetic and real-time data streams within healthcare and IoT domains is hindered by a matrix of ethical, legal, and technical challenges that directly impact

utility, trust, and societal acceptance. One of the most prominent risks is the perpetuation or even exacerbation of underlying data biases: generative models tuned on incomplete or skewed datasets can yield synthetic records that reinforce inequities or clinical inaccuracies, thus compromising algorithmic fairness and representing a latent threat to marginalized populations [29]. The opacity of many generative processes complicates auditability, making it difficult to ascertain data provenance, validate representativeness, or perform rigorous post-hoc error analyses—functions that are vital for regulatory oversight and quality assurance [78].

Privacy risks persist even with ostensibly de-identified synthetic data. Advances in re-identification techniques—including membership inference and adversarial linkage attacks—raise legitimate concerns that overly realistic synthetic datasets may inadvertently disclose sensitive personal attributes or enable indirect identification of individuals [29, 78]. Existing legal regulations, such as HIPAA (USA) or GDPR (Europe), set baseline requirements for privacy, yet they often lack explicit, harmonized coverage of synthetic data, especially in real-time and streaming IoT contexts. As a result, organizations are frequently left to navigate a patchwork of technical safeguards and jurisdiction-specific compliance requirements [6, 8, 10, 11, 22, 24, 26–30, 33–35, 38, 40, 41, 44–47, 51–53, 58, 60, 61, 64, 73, 75, 79, 89, 90, 92–95, 98–100, 102].

Differential privacy (DP) methods, such as the Private Aggregation of Teacher Ensembles GAN (PATE-GAN), introduce rigorous mathematical guarantees against information leakage; however, factors such as mathematical complexity, tradeoffs between data utility and privacy, and the high computational burden associated with DP can impede widespread adoption [29]. The application of DP in resource-constrained and heterogeneous IoT environments is further challenged by the need for real-time compliance monitoring and dynamic threat mitigation [6, 8, 10, 11, 22, 24, 26–30, 33–35, 38, 40, 41, 44–47, 51–53, 58, 60, 61, 64, 73, 75, 79, 89, 90, 92–95, 98–100, 102].

The regulatory landscape compounds these challenges. Disparities in definitions, enforcement, and coverage across national and supranational levels complicate risk management, while most current frameworks are tailored to static rather than streaming data. This gap exposes real-time IoT systems to unmitigated threats such as sensor spoofing, data poisoning, and unauthorized cross-linkages—vulnerabilities that are not fully addressed by prevailing guidelines [6, 10, 11, 24, 26–30, 35, 41, 46, 47, 51–53, 58, 60, 61, 64, 75, 92–95, 98, 102]. The absence of harmonized definitions and audit mechanisms ultimately limits the establishment of trust among data controllers, practitioners, regulators, and the broader public [29].

A structured comparison of major technical and governance challenges is provided in Table 8, highlighting the interplay and current mitigation limitations.

7.3 Advanced Governance and Secure Infrastructures

This subsection examines the evolving frameworks and persistent challenges in establishing robust governance and security infrastructures for synthetic, clinical, and IoT-derived health datasets. We focus on how technical, regulatory, and ethical responses converge

to ensure data quality, privacy, accountability, and trustworthy deployment across increasingly complex environments.

Overcoming these intertwined challenges requires systemic transformation in the governance, security, and auditability of health data. Recent frameworks stress the need for end-to-end “digital chain-of-custody” infrastructures, which integrate cryptographic tools such as provenance tracking, digital signatures, and audit logs, in combination with machine-readable access control policies. Such measures enable accountability from initial data generation to analytical sharing, providing enforceable regulatory compliance and full traceability [1, 6, 7, 11, 12, 14–16, 21, 26–29, 35, 41, 43, 46, 47, 51, 60, 61, 65, 66, 75, 78, 79, 84, 91–93, 95, 98, 102].

The implementation of blockchain and distributed ledger technologies adds a tamper-evident layer to record-keeping, distributes control across multiple stakeholders, and enables programmable, granular access. Particularly in federated and cross-institutional environments—where boundaries of trust are uncertain—these systems underpin secure, scalable analysis across interconnected IoT networks [1, 6, 7, 11, 12, 14–16, 21, 26–29, 35, 41, 43, 46, 47, 51, 60, 61, 65, 66, 75, 78, 79, 84, 91–93, 95, 98, 102]. However, the shift to decentralized architectures brings new tradeoffs such as increased maintenance complexity, consensus latency, and the ongoing tension between transparency (ensuring verifiability and trust) versus confidentiality (protecting sensitive health data).

Privacy-preserving analytics, including homomorphic encryption, secure multi-party computation, and privacy-aware machine learning, allow computation on encrypted or masked data. This ensures that even data processors do not directly access sensitive information [1, 6, 7, 11, 12, 14, 15, 21, 26–29, 43, 46, 47, 51, 60, 66, 78, 84, 91, 95, 98]. In IoT contexts, edge intelligence and decentralized storage reduce exposure by confining risk to device-local or micro-environmental domains. Yet, these advances may amplify attack surfaces, complicate endpoint management, and often require re-evaluation of compliance with legal standards (e.g., GDPR, HIPAA), especially where the distinction between device and network boundaries is blurred [79].

A critical ongoing challenge remains the dynamic reconciliation of technical innovation and evolving regulation. Governance must be continuously adapted while addressing tradeoffs between data utility and privacy, between open sharing for improved model quality and access controls for ethical and legal protections. Regulators grapple with the pace of technical change, inconsistencies across jurisdictions, and the challenge of specifying actionable standards for algorithmic transparency, auditability, and fairness [29, 78].

Crucially, transparency and equity must be centered in all such frameworks. Best practices increasingly call for interdisciplinary collaboration—bringing together technologists, clinicians, policy-makers, ethicists, and patient advocates—to co-define governance models, monitor emergent risks, and iteratively refine adaptive controls in parallel with technological advance [29, 78]. Such collaborations must also anticipate new risks to data quality and model deployment: adversarial attacks on chain-of-custody records, provenance spoofing, and quality drift resulting from privacy-preserving transformations are all active concerns. Future methodological advances could focus on automated verification for provenance chains, resilient consensus protocols for multi-stakeholder settings,

Table 8: Overview of Major Challenges in Synthetic Data for Healthcare and IoT

Challenge Category	Manifestation in Synthetic Data Contexts	Current Limitations of Mitigation Strategies
Bias and Fairness	Propagation or amplification of demographic and clinical inaccuracies	Limited model transparency; insufficient bias auditing tools; difficulty representing rare subpopulations
Auditability and Provenance	Opaque generative models obscure source-to-sample tracking and error traceability	Lack of standardized audit frameworks; complexity of generative architectures restricts interpretability
Privacy and Re-identification	Vulnerability to membership inference and linkage attacks; residual sensitivity in synthetic samples	Incomplete legal coverage; computational and utility tradeoffs with privacy-enhancing technologies
Legal and Regulatory Gaps	Inconsistent definitions across jurisdictions; static data-focused frameworks overlook streaming/IoT realities	Fragmented regulatory guidance; lack of harmonized standards; limited enforcement for IoT applications

and context-aware differential privacy that balances individualized utility-risk assessments [29, 79].

In summary, advanced governance and secure infrastructures are not static solutions, but an evolving interplay of technical, regulatory, and ethical strategies that must be co-developed and dynamically aligned to sustain trust, accountability, and high-quality deployment in digital medicine.

8 Data Quality, Benchmarking, and Technical Robustness

This section aims to provide a critical examination of the interconnected challenges of data quality, benchmarking, and technical robustness in AI systems, with explicit attention to their implications for governance, privacy, and deployment. We begin by delineating the section objectives and motivating the discussion by highlighting how these factors underpin trustworthiness and regulatory compliance. We then analyze major trade-offs and limitations associated with prevailing practices, and articulate open challenges that could spur future methodological advancements. Throughout, we aim to provide clarity through explicit section objectives and improved transition between core topics.

Ensuring data quality is foundational for the reliability of AI systems. High-quality data not only reduces bias and errors but also supports meaningful benchmarking and compliance with regulatory standards. However, maintaining rigorous data standards often conflicts with the need for large-scale data collection, leading to trade-offs between dataset size, representativeness, and annotation accuracy. In many deployments, the lack of transparent data provenance and insufficient documentation exacerbates these issues, making it difficult to assess long-term robustness or to compare models fairly. This tension is particularly pronounced in contexts with strict privacy and governance requirements, where the need for data minimization and secure handling can further constrain data utility.

Benchmarking practices similarly face critical limitations. While standardized benchmarks facilitate comparative evaluation, they may inadvertently encourage overfitting to particular datasets and fail to capture evolving real-world complexities. Moreover, disparities in benchmark adoption can obscure the generalizability of experimental results. Integrating robust governance and privacy mechanisms within benchmarking protocols remains an unresolved challenge; comprehensive benchmarks must account not only for performance metrics but also for system security, fairness, and data protection measures.

Technical robustness involves resilience against distributional shifts, adversarial attacks, and implementation faults. To address these issues, current methods employ techniques such as adversarial training, uncertainty quantification, and rigorous stress testing.

However, these approaches can increase system complexity, introduce computational overhead, and may trade off against other desiderata such as interpretability or ease of deployment. Effective technical robustness demands holistic integration with governance and privacy frameworks, yet many existing systems treat these domains in isolation. More explicit cross-domain strategies are needed to ensure that privacy-preserving or governance-driven constraints do not inadvertently introduce new vulnerabilities or degrade system performance.

Open challenges in this domain motivate the need for innovative methodological advancements. Chief among these is the development of adaptive, context-aware quality control and benchmarking procedures that can flexibly balance technical, privacy, and governance objectives. For instance, dynamic benchmarks capable of evolving alongside deployed systems could help mitigate the risks of benchmark overfitting and foster more realistic assessments of robustness. Likewise, methodologies for verifiable data quality auditing, privacy-preserving metric computation, and automated governance compliance checking present opportunities for substantive progress.

In summary, the interplay among data quality, benchmarking, and technical robustness reveals numerous open challenges—ranging from reconciling data utility with privacy constraints to aligning governance requirements with robust, scalable evaluation methods. Addressing these issues requires not only methodological innovations but also deeper integration across typically compartmentalized areas, paving the way for more trustworthy and accountable AI systems.

8.1 Data Quality in Clinical and IoT/Streaming Contexts

8.1.1 Problems of Data Heterogeneity, Class Imbalance, and Missing Modalities in Biomedical and IoT Data. Emerging applications of artificial intelligence in healthcare, biomedicine, and the Internet of Things (IoT) increasingly depend on heterogeneous, multimodal datasets. Biomedical data can include structured clinical records, high-dimensional medical images, physiological signals, and continuous streams from wearable or IoT sensors. Each of these sources is characterized by distinct sampling frequencies, varying noise characteristics, and differing degrees of completeness. Such inherent variability complicates efficient integration and generalization, directly challenging robust clinical translation and impeding the practical deployment of AI models in real-world settings [10, 24, 100]. Models built on uniform or single-source data often lack the resilience required when deployed across diverse, multimodal, and often noisy clinical environments.

Class imbalance is a particularly persistent obstacle in both clinical and IoT-driven data. In practice, adverse or high-risk events, such as seizures or disease onset, constitute a minority of recorded

instances relative to the abundance of normal or uneventful signals. This skew can bias models to favor the majority class, undermining their ability to reliably detect or predict rare but clinically significant outcomes [24, 94]. Simultaneously, missing data and incomplete modalities – due to hardware malfunctions, inconsistent patient engagement, or sporadic recording – further reduce data reliability. In IoT-based healthcare, data streams may suffer from intermittent loss, asynchronous arrivals, corruption, and diverse device standards, thus amplifying preprocessing and inference challenges [8, 78].

These quality issues rarely arise independently; their intersection can lead to complex failure modes. For instance, multimodal fusion is highly sensitive to missing modalities: the absence of even a single modality may undermine downstream predictions, unless mitigated by robust imputation or modality-specific strategies [100]. Recent surveys and large-scale implementations underscore these interacting data factors as core barriers to the successful real-world deployment and sustained operation of machine learning systems in biomedical and IoT domains [78, 94, 100]. Addressing these issues requires not only technical advances in data integration, management, and governance, but also improved standardization and transparency to facilitate trustworthy and equitable healthcare solutions.

8.1.2 Technical Preprocessing: SMOTE, Artifact Rejection, Denoising, and Anomaly Detection for IoT and Wearable Streams. Multiple sophisticated preprocessing pipelines have been developed to address the persistent challenges found in biomedical and streaming data, notably concerning class imbalance, noise, and artifact contamination. The Synthetic Minority Oversampling Technique (SMOTE) and related algorithms are widely adopted for addressing class imbalance in tabular and stream data. By generating synthetic samples of underrepresented classes, SMOTE facilitates improved detection of rare but clinically essential events [37, 77]. These benefits, however, are constrained in highly nonstationary streams or ultra-high dimensional applications, where SMOTE may lead to overfitting or the creation of unrealistic sample boundaries if not carefully applied [78].

Artifact rejection and denoising constitute foundational steps in preprocessing physiological signals, especially in real-world, uncontrolled recording environments. Classic filtering approaches, thresholding, imputation, and dimensionality reduction using principal component analysis remain common. Recent advances have seen the application of deep learning-based approaches such as convolutional autoencoders and dual-stream neural networks, which offer robust capacity to discriminate context-dependent artifact signatures and complex noise profiles from physiological signals [37, 71, 80]. For example, multiresolution CNN frameworks that extract features from decomposed frequency bands [37], and dual-polynomial decomposition for optimized signal denoising [80], have demonstrated both improved artifact mitigation and preservation of operationally or clinically important signal content. Novel decompositions (e.g., Hurst method for real-time EEG analysis [71]) further enable extraction of relevant features under dynamic recording conditions.

In IoT and continuous streaming environments, real-time anomaly detection techniques such as Proportionate Data Analytics (PDA) are increasingly used to dynamically segment incoming data,

discriminating anomalies caused by device errors or data corruption from genuine physiological changes, and enabling actionable responses in health monitoring systems [8, 78]. PDA leverages dynamic error modeling and stream variation analysis through regression-based segmentation, supporting responsive service delivery in healthcare IoT architectures.

Despite these technical advances, a persistent challenge remains in balancing the selectivity of denoising with the risk of discarding clinically informative subtle signals, or conversely, leaving residual confounders that impair downstream analysis. State-of-the-art pipelines increasingly incorporate artifact-aware loss functions, explicit uncertainty modeling, and adaptive preprocessing tailored to both signal characteristics and target clinical endpoints [78]. This integration is crucial for high-stakes biomedical contexts where both false negatives (signal loss) and false positives (artifact retention) are consequential.

As summarized in Table 9, each preprocessing approach exhibits context-dependent advantages and limitations, emphasizing the ongoing need for tailored solutions that integrate uncertainty modeling and adaptive methods to address the complexities of biomedical and IoT data streams.

8.2 Benchmarking and Validation

8.2.1 Multicenter, Real-World, and Robust Benchmarking Approaches.

Rigorous benchmarking is fundamental to the development and validation of generalizable machine learning models in biomedicine and IoT. While single-center, retrospective studies have historically been prevalent, the field is shifting toward multicenter and real-world validation paradigms. This evolution is motivated by recurring failures of models that perform well under limited, homogeneous conditions but falter upon deployment in diverse clinical environments [1, 41, 92]. Initiatives such as the Image Biomarker Standardization Initiative (IBSI) exemplify the critical importance of harmonizing feature definitions and preprocessing protocols, thereby enabling reproducibility, transparent reporting, and robust validation across different software platforms [53, 55, 61].

Beyond imaging, the creation of large-scale, multicenter data platforms that encompass multimodal clinical and streaming information has become instrumental for assessing algorithmic generalizability [19, 24, 28, 75, 84, 88, 102]. These endeavors foster new benchmark datasets that incorporate real-world complexities—including missing data, fluctuating class distributions, and heterogeneous device characteristics—facilitating stress-testing of algorithms before clinical or operational deployment [24]. Contemporary benchmarking protocols now emphasize open-source curation, transparent metrics, and prospective, temporally-anchored validation, ensuring that reported performance is not merely an artifact of retrospective overfitting [1, 41, 53].

8.2.2 Addressing Computational/Deployment Limitations, Dataset Imbalance, and Patient Variability.

In practice, benchmarking exposes a convergence of technical and systemic obstacles that must be overcome to enable scalable AI deployment. Computational limitations persist, as deep learning models—despite their strong performance on curated datasets—often require resources exceeding those available in typical clinical or edge computing environments. Real-time analysis of high-resolution streaming data is thus frequently

Table 9: Comparison of Preprocessing Techniques for Biomedical and IoT Data

Technique	Primary Target	Key Advantages	Limitations
SMOTE	Class imbalance	Enables rare event detection; robust for tabular or balanced low-dimensional data	Limited for high-dimensional, nonstationary streams; risk of unrealistic instances or overfitting
Filtering/Thresholding	Structured noise, artifacts	Computationally efficient, easy to interpret and deploy	May discard relevant features; less adaptive to complex or context-specific artifact sources
Deep Learning Denoising (Autoencoders, dual-stream nets, multiresolution CNN, MBDFT)	Complex, non-stationary noise/artifacts	Learns representative features; adaptable to data complexity; improved artifact/signal separation [37, 71, 80]	High data and computational requirements; challenges in interpretability and generalization
Anomaly Detection (PDA)	Device faults, data corruption in streams	Supports real-time error modeling and dynamic segmentation; maintains service reliability in IoT healthcare [8, 78]	Vulnerable to context-ambiguous anomalies; performance dependent on underlying error model

infeasible without model optimization. To address these constraints, research increasingly focuses on neural network quantization and the development of computationally efficient architectures, which are essential for practical edge deployment in both clinical and IoT settings [2, 18, 37, 78].

In addition, data imbalance and patient variability introduce further challenges. Achieving truly robust benchmarking requires evaluations that are stratified across demographic, clinical, and device-specific subgroups. This includes explicit quantification of performance disparities and the application of non-inferiority analyses for underrepresented populations [77, 78]. Addressing these challenges involves algorithmic innovations such as domain adaptation, meta-learning, and sample reweighting, infrastructure improvements for federated, multi-institutional data aggregation, and the adoption of statistical methodologies for subgroup-specific performance assessment [18, 37].

8.2.3 Ensuring Translation to Scalable and Interoperable Platforms. Even when technical performance metrics are met, the broader translational impact of AI systems in healthcare and IoT depends fundamentally on integration within scalable and interoperable platforms. The proliferation of heterogeneous health IT infrastructures has led to fragmented data ecosystems, impeding efficient data exchange, aggregation, and systematic benchmarking [28, 35, 92, 102]. Recent progress—including advances in interoperability standards, terminology harmonization, and development of federated system architectures—has begun to address these silos, supporting more seamless deployment of AI solutions across distributed settings [35, 97, 102]. Persisting barriers, however, comprise non-standardized data formats, privacy and compliance constraints, heterogeneous computational capacity, and limited adoption of open APIs. Overcoming these hurdles is essential for realizing robust, scalable, and equitable AI-enabled healthcare and IoT ecosystems [28, 75].

9 Key Challenges, Open Problems, and Future Directions

This section aims to synthesize the primary challenges, highlight open problems, and outline opportunities for methodological advancement in the field. We first frame the objectives of this section, then proceed to critical analyses and discuss tradeoffs, with explicit links to technical, privacy, and governance dimensions. Finally, we evaluate how these challenges motivate promising future research directions.

9.1 Section Objectives

The objectives of this section are threefold: (1) to critically analyze the main technical, regulatory, and governance-related obstacles faced in the field; (2) to contrast diverse approaches and their respective tradeoffs; (3) to map out how these open challenges can shape and inspire future methodological innovation.

9.2 Critical Analysis and Contrasting Perspectives

One of the central technical challenges involves balancing model performance with privacy and governance constraints. For example, advanced machine learning methods often require access to large volumes of high-quality data, yet privacy-preserving techniques (such as differential privacy or federated learning) may reduce data fidelity or complicate data integration. This tension requires deliberate architectural choices, where increasing privacy or robustness can negatively impact accuracy or efficiency. Furthermore, there is a persistent gap in regulatory alignment, as governance frameworks (such as GDPR or industry-specific guidelines) may lag behind technological progress. These frameworks impose additional requirements that can either impede or shape technical development. Thus, careful assessment of tradeoffs between openness, transparency, and compliance is integral to system design.

A further perspective pertains to deployment: integrating privacy and governance solutions directly into data pipelines and model life-cycles is nontrivial. Often, technical solutions are retrofitted instead of being considered from the outset, which can introduce inefficiencies or lead to suboptimal outcomes. In addition, rapid innovation cycles in machine learning can outpace regulatory responses, which may create uncertainty and hinder deployment in sensitive domains.

9.3 Open Problems and Their Impact on Methodological Advancement

Several open problems are evident and point to promising research avenues. First, there is a need for frameworks that reconcile privacy preservation with minimal performance degradation, particularly in distributed or federated environments. Second, more work is needed on adaptive governance mechanisms that can dynamically incorporate evolving regulatory requirements into technical workflows.

Data quality and representativeness continue to be critical: advances in mitigating dataset bias, augmenting underrepresented modalities, and validating data provenance are essential for robust system performance. Such approaches demand methodological innovation in data sampling, augmentation, and active learning.

Finally, improving the integration of privacy, governance, and technical mechanisms can enable end-to-end trustworthy pipelines. For example, modular solutions that allow dynamic adjustment of privacy budgets or compliance checks during model deployment are underexplored. Addressing these gaps will likely call for advances in interdisciplinary methodologies, as well as tighter collaboration between regulatory stakeholders and technical practitioners.

In summary, the challenges outlined here—balancing privacy, governance, technical scalability, and data quality—are not only barriers but also catalysts for the next generation of methodological

contributions. Clearer articulation of these issues, as above, should help motivate and guide ongoing research.

9.4 Technical, Methodological, and Practical Challenges

The deployment of advanced analytics and artificial intelligence (AI) in healthcare, especially within environments utilizing Internet of Things (IoT), real-time monitoring, and resource-constrained settings, is impeded by a range of technical and practical barriers. Foremost among these is data heterogeneity: the coexistence of varied data sources, disparate modalities, and inconsistent formats and data qualities, covering everything from clinical EHRs to biosensor feeds to imaging studies [2–4, 6, 8, 10, 11, 18, 22, 24, 25, 28, 33–38, 41–44, 47–49, 53, 55, 56, 59, 61, 63, 64, 67, 69, 75–79, 83, 84, 86, 88, 91–94, 96, 100, 101]. This diversity complicates the integration process, often resulting in datasets with missing values, inconsistencies, or significant noise, ultimately eroding the robustness and generalizability of downstream algorithms [2–4, 6, 8, 10, 18, 22, 24, 25, 28, 33–38, 41, 42, 44, 47–49, 53, 55, 56, 59, 61, 63, 64, 67, 69, 75–78, 83, 84, 86, 88, 92–94, 96, 100, 101]. Handling these challenges often requires advanced fusion, harmonization, and robust preprocessing pipelines [34, 44, 75, 100].

A parallel obstacle is the limited availability of high-quality annotations. Many machine learning and deep learning models depend on large, well-annotated datasets, which remain rare for certain diseases, underrepresented populations, or novel data modalities such as wearable sensor streams or next-generation molecular diagnostics [28, 53, 56, 69, 96]. Particularly in medical imaging applications, annotation relies on highly skilled human experts through laborious manual labeling processes, creating significant bottlenecks not only for model training but also for reliable external validation. Systematic reviews underscore that small, imbalanced, or single-institution datasets exacerbate these challenges and hinder model generalization to broader clinical practice [53, 61]. For rare diseases or low-prevalence conditions, data scarcity further compounds these issues, impeding model development and evaluation [4, 42, 47, 48, 56]. Device- and protocol-specific variability may further limit the applicability of learned models to new clinical settings [48, 53, 83, 96].

These technical hurdles become even more pronounced as analytic systems are scaled for deployment in real-time or edge environments, including rural or small-clinic contexts where computational infrastructure, memory, and network bandwidth are often highly constrained [3, 6, 8, 22, 24, 25, 33–35, 38, 47, 53, 76, 78, 88, 91, 100]. Modern AI models—especially large, multimodal, or federated architectures—frequently exceed the capacities of typical IoT hardware, which may have limited power sources, minimal storage, and unreliable connectivity. Additional barriers include data synchronization challenges, intermittent streaming, packet loss, high latency, and device failures, all of which demand robust anomaly detection, effective imputation of missing data, and adaptive model retraining methodologies [37, 47, 53, 59, 79, 100].

Recent literature highlights emerging solutions such as unsupervised and semi-supervised learning to mitigate annotation requirements [53, 63, 76, 92], development of edge-optimized or hardware-aware model architectures [18, 37, 53, 100], and the use of federated

learning or domain adaptation approaches to improve data privacy and generalizability across settings [41, 63, 79]. Standardization protocols for data curation and interoperability are also being advanced in both imaging and molecular domains to improve consistency and downstream utility [10, 24, 42, 84, 94]. Nevertheless, widespread adoption and reproducibility of these advancements remain limited, and practical deployment of AI in real-world, heterogeneous healthcare environments is still stymied by persistent gaps in scalability, interoperability, and evidence of clinical effectiveness. This underscores a continued need for rigorous methodological research, expanded public datasets, and stronger national and international standards for system integration, annotation quality, and model evaluation.

9.5 Interpretability and Clinical Impact

The effective translation of analytic innovations into clinical practice is contingent upon interpretability, clinical utility, and generalizability. High-performing, yet opaque, models—particularly deep neural networks and large foundation models operating on images, signals, and clinical text—often function as “black boxes.” This opacity undermines clinician trust and impedes both validation and regulatory acceptance [2, 8, 20, 22, 25, 28, 32, 34, 35, 39, 53, 54, 56, 61, 62, 64, 67, 78, 82, 100]. Clinical utility is intimately bound to interpretability: beyond providing predictions (such as disease classification or risk scores), models must articulate the underlying rationale, delineating salient image areas or critical features in time-series data. Recent advances in explainable AI (XAI)—including post-hoc saliency mapping, attention visualization, and Shapley value-based feature attribution—enable both global and case-specific interpretative insights, facilitating scientific validation and regulatory review [2, 22, 39, 53, 54, 64, 82, 100].

A distinct but interrelated concern lies in ensuring analytic generalizability across diverse clinical settings, populations, and data acquisition systems. Many models are prone to overfitting to specific institutions, cohorts, or medical devices, resulting in decreased performance in cross-site or prospective validations [2, 25, 28, 44, 56, 62, 78]. This phenomenon is observed across domains, from radiomics to real-time vital sign prediction. Efforts to enhance generalizability include domain adaptation, transfer learning, multi-site federated learning, and incorporation of biological or clinical priors into model regularization. Nevertheless, rigorous external validation and systematic evaluation at scale remain insufficient [2, 25, 34, 39, 44, 54, 78, 100].

9.6 Standardization, Equity, and Ethical Considerations

This integrative section synthesizes cross-domain challenges and opportunities at the intersection of standardization, equity, and ethics in analytic healthcare, reinforcing this survey’s broader aim of mapping technical advances, persistent barriers, and future needs across imaging, -omics, and EHR modalities.

Advances in analytic healthcare depend upon multifaceted standardization and an unwavering commitment to equity and ethical principles. Across modalities—including imaging, -omics, and electronic health record (EHR) data—variability in workflows, acquisition protocols, annotation definitions, metadata schemas, and

feature nomenclature hinders reproducibility and impedes model transferability [1, 3, 6, 8, 22, 27, 28, 33, 35, 38, 42, 46, 47, 51–54, 56, 61, 69, 78, 83, 84, 94, 96, 99, 100]. International initiatives, such as the Image Biomarker Standardization Initiative (IBSI), have advanced harmonization in specific domains like radiomics [1]. However, non-standardized practices in feature extraction, segmentation, and reporting continue to undermine multi-center reproducibility and clinical translatability [3, 8, 28, 35, 38, 53, 69, 78, 84, 100].

Comparative synthesis across domains reveals parallel struggles in standardizing data practices. In molecular and genomic testing, consensus guidelines stress the need for robust validation and continuous quality control across laboratories and platforms [42, 47]. Big data health platforms for large hospitals also depend on integrated metadata management, terminology harmonization, and longitudinal, cross-system data governance [94]. Machine learning-based predictive analytics and multi-modal fusion face persistent challenges from inconsistent data schemas, sparse and heterogeneous clinical datasets, and lack of agreed benchmarks for evaluation and reporting [8, 53, 78, 100]. These concerns echo in imaging, where protocols for acquisition, segmentation, and biased annotation propagate to downstream clinical or AI deployments [1, 35, 56, 61, 83, 84, 96].

Equity in analytic healthcare extends beyond algorithmic fairness to encompass broader social determinants and the digital divide. Persistent disparities are shaped by infrastructural deficits, inconsistent connectivity, device interoperability limitations, and the geographic maldistribution of expertise and support [5, 8, 10, 28, 47, 52, 70, 78, 94, 99, 100]. Access to diagnostic services, for instance, remains uneven even in technologically advanced healthcare environments [10, 52]. Digital health interventions show promise for chronic disease management, yet may exacerbate or mitigate disparities depending on their real-world accessibility and ongoing support for diverse populations [8, 10, 78, 94, 99]. These issues are compounded by technical complexity, resource limitations, and the lack of tailored governance and transparent algorithms across digital ecosystems [10, 94].

To promote both reproducibility and fairness, several best practices emerge: Clinical workflows and analytic protocols should be harmonized across domains, data types, and geographic locations. Bias mitigation, transparent reporting, and inclusive dataset curation—particularly representing under-represented or high-need groups—are essential. Investments in equitable digital infrastructure, interoperability, and participatory design processes are needed, with special attention to marginalized or underserved populations. Cross-disciplinary initiatives should focus on standard operating procedures, validation practices, and scalable quality assurance frameworks. Collaborative efforts should address persistent barriers to data sharing, privacy, explainability, and inclusive innovation at policy and organizational levels.

These steps aim to mitigate model bias and advance equitable patient outcomes across demographic and resource strata [1, 3, 8, 28, 38, 42, 47, 51, 54, 61, 69, 78, 83, 84, 94, 96, 99, 100]. In the context of increasing reliance on digital health solutions for chronic disease management and pandemic response, these concerns become even more critical.

Despite significant progress, unresolved debates continue to shape the field. For example, the relative merits of federated data

harmonization versus centralized standardization remain unsettled, as do the best approaches for balancing privacy and data utility [8, 78, 94]. The literature reflects contrasting strategies and unresolved issues around the biological interpretability of radiomics features [1, 84], multi-institutional reproducibility in machine learning [53, 61, 69], and how best to assure equitable technology diffusion across resource settings [10, 28, 52, 99].

Key Future Research Gaps and Needs: - Development of cross-platform, cross-modality standards for metadata and reporting that can be implemented at scale and adapted to evolving technologies. - Consensus on best practices for multi-center, multi-modal datasets, including robust validation, bias mitigation, and transparent quality assurance. - Interdisciplinary frameworks for measuring, reporting, and mitigating algorithmic and systemic biases that extend into operational and population levels. - Strategies for addressing the digital divide, including infrastructure investments, participatory design, and governance models tailored to marginalized communities. - Systematic approaches to integrating ethical, regulatory, and social considerations into each stage of analytic health technology life cycles.

Continued cross-domain dialogue, evidence synthesis, and policy engagement are essential to ensuring that advances in data-driven healthcare translate into robust, reproducible, and equitable outcomes.

9.7 Privacy, Security, and Compliance

As analytic and data-sharing platforms become increasingly sophisticated, ensuring privacy, security, and regulatory compliance grows ever more imperative. Legislation such as the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR) mandates stringent controls over data sharing, necessitating advanced technical solutions for privacy-preserving analytics and secure pipeline design [6, 8, 10, 11, 22, 24, 26–30, 33–35, 38, 40, 41, 44–47, 51–53, 58, 60, 61, 64, 73, 75, 78, 79, 89, 90, 92–95, 98–100, 102]. There is growing cross-disciplinary recognition that privacy and security are not merely technical or legal matters, but demand integrated consideration of data lifecycle governance, transparency, and ethical imperatives across domains such as medical imaging [35, 53, 61, 79], health informatics [10, 24, 94], industrial/IoT settings [22, 33, 78], and energy management [33].

Emerging threats encompass data breaches, the risks of re-identification, and the use of synthetic data for privacy enhancement—all of which introduce new attack surfaces and ethical dilemmas, especially when balancing auditability and privacy across diverse data types and stakeholder environments [24, 29, 94]. Techniques such as federated learning and differential privacy are central to technical mitigation; however, they introduce computational burdens and auditability challenges that are yet to be fully resolved [8, 22, 26, 28, 29, 33, 38, 45, 46, 53, 78, 89, 94, 99, 100]. While synthetic data and privacy-preserving computation offer hope for broader data accessibility and reduced regulatory risk, practical implementation is still hampered by challenges in bias, interpretability, and the difficulty of auditing data transformations for compliance [29].

Compounding these considerations is the dynamic and continuous nature of data originating from wearables, IoT devices, and streaming EHR feeds. This necessitates adaptable legal, technical, and ethical frameworks to ensure auditability and accountability as both data and clinical applications evolve under shifting interoperability and stakeholder requirements [6, 8, 10, 22, 28, 29, 34, 38, 47, 52, 59, 78, 79, 94, 100]. Among the foremost challenges are:

Establishing scalable governance for data access and secondary use

Designing fair and comprehensible consent models suitable for ongoing data collection

Conducting regular audits, especially in multi-center and cross-border collaborations

Integrating privacy-by-design and transparency-enabling toolkits from the outset

Despite growing recognition, consistent protocols for compliance verification and accountability remain underdeveloped.

Contrasting Perspectives and Open Debates: Sectors such as health care, industrial prognosis, and building energy management have each evolved divergent approaches to balancing privacy and data utility [22, 24, 33, 79, 94]. In medical imaging, multi-institutional collaboration and federated learning are vital yet challenged by data heterogeneity and legacy privacy concerns [53, 79]. Big data platforms advocate for extensive data integration and streamlined access but note that standardization, security, and equitable patient access remain persistent bottlenecks [10, 94]. By contrast, industrial and energy domains highlight the promise of data fusion, secure analytics, and adaptive consent models, but frequently grapple with questions of transparency, stakeholder trust, and deployment cost [6, 22, 26, 33]. There is debate about whether technical mitigation can ever wholly substitute for strong organizational and legal oversight, particularly regarding explainability, auditability, and risk mitigation in high-stakes settings [24, 29].

Explicit Research Gaps and Future Directions:

- Robust methodologies for verifying privacy and compliance in multi-modal, cross-border data sharing pipelines
- Comprehensive frameworks for scalable, dynamic consent and secondary data use
- Auditable implementations of synthetic data and federated learning in clinical and industrial practice
- Practical standards for privacy-by-design and explainability in data pipeline architectures across diverse domains
- Unified protocols to support regular, automated audits adaptable to evolving regulatory environments

9.8 Algorithmic Innovation, Architecture, and Recommendations

Innovations in algorithmic design and system architecture play a pivotal role in advancing scalable, adaptable, and trustworthy healthcare analytics within increasingly complex and data-rich environments. This section synthesizes developments in continual and federated learning, hybrid joint models, and self-supervised approaches—each responsive to challenges in heterogeneity, annotation cost, and decentralized data landscapes intrinsic to healthcare systems equipped with IoT and intermittent connectivity [3, 6, 8, 22, 26, 28, 33–36, 38, 47, 49, 53, 58, 61, 63, 64, 87, 88, 99, 100]. These

algorithmic schemes increasingly underpin personalized medicine, robust disease surveillance, and automated decision support.

Despite these advances, competing priorities shape real-world implementation. Architectures that enable modularity, plug-and-play interoperability, and principled ethics are highly advocated to accelerate deployment and align with evolving clinical and regulatory landscapes [1, 3, 6, 7, 11, 12, 14–16, 21, 22, 25–28, 30, 33–35, 38, 42–44, 47, 49, 51, 52, 54, 55, 58, 60–62, 65, 66, 74, 75, 78, 82, 84, 89, 91–94, 99, 100, 102]. However, the reality of deployment is shaped by persistent tensions, summarized in Table 10, where trade-offs between explainability, resource efficiency, and ethical compliance frequently arise.

A notable challenge is the absence of comprehensive, validated frameworks and benchmarks for truly modular, interoperable analytic platforms that ensure transparency, ethics, and governance across the diversity of clinical domains. Efforts to standardize data (e.g., reference materials for NGS [47]), harmonize imaging methodologies [1, 84], and develop open, API-driven integration and robust governance structures show promise but necessitate broader adoption and multi-sector coordination [1, 3, 6, 22, 25, 26, 28, 33–35, 38, 47, 49, 51, 52, 54, 55, 60, 61, 78, 84, 89, 93, 94, 100].

Future architectures must be explicitly designed to address key needs for auditability, explainability, scalability, and security while remaining flexible to the shifting requirements of genomics, imaging, clinical narratives, and temporal multisource data streams. There is increasing consensus that effective healthcare analytic systems should support: (a) harmonization and real-world benchmarking across modalities and institutions, (b) explainability and transparency extending from model architecture to outputs, (c) scalable deployment from centralized data centers to edge devices, and (d) robust mechanisms for ethical governance, audit, and regulatory compliance across diverse jurisdictions [28, 34, 35, 61, 88, 94, 100].

Unresolved debates persist in the literature concerning the prioritization of model accuracy versus transparency, the relative advantages of centralized versus federated architectures, trade-offs between data minimization and multimodal fusion, and the challenge of delivering robust performance under heterogeneous, low-quality, or incomplete data circumstances [6, 8, 53, 88, 94, 99, 100]. Comparative studies often reveal that no single strategy is universally superior; rather, hybrid models leveraging continual and federated learning, robust self-supervision, and cross-modal fusion frequently offer the best pathway to adaptable, scalable solutions [8, 36, 49, 58, 63, 64, 78, 88, 94, 99, 100]. Continued research is required to address inherent trade-offs and context-specific requirements, with calls for systematic benchmarking and transparent reporting across institutions and modalities [1, 28, 47, 61, 84].

Section Summary and Future Research Gaps: - Establish universally accepted modular frameworks and real-world benchmarks for cross-domain, interoperable analytic architectures. - Develop explainable, audit-ready algorithms capable of robust operation under noisy, incomplete, or imbalanced multimodal data. - Advance harmonization principles for integrating evolving clinical, omics, imaging, and contextual data streams at scale. - Foster effective ethical governance ecosystems supporting legal, societal, and regulatory imperatives as AI integration accelerates. - Investigate hybrid model design, balancing federated, continual, and centralized approaches for optimal resource efficiency, scalability,

Table 10: Core Algorithmic Tensions Limiting Healthcare Analytics Deployment

Aspect	Desirable Outcomes	Limiting Trade-offs/Challenges
Explainability	Transparent, trustworthy predictions; regulatory compliance	Reduced model accuracy, higher computational cost
Interoperability	Seamless integration with legacy and modern systems	Increased system complexity; standardization gaps
Resource Efficiency	Feasibility on edge/IoT devices; sustainable operation	Model miniaturization can reduce accuracy; limited scalability
Ethical Governance	Responsiveness to legal, clinical, and societal requirements	Fragmented standards; limited auditability and benchmarking

and local adaptation. - Enable open, transparent benchmarking and data sharing to facilitate comparative assessments and foster reproducibility in diverse healthcare contexts.

9.9 Summary

In summary, this survey has explored the objectives and scope of healthcare analytics and AI, focusing on critical challenges such as data heterogeneity, annotation scarcity, system scalability, interpretability, equity, standardization, privacy, compliance, and architectural sustainability. Distinct analytic strategies—ranging from traditional statistical modeling to modern machine learning and deep learning approaches—have been evaluated within clinical, operational, and public health domains. Alternative approaches often offer contrasting strengths; for example, deep learning methods may provide superior predictive accuracy but challenge transparency and interpretability, whereas rule-based systems and classical statistical models facilitate more transparent decision-making processes but may be less scalable to large, unstructured datasets. Ongoing debates revolve around the trade-offs between accuracy and interpretability, centralized versus federated data architectures, and the impact of regulatory frameworks on model deployment in practice. A synthesis of these perspectives underscores the importance of balancing technical rigor, ethical considerations, and sector-specific requirements. Ultimately, integrative approaches that harmonize methodological transparency, technical innovation, and ethical foresight are essential to realizing the transformative and equitable potential of analytics and AI in medicine.

10 Scalability, Toolkits, Standards, and Analytical Ecosystems

The rapid expansion of Artificial Intelligence (AI) applications across diverse domains has necessitated not only improvements in algorithmic performance, but also rigorous inquiry into the accompanying ecosystems supporting development and deployment. This section synthesizes advancements and challenges in scalability, toolkits, standards, and analytical ecosystems, which collectively underpin practical progress in the field. By discussing each aspect in turn, we aim to provide a holistic overview of the infrastructural and methodological landscape, clarifying how these components interact and where future improvements might be realized.

Within this context, we first examine how scalability is achieved through distributed architectures and advanced resource management. Next, we review the role of toolkits in facilitating reproducible and efficient experimentation. This is followed by a discussion of emerging standards—crucial for interoperability—and a survey of the expanding analytical ecosystems that frame current research and industry practices.

At the conclusion of each major subsection, we summarize explicit, bullet-pointed future research gaps or open questions to guide ongoing investigation.

10.1 Scalability

The proliferation of large-scale datasets and increasingly complex AI models has elevated scalability as a central concern in both academic and commercial settings. Resource allocation, parallelization, and dataset partitioning have each emerged as critical technical strategies. Distributed frameworks, such as those enabling parallel training over multiple GPUs or compute clusters, are now standard practice, greatly reducing time-to-insight for model development.

Scaling challenges intensify when addressing issues such as heterogeneous hardware, variable network topologies, and dynamic workload balancing. New research continues to focus on developing adaptive algorithms for efficient workload distribution and on minimizing communication overhead.

Future research gaps and open questions include: - How can current distributed training paradigms be adapted for increasingly heterogeneous hardware environments? - What novel algorithms can address the bottleneck of inter-node communication as model and dataset sizes continue to grow? - How might dynamic resource scaling be optimized in response to fluctuating workload demands in real-time AI applications?

10.2 Toolkits

AI research and deployment are profoundly shaped by the availability of robust, open-source toolkits. These frameworks abstract away much of the underlying complexity associated with hardware, low-level numerical operations, and distributed computing, thus lowering barriers to entry and fostering innovation. Prominent toolkits now offer extensive support for automated differentiation, optimized backends, and seamless integration with cloud platforms.

However, the evolution of toolkits also exposes tensions around version compatibility, long-term support, and the standardization of APIs. Further, reproducibility remains a concern, especially in the context of complex pipeline dependencies and evolving environmental dependencies.

Future research gaps and open questions include: - What best practices and technical mechanisms can further advance reproducibility and robustness in toolkit-based AI experimentation? - How might toolkits provide better support for modular, reusable components adaptable across diverse application requirements? - In what ways can toolkits facilitate seamless migration between local and cloud-based development environments?

10.3 Standards

The adoption of standards in AI has become increasingly important for ensuring interoperability, safety, and regulatory compliance. Standards affect not only file and data formats but also model exchange, benchmarking protocols, and documentation requirements. Active initiatives seek to harmonize practices across toolkits and platforms, reinforcing both scientific rigor and commercial viability.

Despite this progress, standardization efforts are challenged by rapid advances in both hardware and software, the multiplicity of competing platforms, and the diversity of application domains. Ongoing debate surrounds the establishment of common benchmarks, transparency in documentation, and legal considerations tied to intellectual property and data privacy.

Future research gaps and open questions include: - How can standardization keep pace with rapidly evolving methods and hardware? - What frameworks are needed to balance transparency and intellectual property in standard documentation? - Which new benchmarks are most representative for emerging, safety-critical AI domains?

10.4 Analytical Ecosystems

AI analytical ecosystems comprise the integrated toolchains, software libraries, and collaborative platforms that support the end-to-end lifecycle of research and deployment. These ecosystems enhance productivity, foster collaboration, and facilitate the aggregation and analysis of large-scale experimental results. Increasingly, they integrate visualization tools, experiment tracking systems, and interconnected data management pipelines.

Nevertheless, significant obstacles remain in unifying disparate ecosystem components, managing data provenance, ensuring reproducibility at scale, and promoting open science across institutional boundaries.

Future research gaps and open questions include: - How can analytical ecosystems be further streamlined for multi-institutional, cross-disciplinary collaboration? - What advances are required in provenance tracking and experiment management for large-scale reproducible research? - Which incentives and architectures best promote community-driven growth and sustainability of open analytical ecosystems?

By systematically addressing these core infrastructural pillars, the AI community can support more scalable, reproducible, and impactful research, and more efficient and trustworthy deployment across application domains.

10.5 Key Datasets and Software Toolkits

The exponential escalation of multi-modal, clinical, and Internet of Things (IoT) data volumes has necessitated a robust foundation of centralized datasets and open-source software toolkits. These developments underpin both methodological advances and translational applications across healthcare and analytical domains. Among the most influential centralized datasets is UniMod1K, which offers synchronized RGB, depth, and language data—addressing the long-standing challenge of multi-modality alignment—thus supporting advanced fusion models for object tracking and monocular depth estimation [85]. ImageNet-ESC, extending the paradigmatic ImageNet dataset into the audio-visual sphere, further promotes few-shot

learning by leveraging cross-modal associations and is extensively employed for benchmarking adaptation capabilities in both academic and industrial settings [55, 83]. Each of these datasets reflects domain-specific innovations: UniMod1K targets the integration challenges pertinent to vision and language, while ImageNet-ESC exemplifies the value of cross-modal adaptation in scenarios such as medical image segmentation and endoscopic diagnosis [55, 58, 83].

In digital health, the MIT-BIH Arrhythmia database and CHB-MIT seizure corpus provide vast, annotated electrocardiogram (ECG) and electroencephalogram (EEG) datasets. These resources are invaluable for developing and validating machine learning algorithms, fostering reproducible studies in arrhythmia detection and seizure prediction, respectively [3, 8, 13, 17, 19, 37, 38, 48, 58, 77–79, 86, 96]. Notably, contemporary studies employing MIT-BIH highlight the role of pre-trained convolutional neural networks coupled with sophisticated time-frequency transforms (e.g., continuous wavelet transforms) to maximize classification accuracy for arrhythmic events, emphasizing both performance and clinical interpretability [86]. Similarly, the CHB-MIT and Kaggle’s intracranial EEG datasets enable development of advanced deep learning systems—such as multiresolution convolutional neural networks leveraging frequency band decomposition—for real-time, patient-specific seizure forecasting in the clinical and home environments [18, 37, 78]. In comparative evaluations, such neural network models reach sensitivities up to 85% on benchmarked datasets, and their pipeline architectures are designed for prospective deployment in wearable devices and IoT-based monitoring [18, 37]. Collectively, this ecosystem facilitates algorithmic benchmarking, enables rigorous cross-institutional comparisons, and underpins the progress of scalable, generalizable AI in healthcare and sensor-driven analytics.

Software toolkits have concomitantly evolved to address the growing heterogeneity and complexity of analytics challenges. The `scikit-multimodallearn` library exemplifies general-purpose, open-source design tailored for multi-modal supervised learning, offering seamless integration with the broader Python machine learning ecosystem and providing specialized formatting algorithms for handling heterogeneous input types [13, 18]. This design supports workflows ranging from classification and regression to exploratory multi-modal analytics, thereby enabling both foundational research and rapid prototyping across disciplines. Radiomics platforms—particularly those stemming from the Image Biomarker Standardization Initiative (IBSI)—play a pivotal role in standardizing the extraction and interpretation of high-dimensional features from medical images across modalities such as CT, PET, and MRI, thereby substantially improving reproducibility and diagnostic reliability [1, 13, 35, 36, 63, 84]. These platforms have catalyzed large-scale studies in oncology, cardiology, and neurology, facilitating harmonized methods for imaging-based phenotype discovery and cross-center benchmarking. Furthermore, open-source code repositories associated with recent publications increasingly supply pre-trained models, annotation utilities, and reproducible computational pipelines that lower barriers to clinical and industrial adoption in areas such as cross-modal analytics, federated medical image analysis, sensor integration, and health monitoring [19, 48, 49, 78, 79]. The contemporary ecosystem is further strengthened by the growing emphasis on modularity, scalability,

and high-quality documentation, underpinned by well-specified interfaces and reference datasets, ensuring alignment with the technical demands of large-scale deployment.

Beyond data and software, the rigor of annotation and evaluation remains foundational for robust analytics—particularly in high-stakes domains such as clinical validation and IoT-driven automation. Standardized metrics, including positive percentage agreement (PPA), positive predictive value (PPV), response and delivery times, variation factors, and delivery accuracy, are now routinely utilized to enable fair benchmarking and to monitor performance against established baselines [1, 27, 28, 35, 42, 47, 51, 53, 54, 61, 76, 78, 84, 85, 99]. These metrics are embedded within regulatory frameworks, as demonstrated in next-generation sequencing and imaging analytics, where stringent, error-based workflows involving reference controls and multi-center validation are required for reliability, reproducibility, and auditability [1, 42, 47, 53, 61, 84]. Contrasting perspectives persist regarding key evaluation challenges. Heterogeneity of annotation formats, class imbalance, inconsistencies in ground truth assignment, and variability in domain-appropriate metric selection continue to pose obstacles to model generalizability and clinical translation [27, 28, 47, 51, 78, 99]. For instance, harmonization efforts in radiomics have highlighted the tradeoff between reproducibility and the need for flexible, task-specific feature sets [1, 35, 84]. In the context of EEG and ECG analytics, debates continue regarding the optimal balance between automated and expert-generated labels, and handling domain shifts across institutions and populations [18, 37, 86]. These unresolved aspects underscore an ongoing need for multi-institutional, diverse dataset curation, method transparency, and careful selection of performance metrics tailored to both translational relevance and regulatory standards. Continued attention to these challenges will be critical as the field advances toward automated, interoperable analytics and clinical decision support systems, driving further convergence of domain-specific and general-purpose strategies.

10.6 Secure, Scalable, and Interoperable Analytical Ecosystems

The expansive proliferation of distributed data sources—including federated clinical repositories and diverse IoT sensor streams—has crystallized the demand for analytic ecosystems that are secure, privacy-preserving, interoperable, and efficient at scale. Distributed and federated analytic approaches have emerged as primary solutions to the privacy constraints inherent in health and IoT data. These approaches enable collaborative model training without necessitating cross-institutional raw data exchanges [7, 11, 12, 14–16, 21, 41, 43, 46, 60, 65, 66, 75, 91–93, 95, 98, 102]. For instance, federated learning strategies such as FedAvg and FedProx have demonstrated near-centralized performance in distributed medical imaging tasks, all while maintaining robust privacy guarantees [41]. These frameworks have been evaluated on heterogeneous datasets across multiple modalities and pathology domains, highlighting strong generalizability. However, they also reveal persistent limitations, including inter-site data heterogeneity, communication bottlenecks, and challenges synchronizing model updates [10, 46, 75, 94, 95].

Security and auditability are increasingly enhanced by the integration of blockchain and related ledger technologies, which offer transparent, tamper-evident transaction records of both data access and analytic workflow execution [7, 12, 14, 16, 21, 41, 62, 65, 91, 93]. Combining blockchain-backed data provenance, secure model aggregation, and robust API-level integration enables the construction of verifiable analytical pipelines, which are crucial for regulated clinical environments and IoT deployments alike [1, 6, 26–28, 35, 47, 51, 61, 66, 78, 79, 84, 102]. The merger of federated analytics and blockchain architectures addresses pressing concerns such as data sovereignty, tamper resistance, and multi-institutional coordination. Nevertheless, these benefits often come at the cost of increased system complexity, transaction latency, and heightened resource demands, necessitating careful trade-off analysis in real-world settings [1, 8, 78].

The assurance of efficiency, reproducibility, and regulatory compliance in large-scale, interconnected deployments demands not only technical innovation but also robust standardization and governance frameworks [22, 26–28, 30, 33, 34, 38, 47, 49, 51, 53, 54, 58, 78, 79, 92, 94, 95, 99]. Landmark initiatives—for example, the IBSI project for radiomic feature harmonization and major efforts toward electronic health record interoperability—have yielded essential consensus protocols guiding data formatting, algorithmic benchmarking, and metric reporting, thereby fostering reproducibility and translational potential [13, 30, 36]. Comprehensive data platforms such as WCH-BDP exemplify these principles through their integration of interoperable data lakes, rigorous governance with standardized terminologies, natural language processing-based data structuring, and layered security frameworks, all designed to enable rapid and secure analytics at scale [64]. Notwithstanding these advances, the reality of deployment continues to be shaped by a variety of ongoing challenges:

- Incomplete or imperfect standardization across data sources and analytic processes

- Persistent data silos and mismatched ontologies hindering integration

- Technical heterogeneity across institutions limiting interoperability

- Disparities in resource allocation impacting scalability

- Evolving requirements for multi-stakeholder governance and consensus

The range of domains where secure and scalable analytical ecosystems are critical extends across healthcare, industrial Internet-of-Things (IIoT), scientific research, and energy infrastructure. In healthcare, the focus is often on integrating multimodal clinical, omics, and sensor data under stringent privacy and regulatory regimes. Recent work demonstrates both the promise and complexity of federated learning and big data platforms for clinical data integration and predictive analytics [8, 53, 64, 79, 94]. In industrial and energy domains, data fusion approaches leverage heterogeneous sensor streams and real-time machine learning for prognosis, monitoring, and optimized control, although technical and governance-related hurdles remain a challenge [6, 22, 26, 33, 38]. Across all settings, interoperability issues—arising from mismatched ontologies and technical standards—remain persistent, with significant disparities in infrastructure and resource allocation between institutions or stakeholders [10, 94].

There is also active debate within the literature regarding best practices and long-term strategies for balancing privacy, scalability, and utility. For example, while federated analytics and blockchain integration show promise for privacy and auditability, they present new trade-offs in computational efficiency and system complexity [1, 8, 78, 79]. Contrasting perspectives concern the extent to which technical harmonization (such as feature definition or algorithm standardization) versus governance (such as data-sharing agreements and oversight) should be prioritized. Furthermore, while standardization is often cited as foundational for reproducibility and translational impact, critics point to the practical limitations of omnibus protocols in fast-evolving technological domains and argue for more adaptive regulatory and technical frameworks [30, 53, 94, 95].

Superimposed on these infrastructure issues is a pressing requirement for analytical transparency, explainability, and trustworthiness, prerequisites for both clinical adoption and regulatory acceptance. Techniques such as comprehensive model auditability, embedded conceptual knowledge representation, graph-based causal modeling, formal verification, and explainability have been identified as foundational for future-proofing analytic pipelines and ensuring compliance within medical AI and IoT ecosystems [28, 34, 49, 53]. Despite their critical importance, these approaches frequently encounter real-world barriers: high annotation overhead, complexity of deployment, and challenges to computational scalability all temper their immediate impact in operational settings. Addressing these limitations requires sustained collaborative efforts spanning technical, clinical, and governance domains, including embedded standards and co-design with end-users. Such efforts remain pivotal for building impactful, sustainable analytics infrastructures across health, scientific, and industrial sectors.

A comparative perspective suggests that while technical solutions are increasingly sophisticated, there is no universally optimal strategy: trade-offs in privacy, efficiency, interoperability, and trustworthiness must be continuously revisited and aligned with domain-specific objectives, available resources, and evolving governance standards. Open debates and unresolved issues persist around the most effective blend of federated, blockchain, and data fusion approaches, particularly as the volume, diversity, and sensitivity of multimodal data continue to grow.

11 Conclusions, Synthesis, and Outlook

In this survey, we have provided a comprehensive examination of the major developments and challenges in the interdisciplinary intersection of AI domains. The synthesis of techniques and strategies from various subfields has demonstrated both significant progress and persistent obstacles requiring future exploration. As AI systems increasingly find application across disciplinary boundaries, deeper integration and collaboration will be essential.

To ensure seamless reading, we summarize the core themes and their implications before projecting potential research directions.

A primary theme emerging from recent work is the necessity for frameworks that unify perspectives across domains like machine learning, knowledge representation, and human-computer interaction. Researchers have made strides in bridging these gaps, yet methodological dissonances persist and often lead to incompatible

solutions. Addressing these challenges will significantly advance the design and deployment of robust AI systems.

The syntheses presented underscore the importance of cross-disciplinary evaluation metrics, standardized benchmarks, and shared vocabularies. While table-based overviews have been helpful in advancing community-wide understanding, more dynamic and integrated frameworks are required to foster meaningful dialogue and comparison.

To facilitate unified progress and inspire future research, we now highlight a set of research gaps and questions as explicit points for further investigation:

- How can standardized frameworks be established to support interoperability between emerging AI architectures across fields?
- What strategies can ensure robust evaluation practices that reflect both domain-specific requirements and generalized performance expectations?
- Which methodologies best facilitate transparency, interpretability, and human-in-the-loop collaboration—especially when integrating diverse AI technologies?
- How can learned representations and reasoning processes be meaningfully shared and exchanged between distinct subdomains?
- What socio-technical factors must be considered to ensure equitable, fair, and broadly beneficial outcomes, particularly for AI systems operating at disciplinary intersections?

Addressing these research gaps will strengthen the theoretical and practical foundations of cross-disciplinary AI. Enhanced collaboration and harmonization will empower future systems to meet the multifaceted needs of real-world applications.

Through continued investigation and synthesis, we anticipate further convergence of methods and concepts, paving the way for transformative advances in the field.

11.1 Synthesis of Advances Across Biomedical Signal Processing, Multimodal and Cross-Modal Analytics, Deep Learning, IoT/Real-Time Systems, Synthetic Data, and Explainable AI

The rapid convergence of advances in biomedical signal processing, multimodal and cross-modal analytics, deep learning, IoT-enabled real-time monitoring, synthetic data generation, and explainable artificial intelligence (XAI) has fundamentally reshaped the landscape of healthcare analytics and clinical operations [1–15, 17–39, 41–44, 47–49, 51–64, 66–72, 75–81, 83–88, 91–94, 96, 97, 99–102]. Signal processing remains the methodological foundation for precise feature extraction from biosignals such as EEG, ECG, sEMG, and medical imaging. Advanced signal processing methods, including rTV-gPDC for robust nonlinear causality analysis in multivariate physiological time series [81], MODWT-based multiresolution decomposition for seizure prediction [37], and dual-polynomial multiresolution techniques for myoelectric sEMG [80], are now routinely employed to improve signal integrity, attenuate noise and artifacts, and address nonlinearity within both clinical and IoT-driven contexts [15, 21, 37, 80, 81, 91]. Recent comparative studies also focus on optimizing time-frequency transformation methods (CWT vs. STFT) for ECG signal classification, revealing the superiority of certain wavelets in diagnostic performance and computational speed when feeding deep networks [86].

In parallel, deep learning architectures—notably convolutional neural networks (CNNs), transformers, and advanced encoder-decoder models—have established state-of-the-art benchmarks in medical data classification, detection, segmentation, and registration, frequently achieving diagnostic performance matching or surpassing human experts [1, 13, 42, 52, 53, 55, 58, 76, 85]. For example, 3D-UNet-based architectures with dense and residual blocks enable efficient and accurate coronary artery segmentation from CCTA [85], multiresolution CNNs support robust preictal/interictal EEG discrimination for seizure prediction [37], and dual-stream transformer frameworks (e.g., TransMatch) promote feature-level alignment for unsupervised deformable image registration [19]. The effectiveness of these models is significantly enhanced by sophisticated innovations in data fusion and multimodal learning. Frameworks leveraging cooperative, late, early, and intermediate joint representation learning, as well as cross-modal adaptation and robust multi-view co-training, efficiently resolve challenges associated with high heterogeneity, complementarity, and missingness, thereby enabling robust domain adaptation and comprehensive modeling of both physiological and regulatory processes [2, 19, 23, 28, 30, 32, 36, 37, 41, 51, 62–64, 75, 79, 88, 92, 93, 97, 102]. Cutting-edge studies further highlight advances in model selection for informative modality subsets under cardinality constraints [32], the application of cross-modal loss functions and causality interventions [41, 62, 75], and multi-view fusion for robust seizure detection in EEG [2].

These methodological advances are accompanied by a transformation of healthcare delivery, largely attributable to the integration of IoT and real-time systems. Ubiquitous sensor networks, scalable analytics pipelines, and federated computation now support point-of-care diagnostics, home monitoring (such as wearable EEG and IMU for epilepsy detection in unsupervised environments) [18, 49, 50, 60, 78], and the optimization of operational workflows across the health system [72, 78, 94, 99]. Novel proportionate data analytics methods for medical data streams in IoT contexts [78] and hybrid recurrent modeling for menstrual health monitoring [49] showcase the capabilities of adaptive, real-time clinical monitoring.

Key methodological progress also stems from the introduction of privacy-preserving synthetic data generation techniques, such as generative adversarial networks (GANs), variational autoencoders (VAEs), and agent-based simulations. These approaches address limitations in data sharing, rare-event modeling, and regulatory compliance, while simultaneously necessitating the development of robust digital trust, audit, and chain-of-custody frameworks to mitigate risks relating to bias, re-identification, and provenance tracking [29, 57, 79, 81]. For example, digital chain-of-custody solutions and differential privacy mechanisms are proposed to secure synthetic data use cases in clinical contexts [29], and aligned whole-slide image (WSI) registration methods facilitate large-scale analysis of tumor heterogeneity while greatly reducing expert workload [57].

Additionally, the embedding of explainable AI mechanisms—most notably, SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and post-hoc saliency mapping—directly facilitates regulatory transparency, clinician trust,

and eventual clinical adoption. Recent works demonstrate the practical benefits of these mechanisms: SHAP analysis for self-explaining diabetes diagnosis interfaces [20], XAI-augmented multi-view EEG seizure detection [2], and comprehensive post-hoc explainability frameworks for biomedical time series classification that resonate with clinician expectations [39]. Empirical evidence demonstrates tangible improvements in diagnosis, risk prediction, and operational support [2, 6, 20, 29, 39, 75, 79]. Collectively, these advances are propelling a systemic transformation from reactive, retrospective healthcare toward a proactive, data-driven, and adaptive paradigm.

11.2 Recap of IoT-Specific Strategies: Proportionate Data Analytics, HRLS-TS for Real-Time Monitoring, and Dynamic Error Detection

IoT-focused data analytics methodologies have matured considerably, enabling them to address the inherent complexity, noise, and heterogeneity of biomedical and operational data streams. Proportionate Data Analytics (PDA) exemplifies these advancements by providing an adaptive framework designed to distinguish between natural data variation and authentic anomalies within heterogeneous real-time signals. This distinction is crucial for maintaining an optimal balance between sensitivity (detecting true anomalies) and specificity (reducing false alarms), thus preventing system overload and ensuring reliable system performance [78]. PDA adopts regression-based statistical modeling to dynamically calibrate error detection thresholds, using error and variation decomposition across multiple, recurring time windows. This enables the system to maintain high identification and delivery ratios regardless of fluctuations in data quality, as demonstrated by its performance across key metrics such as accuracy, identification ratio, delivery, variation factor, and processing time.

Additionally, the Hybrid Recurrent Long Short-term based Tyrannosaurus Search (HRLS-TS) algorithm highlights the effectiveness of integrating deep learning with evolutionary computation for real-time, context-aware biomedical monitoring. For example, in menstrual physiology tracking, HRLS-TS leverages LSTM-based temporal modeling, enabling it to handle nonstationary data streams, while incorporating adaptive metaheuristic optimization to facilitate hyperparameter and feature selection. This hybrid approach achieves both high predictive accuracy and computational efficiency under the demanding requirements of streaming IoT healthcare applications [49].

Collectively, innovations such as PDA and HRLS-TS exemplify the ongoing evolution in IoT healthcare analytics, reflecting the field's growing ability to manage signal variability and noise while maintaining scalability and delivering actionable insights effectively for both clinical and operational decision-making.

11.3 Implications for Disease Detection, Personalized/Precision Medicine, and Clinical/Operational Workflow Integration

This survey aims to systematically review the integration of multimodal data, cross-modal analytics, and AI-driven approaches across disease detection, precision medicine, and healthcare operations,

highlighting technological trends, methodological progress, and implementation challenges. In this synthesis, we evaluate how the convergence of the discussed breakthroughs is accelerating healthcare transformation while linking these implications to the survey's core objectives.

The convergence of technological and methodological breakthroughs discussed herein is accelerating healthcare transformation across disease detection, personalized and precision medicine, and workflow optimization. For disease detection, proactive analytics leveraging multimodal and cross-modal signals—including organ-specific liquid biopsies, multi-omic profiles, and continuous sensor-based physiological monitoring—facilitate earlier risk identification, often preceding the onset of overt symptoms or irreversible tissue pathology [10, 14, 52, 57, 79]. In key domains such as infectious disease and oncology, rapid, scalable, and high-resolution stratification is now achievable—propelled by advances in molecular diagnostics, digital pathology, and AI-driven imaging and sequence analysis [9, 11, 27, 30, 43, 52, 56, 63, 79, 83, 96].

Transitioning from detection to intervention, personalized and precision medicine initiatives are increasingly feasible as granular, multimodal patient phenotyping becomes the norm; integration across clinical, molecular, imaging, sensor, and environmental data streams enables sophisticated analytics pipelines capable of modeling intricate interactions and inferring causal relationships [23, 28, 36, 41, 42, 44, 52, 53, 55, 57, 92, 101, 102]. Research demonstrates that real-time digital interventions—including continuous glucose monitoring feedback systems and multi-source longitudinal tracking—lead to more tailored treatments, dynamic intervention adjustments, improved adherence, and measurable outcome improvements for chronic and complex conditions [8, 50, 81, 86]. These developments are well-aligned with the survey's objective of clarifying how multi-source data analytics can directly impact individualized patient trajectories.

A further central objective is the clinical and operational integration of these methodologies. Automated systems for segmentation, scheduling, triage, and capacity management—enabled by deep learning, time-series analytics, and explainable AI—reduce diagnostic bottlenecks, optimize resource allocation, and minimize delays in critical care pathways (e.g., cardiology, surgery, radiology) [3, 6, 22, 25, 38, 55, 85, 86]. In parallel, federated and cloud-based hospital data platforms are driving the interoperability and accessibility of analytics across multi-institutional settings, though continuing challenges in data harmonization and standardization persist [17, 77]. The ongoing adoption of explainable AI and integrated feedback systems is laying the groundwork for a more transparent, collaborative, and continuously learning healthcare environment.

In summary, these implications underscore the overarching goals of this survey: to map the landscape of methods enabling earlier and more accurate disease detection, support actionable and personalized decision-making, and enhance workflow efficiencies through integrated multimodal and cross-modal analytics. The field is rapidly evolving toward more holistic, patient-centered, and operationally efficient healthcare, though barriers in standardization, equity, and real-world implementation must still be addressed.

11.4 Future and Persistent Challenges: Standardization, Global Scalability, Heterogeneity, Explainability, Digital Equity, Privacy/Security, Responsible AI, and Collaborative Research

Despite significant progress, several persistent and systemic challenges must be addressed to translate these advances into large-scale, equitable, and clinically impactful solutions. Chief among these is the need for rigorous standardization—both in feature definition (for example, through initiatives such as the Image Biomarker Standardization Initiative and advances in radiomics/texture analysis) and in clinical reporting. Even subtle inconsistencies in data computation or documentation can undermine reproducibility, limit interoperability, and impede clinical adoption [1–39, 41–44, 46–49, 51–64, 66–72, 75–81, 83–88, 91–94, 96, 97, 99, 100, 102].

Additional barriers include:

Lack of universal data standards: Inconsistent structure, labeling, and exchange protocols impede interoperability and multi-center collaborations [17, 68, 77].

Global scalability and heterogeneity: State-of-the-art AI and signal processing models often demonstrate reduced generalizability outside well-annotated, homogeneous cohorts, calling for improved domain adaptation, quality-aware fusion, and dynamic modality selection [32, 57, 71, 97].

Explainability: Progress toward actionable and domain-relevant explanations is critical for supporting clinical accountability, user trust, and regulatory acceptance [6, 20, 75, 79].

Digital equity and privacy/security: Variability in access to analytics, infrastructure, and digital literacy—both inter- and intra-regionally—risks entrenching health disparities. Concurrently, the transition to granular, continuous, interoperable data streams heightens privacy and security risks, necessitating progress in cryptography, differential privacy, and auditable governance [39, 68, 79, 81, 81, 86].

Responsible AI and collaborative research: Ensuring responsible, bias-mitigated AI deployment requires regulatory harmonization and inclusive frameworks that bring together multidisciplinary stakeholders across research, clinical, technical, regulatory, and patient spheres [1–39, 41–44, 46–49, 51–64, 66–72, 75–81, 83–88, 91–94, 96, 97, 99, 100, 102].

To provide a clear overview, the following table summarizes the persistent challenges along with their identified impacts and key needs:

In summary, the synthesis of progress across biomedical signal processing, multimodal and cross-modal analytics, deep learning, IoT/real-time systems, synthetic data methodologies, and explainable AI marks a decisive step toward more precise, predictive, and participatory healthcare. Nevertheless, realization of this promise will depend upon concerted and sustained efforts to standardize, validate, explain, secure, and equitably distribute these innovations at scale—always guided by ethical, social, and clinical imperatives.

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Table 11: Persistent Challenges and Required Interventions for Scaling Biomedical AI in Healthcare

Challenge	Impact	Key Needs and Solutions
Standardization	Limits reproducibility, interoperability, clinical trust	Universal data formats, reporting standards, feature harmonization (e.g., Image Biomarker Standardization Initiative)
Global Scalability and Heterogeneity	Reduces accuracy in diverse/underrepresented groups	Domain adaptation, quality-aware fusion, data augmentation for imbalanced datasets
Explainability	Slows clinical adoption, impedes trust and accountability	Domain-relevant, actionable explanations (e.g., SHAP, LIME); regulatory guidance on XAI
Digital Equity and Privacy/Security	Exacerbates health disparities, threatens confidentiality	Policy-driven infrastructure investments, digital literacy programs, advanced privacy and security technologies
Responsible AI and Collaborative Research	Risks bias, misdeployment, ethical lapses	Inclusive stakeholder collaboration, rigorous validation, transparent and ethical governance

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