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Toward trustworthy digital healthcare: A system-level convergence of IoMT, large language models, and explainable AI

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A R T I C L E I N F O

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A B S T R A C T

The Internet of Medical Things (IoMT) enables continuous monitoring, remote diagnosis, and personalized treatment through interconnected medical devices operating across edge, cloud, and local environments. As a communication-centric infrastructure, IoMT depends on interoperability, low-latency networking, and coordinated intelligence to support reliable healthcare services. Realizing its full potential requires computational models that are interpretable, robust, and trustworthy. Large Language Models (LLMs) offer strong capabilities in natural language generation and contextual reasoning for clinical documentation, patient interaction, and decision support, yet their black-box behavior raises concerns regarding transparency and clinical trust. Explainable Artificial Intelligence (XAI) addresses these challenges by providing mechanisms for interpretability and accountability. Although IoMT, LLMs, and XAI have each advanced significantly, prior studies have largely examined them as separate research directions or through limited partial integrations. This work presents a unified system-level analytical study of their convergence in healthcare, positioning IoMT as the foundational infrastructure, LLMs as the contextual reasoning layer, and XAI as the trust-enabling layer for transparency and accountability. Furthermore, the paper systematically examines this convergence through rigorous analysis of architectural foundations and diverse healthcare application domains, and presents clinically grounded case studies to offer a unified, comprehensive, and forward-looking perspective on trustworthy digital healthcare systems.

1. Introduction

The provision of medical care has always been central to human society, yet contemporary healthcare systems are increasingly strained by levels of demand that exceed earlier expectations. Global population growth, aging demographics, and recurring large-scale public health crises continue to place sustained pressure on existing healthcare infrastructures [1]. These challenges have accelerated the need for scalable, technology-driven solutions that can extend care delivery beyond traditional clinical environments while maintaining reliability and quality. In this context, the Internet of Medical Things (IoMT) has emerged as a practical paradigm for enhancing healthcare accessibility, efficiency, and continuity of care.

As a specialized extension of the Internet of Things (IoT), IoMT integrates wearable sensors, smart medical devices, and networked monitoring systems to enable continuous acquisition and transmission of patient data through cloud, edge, and hybrid platforms [2,3]. Rather than replacing conventional care models, IoMT-based systems increasingly complement clinical practice by supporting continuous observation, remote monitoring, and early intervention outside hospital settings. Such capabilities are particularly valuable for populations requiring long term or frequent care, including older adults, patients with chronic diseases, and individuals with limited mobility [4]. By reducing in-person consultations, IoMT supports proactive care delivery and more efficient use of clinical resources.

The integration of Artificial Intelligence (AI) has further expanded the role of IoMT by embedding analytical intelligence directly into healthcare workflows. AI-enabled IoMT platforms can process real-time physiological signals and historical patient data to support early diagnosis, predictive risk assessment, and personalized treatment planning [5–7]. This evolution reflects a transition from passive data collection toward intelligent, context-aware healthcare systems capable of assist-

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Table 1
Comparative analysis of existing studies and this work with respect to the convergence of IoMT, LLMs, and XAI in healthcare.

Ref.	IoMT	IoMT Arch.	IoMT Pillars	IoMT Tech.	IoMT Apps	IoMT Datasets	LLMs in HC	LLMs in IoMT	XAI in HC	XAI in IoMT	IoMT–LLM–XAI	Agentic Edge AI	Case Studies	Future Work
Ours	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
[13]	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
[14]	✓	✗	✗	✓	✓	✓	✗	✗	✗	✗	✗	✗	✗	✓
[15]	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗	✗	✓	✓
[16]	✓	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✓	✓
[17]	✓	✓	✗	✓	✓	✗	✗	✗	✗	✗	✗	✗	✓	✓
[18]	✓	✓	✗	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
[19]	✗	✗	✗	✗	✓	✓	✗	✗	✓	✓	✗	✗	✓	✓
[20]	✓	✓	✓	✓	✓	✗	✗	✗	✓	✓	✗	✗	✓	✓

ing clinical decision-making. However, the increasing complexity of AI models also introduces concerns related to transparency, interpretability, and trust, particularly in safety-critical medical settings. Within this broader AI landscape, Large Language Models (LLMs) have gained significant attention due to their capacity to process unstructured clinical information, summarize medical records, and generate natural language outputs that facilitate communication among clinicians, patients, and digital systems [8,9]. When integrated with IoMT infrastructure, LLMs enable the transformation of heterogeneous sensor data and clinical documentation into contextualized, human-readable insights that support intelligent clinical workflows. At the same time, many high performance AI systems, including LLMs, operate as opaque models, limiting clinicians' ability to understand, validate, and trust model outputs [10]. These limitations pose significant challenges for clinical adoption, regulatory compliance, and ethical accountability. Explainable Artificial Intelligence (XAI) addresses these challenges by providing mechanisms that enhance model transparency and clarify decision-making processes. In healthcare environments, where decisions carry substantial clinical and ethical consequences, XAI plays a critical role in supporting trust, interpretability, and responsible deployment of AI-driven decision support systems [11,12]. When combined with IoMT and LLM-driven intelligence, XAI serves as a foundational component for building trustworthy and accountable healthcare ecosystems. The convergence of IoMT, LLMs, and XAI represents a promising yet insufficiently explored direction in the development of advanced healthcare systems. In such integrated architectures, IoMT serves as the data acquisition and communication backbone, LLMs provide high-level reasoning and contextualization, and XAI ensures interpretability and accountability across the decision pipeline. Although substantial progress has been achieved within each domain individually, existing studies often address these technologies in isolation or through limited pairwise integrations. A unified, system-oriented analysis of their triadic convergence, with IoMT as the core infrastructure, remains limited.

Motivated by this gap, this paper presents a structured analytical study of IoMT enabled healthcare systems and systematically examines their convergence with LLMs and XAI. By synthesizing architectural principles, integration strategies, and trust-related considerations, this work aims to provide a coherent foundation for designing intelligent, explainable, and patient-centered healthcare systems capable of operating across diverse clinical contexts and resource-constrained environments.

1.1. Related work and prior studies

A substantial body of prior work has investigated the roles of IoMT, LLMs, and XAI in healthcare systems. However, most existing studies address these domains separately or examine only partial overlaps, without fully exploring their combined implications within an integrated healthcare architecture. In particular, earlier studies typically concentrate on IoMT infrastructures or individual AI components, leaving the joint interaction among IoMT, LLMs, and XAI insufficiently examined from a system-level perspective.

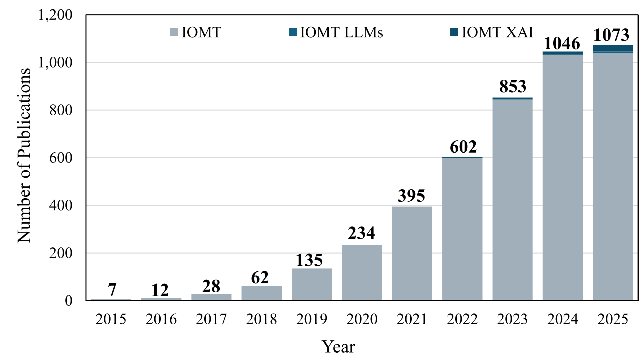

Fig. 1. Publication trends highlighting increasing research interest in IoMT, LLMs, and XAI for healthcare applications between 2015 and 2025.

Several studies have analyzed IoMT in healthcare by focusing on system architectures, enabling technologies, deployment layers, and application domains [13–18]. These works provide valuable discussions on communication models, device ecosystems, data management strategies, and security considerations, and some extend their scope to emerging integrations with deep learning, blockchain, or cloud-based platforms. While these contributions enhance understanding of the structural and operational foundations of IoMT, they generally offer limited analysis of explainability requirements or the emerging influence of language-driven intelligence within medical systems.

Parallel to this, a number of studies have examined XAI in healthcare, with attention to transparency, interpretability, and trust in medical AI applications [19,20]. These works discuss how XAI techniques can improve clinical confidence and regulatory alignment, including the use of lightweight and interpretable models suitable for IoMT environments. Nevertheless, such studies rarely consider the role of large language models or the implications of language-based interaction when combined with continuous sensing and data streams provided by IoMT infrastructures. Despite the relevance of these individual research directions, the literature lacks a unified examination of how IoMT, LLMs, and XAI can be jointly integrated within a coherent healthcare framework. In particular, there is limited work that explicitly positions IoMT as the central infrastructure while analyzing its convergence with language-enabled intelligence and trustworthy AI mechanisms. This gap becomes increasingly significant as healthcare systems move toward more autonomous, interactive, and patient-centered models of care.

As summarized in Table 1, prior studies mainly address isolated parts of the overall landscape such as IoMT foundations, healthcare applications, datasets, or selected XAI related aspects with only limited attention to LLMs in healthcare. These works remain restricted to standalone themes or partial pairwise overlaps and do not progress toward a unified convergence framework. The distinctive contribution of the present study lies in its explicit treatment of convergence dimensions that are entirely absent from the compared literature. Most notably, it is the only

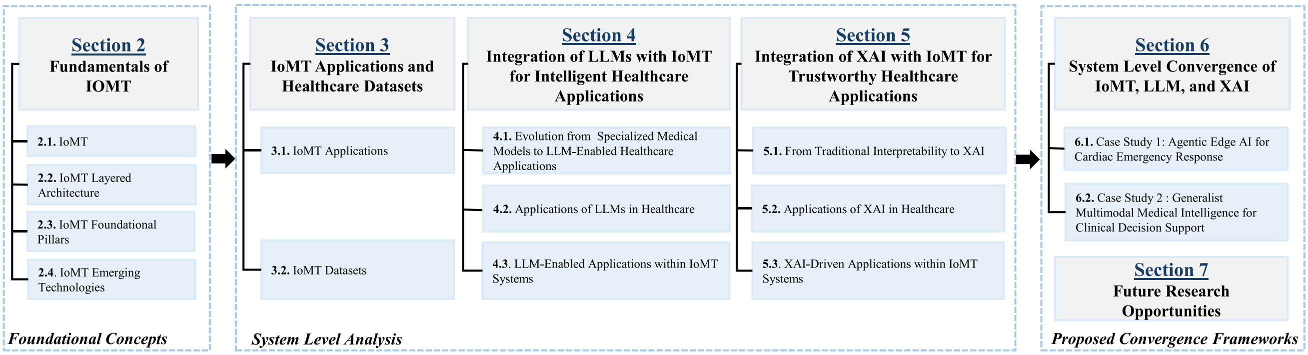

Fig. 2. A detailed overview of the paper structure and topics covered.

study in Table 1 to cover LLMs in IoMT, the full IoMT-LLM-XAI triadic convergence, and forward-looking integration perspectives including agentic edge AI and case studies within a unified healthcare-oriented analysis. These dimensions shift the discussion from examining separate technologies toward understanding how IoMT, LLMs, and XAI can function together as an integrated and trustworthy digital healthcare ecosystem. In contrast to existing literature that treats these domains as separate or pairwise combinations, this work advances a unified system-level analytical framework that treats their triadic convergence as a coherent design problem. The specific contributions are: first, a four-layer taxonomy that maps healthcare datasets to IoMT architecture while identifying integration points for LLM intelligence and XAI trust mechanisms; second, clinically grounded case studies that operationalize the convergence under clinician oversight, privacy preservation, and RAG supported reasoning; and third, a structured research roadmap addressing computational complexity, latency constraints, hallucination risks, and model robustness challenges. By synthesizing architectural principles, integration strategies, and trust-related considerations across sensing, reasoning, and interpretation layers, this study provides a foundation for intelligent, explainable, and accountable healthcare systems that existing literature does not offer.

1.2. Study scope and methodology

This study examines the evolving role of IoMT in healthcare, with particular emphasis on its integration with LLMs and XAI from a system-level perspective. To ground the analysis in existing research and capture representative developments across these domains, a structured literature exploration was carried out using widely adopted academic databases, including Google Scholar, Web of Science, IEEE Xplore, and the ACM Digital Library. Relevant publications were identified using domain-specific search terms related to IoMT, healthcare-oriented IoT systems, language-enabled intelligence, and explainable AI. Following the removal of duplicate records, candidate studies were screened based on topical relevance, with in-depth examination performed for works that contributed directly to understanding architectural design, integration strategies, or trust-related considerations. Studies were included based on direct relevance to IoMT architecture, LLM integration in healthcare, or XAI applications in clinical settings. Works were excluded if they addressed only generic IoT systems without medical application context, or if they lacked sufficient technical detail to contribute meaningfully to the convergence analysis. The screening process prioritized papers reporting concrete integration strategies, architectural specifications, or trust-related mechanisms (interpretability, privacy, robustness) over purely theoretical or peripheral contributions. This criterion ensured that the examined studies could be systematically mapped to the four-layer taxonomy and case study frameworks presented in Sections 2 and 6, respectively.

Fig. 1 illustrates the temporal evolution of research activity within this interdisciplinary space. An overall upward trend is observed between 2015 and 2025, with early activity remaining limited before expanding steadily over time. Research output increases sharply after 2020, reflecting growing interest in intelligent and connected healthcare systems. A pronounced rise in publications is visible between 2021 and 2023, followed by continued growth through 2024 and the end of 2025. Beyond the increase in volume, the thematic emphasis of the literature also evolves across this period. While early studies predominantly focus on IoMT centric infrastructures and sensing technologies, later contributions increasingly address higher-level intelligence, reasoning capabilities, and interpretability mechanisms, including the incorporation of LLMs and XAI. The trend depicted in Fig. 1 reflects a gradual transition from device focused IoMT research toward more comprehensive system-level frameworks that integrate data acquisition, intelligent reasoning, and transparency. This progression highlights the increasing maturity of the field and motivates the need for structured analytical perspectives that examine how IoMT, LLMs, and XAI can be jointly aligned to support intelligent, interpretable, and interconnected healthcare systems.

1.3. Contributions and organization

This paper presents a unified, system-oriented analytical study of the convergence among IoMT, LLMs, and XAI in the context of intelligent and trustworthy healthcare systems. Rather than treating these technologies in isolation, the study synthesizes their interactions from an architectural and design perspective, with a focus on enabling explainable, automated, and patient-centered medical care. The main contributions of this work are summarized as follows:

- We introduce a unified system-level analytical study of the convergence of IoMT, LLMs, and XAI in healthcare, explicitly positioning IoMT as the foundational infrastructure, LLMs as the contextual intelligence layer, and XAI as the trust-enabling layer, addressing a gap not comprehensively covered in prior studies.
- We analyze the foundational elements of IoMT, including architecture, core pillars, and emerging technologies, to establish a system-level understanding of its operational role in healthcare environments.
- We provide a system-oriented analysis of IoMT applications and organize representative healthcare datasets according to IoMT architectural layers, highlighting their relevance for intelligent, remote, and personalized medical care.
- We examine the role of LLMs in healthcare systems, with particular emphasis on their integration with IoMT to enable context-aware reasoning, automation, and intelligent clinical workflows.
- We analyze the role of XAI in supporting trustworthy and transparent AI-driven healthcare systems, focusing on interpretability and accountability within IoMT-based deployments.

- We propose conceptual integration frameworks and clinically grounded case studies that examine how IoMT, LLMs, and XAI can be jointly organized within edge-centric and human-supervised healthcare workflows. These frameworks illustrate how wearable sensing, decentralized agents, knowledge-grounded reasoning, and explainability can support real-time monitoring, personalized decision support, and trustworthy clinical interpretation while preserving clinician oversight, privacy, and accountability.
- We identify key design challenges and outline open research opportunities that must be addressed to advance this emerging interdisciplinary domain.

Unlike existing studies that mainly address isolated domains or partial overlaps, this work integrates architecture, applications, datasets, intelligence, and trust into a single healthcare-oriented convergence framework. Overall, this work serves as a system-level reference for researchers and practitioners aiming to design, deploy, and evaluate intelligent, context-aware, and trustworthy healthcare solutions at the intersection of IoMT, LLMs, and XAI.

The remainder of this paper is organized as follows. Section 2 introduces IoMT in healthcare, discussing its core concepts, layered architecture, foundational pillars, and emerging technologies. Section 3 examines IoMT applications across healthcare domains and analyzes representative datasets that support system development and evaluation. Section 4 explores the integration of LLMs with IoMT and its implications for intelligent healthcare services. Section 5 focuses on the role of XAI within IoMT-based systems. Section 6 synthesizes the unified convergence frameworks of IoMT, LLMs, and XAI, along with representative case studies, to establish a foundation for intelligent, explainable, and adaptive healthcare ecosystems. Section 7 discusses limitations and future directions, and Section 8 concludes the paper. Fig. 2 illustrates the overall structure of the study and helps readers to navigate through the paper.

2. Fundamentals of IoMT

This section provides a comprehensive analysis of IoMT, covering its layered architecture, foundational pillars, and enabling technologies. We also highlight several emerging technologies that enhance IoMT, including hardware security primitives, networking paradigms, data management approaches, and AI techniques.

2.1. IoMT

The Internet of Medical Things (IoMT) refers to the integration of medical devices and healthcare applications with digital communication technologies to support the continuous collection, transmission, and analysis of real-time health data. Rather than operating as isolated systems, IoMT components function as interconnected entities that enable data-driven clinical decision-making across diverse healthcare settings. These systems encompass a broad range of technologies, including wearable devices, physiological sensors, diagnostic platforms, and remote monitoring solutions, all aimed at improving care delivery while enhancing operational efficiency. Prior studies have demonstrated the potential of IoMT to reduce healthcare-related costs [21], improve the responsiveness of medical services, and contribute to better patient outcomes [22]. Its relevance became particularly evident during the COVID-19 pandemic, which significantly accelerated adoption due to the urgent need for remote healthcare solutions such as telemedicine, virtual consultations, and remote diagnostics [13]. During this period, remote health services transitioned from being optional technologies to essential components of everyday healthcare delivery, enabling access to medical support with minimal physical interaction unless clinically necessary.

Wearable sensors, for instance, allow continuous monitoring of physiological signals and facilitate early anomaly detection, while remote monitoring systems support the long-term management of chronic diseases and help reduce unnecessary hospital visits [18]. Beyond individual-level care, data generated through IoMT infrastructures can be leveraged for large-scale predictive analytics, supporting public health surveillance tasks such as early outbreak detection, disease trend analysis, and resource planning [23]. Fig. 3 summarizes the key benefits and enabling technologies that underpin IoMT-based healthcare ecosystems.

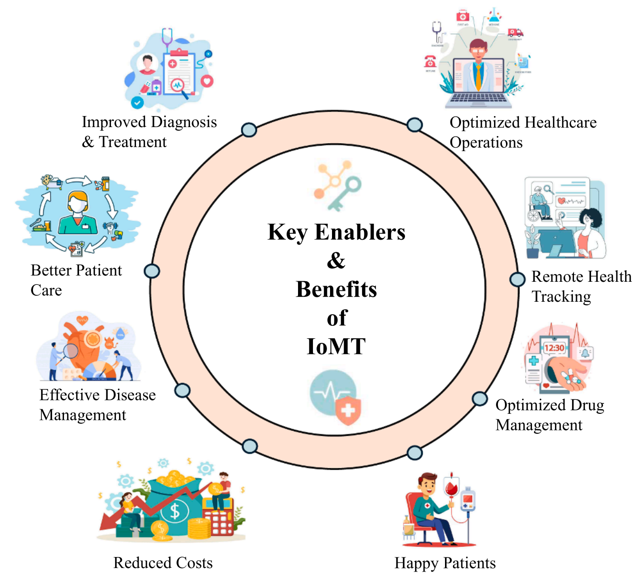

Fig. 3. Key enablers and benefits of the IoMT in enhancing modern healthcare delivery.

2.2. IoMT layered architecture

The widespread availability of Internet connectivity has accelerated the adoption of IoMT-based solutions across a wide range of healthcare domains [18]. To organize the functional complexity of these systems, layered architectural models have become a commonly adopted design paradigm. Such models provide a structured way to separate data acquisition, communication, processing, and service delivery functions, enabling scalability, interoperability, and modular system development [18]. Existing research describes multiple architectural interpretations of IoMT systems, most notably three-layer [24] and four-layer structures [13,18]. While the specific terminology and boundaries of these layers vary across studies, the underlying principles remain largely consistent. In this work, a four-layer architectural perspective is adopted, consisting of the Medical things layer, Communication layer, Platform layer, and Application layer, as illustrated in Fig. 4. This layered view provides a clear system-level abstraction that supports analysis of data flow, intelligence integration, and trust-related mechanisms within IoMT-enabled healthcare environments. The following subsections describe each layer in detail, outlining their primary functions, key components, and relevance to the design and deployment of intelligent healthcare systems.

2.2.1. Medical things layer

This layer serves as the foundation for the IoMT architecture. It is responsible for acquiring physiological and health-related data through connected medical devices, including wearable sensors, implantable tools, diagnostic equipment, and environmental monitors [25]. The Medical things layer is responsible for making IoMT executable. This layer enables the data collection process through multiple forms of sensors from the remote patient sites, transmitting data to healthcare professionals in real-time, which helps medical professionals act proactively. These devices, deployed on the body, in clinical settings, or in home-based care, are equipped with sensors, actuators, and controllers designed to continuously monitor vital parameters. This layer plays a central role in data acquisition, enabling real-time health monitoring and early anomaly detection. Emerging research in this domain addresses sensor biocompatibility, measurement accuracy, miniaturization, and energy efficiency. Advances in power technologies, such as micro-batteries, energy harvesting systems, fuel cells, and supercapacitors support reliable, long-term sensor operation [26].

2.2.2. Communication layer

This layer is responsible for transmitting medical data collected by edge devices to centralized processing platforms or cloud infrastructures [23]. The Communication layer is responsible for transporting sensory data collected from Medical things layer. This data exchange relies on a range of communication technologies, including traditional wired and wireless systems, as well as emerging modalities such as molecular communication. To ensure reliable, secure, and low-latency transmission, this layer incorporates a range of network protocols and standards. Common technologies include Body Area Networks (BAN), Wireless Sensor Networks (WSN), Bluetooth, Zigbee, Wi-Fi, and Radio Frequency Identification (RFID). Furthermore, cellular networks ranging from 2G to the emerging 6G spectrum, as well as Near Field Communication (NFC), are used to accommodate diverse IoMT use cases [13]. These technologies collectively facilitate seamless integration and communication across personal, local, and wide-area healthcare environments, thereby supporting efficient data exchange and coordinated medical services.

2.2.3. Platform layer

The Platform layer plays a central role in IoMT architectures by enabling seamless data integration, real-time analytics, and the deployment of healthcare applications, acting as an intermediary between device-level data acquisition and end-user services [13]. This layer is responsible for aggregating heterogeneous data streams generated by distributed medical devices and ensuring that they can be processed, stored, and accessed in a unified manner. To support these functions, the Platform layer typically relies on a combination of IoT platforms, edge and fog computing frameworks, cloud infrastructures, big data analytics pipelines, Health Information Exchange (HIE) systems, and application programming interfaces (APIs) [25]. Edge and fog components are often employed to perform preliminary processing and latency-sensitive analytics closer to data sources, while cloud-based platforms provide scalable storage, advanced computation, and long-term data management capabilities. Together, these technologies enable efficient data processing, aggregation, and visualization across diverse healthcare environments. Interactive dashboards and visualization tools are commonly integrated within this layer to translate complex analytical outputs into actionable insights for clinicians, administrators, and other stakeholders. The selection of platform technologies is generally influenced by several practical considerations, including scalability requirements, interoperability with existing clinical systems, data security and privacy constraints, regulatory compliance obligations, and the specific operational characteristics of the target healthcare setting. As a result, the Platform layer serves as a critical foundation for enabling reliable, flexible, and analytics-driven IoMT applications.

2.2.4. Application layer

The Application layer represents the topmost tier of the IoMT architecture, where processed data and analytical outputs generated by the Platform layer are translated into end-user services and clinical functionalities. Building upon the integrated data management, analytics, and visualization capabilities of the Platform layer, this layer delivers healthcare applications that directly support clinical decision-making, patient engagement, and operational management [13]. Applications at this layer encompass a wide range of use cases, including remote patient monitoring, telemedicine systems, clinical decision support tools, chronic disease management platforms, and personalized health applications. By leveraging insights derived from real-time and historical data, these applications enable clinicians to track patient conditions, identify abnormal patterns, and intervene in a timely manner. At the same time, patient-facing applications facilitate continuous engagement by providing feedback, alerts, and self-management support outside traditional clinical settings.

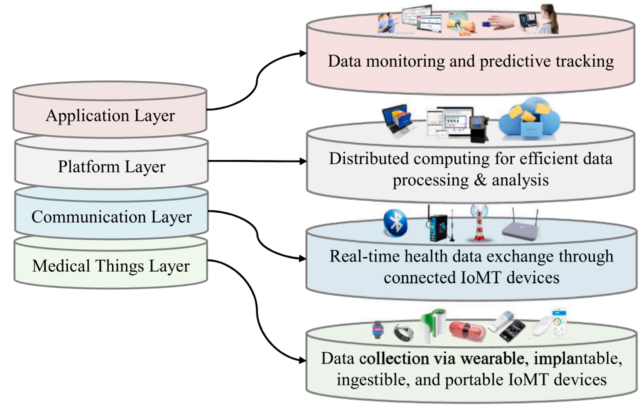

Fig. 4. Layered architecture of the IoMT, illustrating the hierarchical flow of data from medical devices to application-level services.

2.3. IoMT foundational pillars

Although layered architectures provide a structured framework for conceptualizing IoMT systems, it is equally important to recognize the fundamental pillars that underpin the development of reliable, resilient healthcare infrastructure. As depicted in Fig. 5, these pillars represent the core enablers of the IoMT ecosystem. This section examines each pillar and explains how it supports effective, reliable, and scalable IoMT deployment in real-world healthcare settings.

2.3.1. Medical data acquisition

This pillar serves as a foundational component of the IoMT ecosystem by enabling the continuous, real-time collection of health-related data from a wide range of connected devices. This includes physiological, physical, and environmental parameters essential for patient monitoring and clinical decision-making. Various technologies support this process, such as biosensors, diagnostic imaging tools, motion detectors, and temperature sensors [1]. These devices enable accurate data capture across diverse settings, from hospital environments to remote and home-care, laying the foundation for data-driven, responsive healthcare services.

2.3.2. Network connectivity

Network connectivity is a critical pillar of the IoMT ecosystem, enabling secure, seamless, and continuous data exchange among medical devices, sensors, healthcare providers, and other stakeholders [27]. It underpins the entire interconnected infrastructure, ensuring timely and reliable communication across the system components. Effective connectivity is essential to support real-time health monitoring, remote diagnostics, and coordinated care delivery, making it a core enabler of intelligent and responsive healthcare services.

2.3.3. Clinical data intelligence

This constitutes a vital pillar of the IoMT paradigm, offering transformative potential for modern healthcare systems. It involves extracting actionable insights from the vast volumes of data generated by connected medical devices, sensors, and healthcare platforms [28]. By exploiting advanced analytical techniques, including statistical modeling, machine learning, and predictive analytics, this pillar enables the identification of patterns, trends, and correlations. Such insights support data-driven clinical decision-making, improve patient outcomes, and stream-

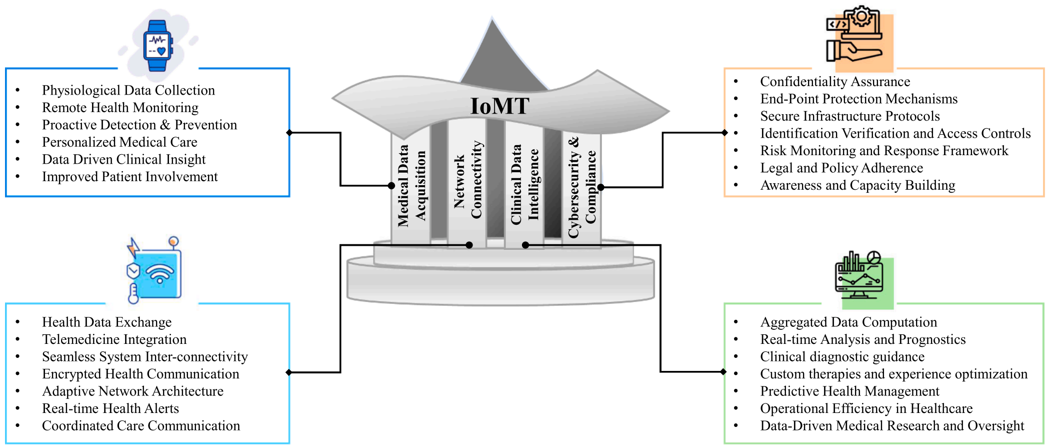

Fig. 5. Key pillars and functional components of IoMT in enabling smart and secure healthcare delivery.

line healthcare workflows through more efficient resource utilization and personalized treatment strategies.

2.3.4. Cybersecurity and compliance

This pillar of the IoMT paradigm ensures the confidentiality, integrity, and availability of sensitive healthcare data, as well as the secure operation of medical devices and systems. The inherently interconnected nature of IoMT which spans various devices, networks, and data sources introduces a broad spectrum of security risks and vulnerabilities [29]. Effectively addressing these challenges requires the implementation of comprehensive strategies encompassing access control, advanced data encryption, real-time threat detection, and strict compliance with regulatory standards such as the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR). These measures are essential to ensure patient data privacy and reinforce trust in IoMT-driven healthcare ecosystems. Despite these advances, important limitations remain in ensuring end-to-end data security across heterogeneous IoMT ecosystems. In practice, secure data sharing, consistent access control, privacy preservation, consent management, and regulatory compliance remain difficult to guarantee when sensitive healthcare data are distributed across multiple devices, platforms, and institutions.

2.4. IoMT emerging technologies

Recent advances in digital health have accelerated the integration of a diverse range of emerging technologies into the IoMT landscape. These innovations play a critical role in improving the performance, scalability, and security of IoMT infrastructures. By enabling high-speed communication, real-time data analytics, and intelligent decision-making, they support the delivery of personalized, adaptive, and resilient healthcare services. A structured overview of the key technological enablers that shape next-generation IoMT systems is presented. Fig. 6 illustrates a proposed conceptual framework that highlights the integration of the presented emerging technologies. Table 2 summarizes key research directions, technological advances, and recent developments shaping emerging IoMT technologies.

2.4.1. Physically unclonable function devices

Physically Unclonable Function Devices (PUFs) are low-cost hardware-based security primitives that enable IoT edge devices to possess unique, tamper-resistant identities. These identities arise from intrinsic manufacturing variations, making them extremely difficult to replicate or forge, thus providing robust protection against cloning and physical attacks [72]. In IoMT environments, PUFs support secure authentication and cryptographic key generation, particularly in edge scenarios where sensors are susceptible to hardware-level threats [73]. Encryption keys can be derived from a device's unique PUF response to protect sensitive medical data and ensure device reliability. Several PUF architectures, including coating, ring oscillator, and arbiter PUFs, enable lightweight device identity and security [74].

2.4.2. Software-defined networking

Software-Defined Networking (SDN) is a transformative network management paradigm that introduces programmability and centralized control into heterogeneous network infrastructures. By decoupling the control plane from the data plane, SDN enables dynamic policy enforcement, flexible routing, and enhanced security through real-time threat detection and mitigation strategies [75,76]. In IoMT settings, this separation supports a more adaptive and scalable communication framework in which the control plane defines the logic and rules for data flow, while the data plane executes forwarding operations accordingly. Common SDN protocols such as OpenFlow, OF-CONFIG, and Open vSwitch Database Management Protocol facilitate standardized communication between these layers. In healthcare environments, SDN can streamline data transmission from edge devices to cloud servers, enabling efficient resource allocation and deployment of scalable e-health applications [17]. Its programmable architecture allows for the implementation of security-as-a-service features, making SDN a valuable enabler of secure and resilient IoMT ecosystems.

2.4.3. Blockchain

As IoMT systems become more widely used in decentralized healthcare settings, questions around who can be trusted with data, how securely it is handled, and whether it can be altered have moved to the forefront. Medical information now flows across many devices and organizations, and this distributed nature makes traditional centralized safeguards less effective. Blockchain has therefore been considered as a practical way to address these concerns, since it manages healthcare data through a decentralized and tamper-resistant structure. In practice, blockchain operates as a distributed ledger in which transactions are stored in cryptographically linked blocks and validated collectively by multiple nodes through a consensus process [17]. By relying on shared verification reduces dependence on a central authority and limits single-point-of-failure risks. The security of the data is further strengthened by built-in cryptographic tools, including hash functions, digital signatures, and public-key cryptography, which help preserve both the confidentiality and authenticity of sensitive health records [77]. Because each transaction remains transparent, traceable, and difficult to alter once recorded, blockchain supports smoother data sharing while encouraging trust among different IoMT stakeholders. These qualities make

Table 2
Comparison of emerging IoMT technologies by research focus, methods, results, and outcomes.

Technology	Ref.	Research focus	Methodology	Results	Key outcomes	Limitations
PUF	[30]	PUF-based three factor authentication in IoMT	Integrated strong or weak PUFs with password and biometrics, verified via ROR and AVISPA tools	Low overhead, robust security	Lightweight secure scheme for resource-constrained devices	Lacks real-world validation and scalability testing
	[31]	PUF-based fuzzy logic authentication for IoMT	IoMT-2FAPF model with fuzzy extractors and challenge-response, tested via Scyther tool	Low overhead, strong security	Ensures mutual authentication and efficiency	Limited real-world and scalability validation
	[32]	Lightweight access control in IoMT using PUF and chaotic maps	PUF-based protocol with chaotic entropy and fuzzy extractors	Low overhead, strong security	Efficient protocol for secure e-healthcare systems	Needs enhancements for post-quantum and side-channel resilience
SDN	[33]	AI-based malware detection for SDN-enabled IoMT	Dual layer detection using XGBoost, LightGBM, DNN, GANs, autoencoders	Accuracy 99.60%, F1 99.66%	Effective real-time detection with high precision for IoMT threats	Limited validation across diverse IoMT setups, scalability issues
	[34]	Advanced malware detection in IoMT using DL-SDN	Hybrid SDN with cuDNNLSTM-CNN, benchmarked against LSTM-GRU, DNN-GRU	Accuracy 99.99%, precision 99.83%, recall 99.33%	cuDNNLSTM achieved high accuracy and operational efficiency	Limited analysis on adaptability to broader threat scenarios
	[35]	SDN-integrated deep learning for IoMT intrusion detection	Hybrid LSTM plus attention framework	Accuracy 99.99%, recall 100%, F1 99.99%, detection time 1.84s	Enabled real-time detection with efficient SDN-based control	Scalability in large-scale IoMT deployments remains unaddressed
Blockchain	[36]	Secure e-health monitoring and data integrity	Raspberry Pi IoMT platform with embedded blockchain and encryption	Secure and traceable health data handling	Ensures EHR privacy, integrity, decentralized access	Limited real-world testing, scalability and resource constraints unaddressed
	[37]	Security and interoperability of EHRs in IoMT	EHRGuard system integrating blockchain with IoMT for secure real-time data handling	Improved service quality, faster access, higher reliability over traditional EHRs	Robust security, data protection, seamless interoperability	Scalability and real-world deployment remain unvalidated
	[38]	Secure and private cross hospital-authentication in IoMT	Double Anonymity Strategy using blockchain smart contracts with three factor authentication	Lower computational cost, strong security	Decentralized, privacy preserving framework for secure cross hospital access	Scalability and real-world deployment not yet explored
AI	[39]	Surgical monitoring and tool positioning in robotic assisted procedures	Preprocessing AKRDF, PWLC-SRGAN super resolution, MI-KMEANS plus E2ARiA-RESNET-50 feature extraction	Accuracy 98.63%, recall 99.15%, F-measure 99.00%	Improves tool tracking and patient safety	Relies on high resolution annotated datasets, limited generalizability
	[40]	Breast cancer diagnosis with IoMT multimodal fusion	TinyViT for histopathology features, LightGBM for multimodal classification	Accuracy 97.8%, recall 99.1%, AUC 98.5%	High diagnostic accuracy with efficient interpretable model	May face challenges with large-scale or highly complex datasets
	[41]	Cyberthreat detection and IoMT data authentication using 1D-CLSTM	RUSBoost for feature selection, 1D-CLSTM for classification, PoAh for authentication	Accuracy 100% (WUSTL-EHMS), 98.55% (ECU-IoHT), time 3.47s	Robust detection and authentication with balanced feature handling	Needs improvement for DoS and Nmap threats, high compute cost on large datasets

blockchain a strong foundation for enabling secure and verifiable data exchange in next-generation healthcare systems [72].

2.4.4. *Artificial intelligence*

The rapid evolution of AI has catalyzed significant transformations in numerous sectors, with healthcare emerging as a key beneficiary. Within the IoMT landscape, the integration of AI, particularly through Machine Learning (ML) and Natural Language Processing (NLP), has introduced powerful capabilities that improve diagnostic precision, streamline clinical workflows, and enable personalized care delivery [78]. These technologies support real-time data interpretation and decision-making by extracting insights from historical and streaming patient data [17]. Thus, AI enables a shift from reactive to proactive healthcare models. However, as AI systems gain autonomy in clinical contexts, they also raise critical concerns about ethical alignment, transparency, and user trust. Ensuring responsible deployment of AI within IoMT requires balancing technological innovation with robust safeguards that uphold accountability and fairness [78].

In summary, these IoMT fundamentals form the backbone on which higher-level AI, such as LLMs and XAI techniques, can operate, as we explore in subsequent sections. Before examining these convergence layers, Section 3 first examines the diverse healthcare applications enabled by IoMT architectures and organizes the representative datasets that support data-driven development across these domains.

3. IoMT applications and healthcare datasets

IoMT enables connected real-time healthcare through the integration of sensors, devices, and communication networks. Its applications span monitoring, diagnosis, treatment, and rehabilitation across diverse clinical domains. These functions rely on rich datasets generated from wearables, medical equipment, and digital health systems. This section presents key IoMT application areas and a structured overview of representative datasets, classified by their role within the IoMT architecture, to support research and development in data-driven healthcare.

3.1. *IoMT applications*

IoMT is becoming essential in transforming modern healthcare by facilitating numerous applications that enhance real-time, patient-centric care. From continuous health monitoring and rehabilitation to chronic disease management and anomaly detection, IoMT technologies enable comprehensive, context-sensitive clinical interventions across diverse environments. These systems leverage interconnected medical devices

Table 3
Comparative overview of recent IoMT applications in healthcare domains-Part I.

Domain	Ref.	Representative Use Case	Technology Employed	Reported Benefits	Observations
Cardiac Monitoring and Management	[42]	Early heart disease prediction with IoMT	TabNet + CatBoost, IoMT integration	Accuracy:99.3%; Real - time alerts	Public Kaggle dataset; Lightweight model
	[43]	Arrhythmia detection using IoMT collected ECG	MS-DSwin-AL Transformer, spectral features	Accuracy:96.01%; Real - time monitoring	MIT-BIH dataset, lightweight and scalable
	[44]	Secure heart disease detection via IoMT + blockchain	BS-THA + OA-CNN hybrid framework	Accuracy:96.41%; Enhanced security	Combines ECG and clinical data; ensures data integrity
Diabetes Management	[45]	IoMT-based early diabetes prediction using survey and clinical data	RF, LightGBM, etc. + Boruta + oversampling	Accuracy:94% (PIDD), 92% (BRFSS); Improved diagnosis	Uses PIDD/BRFSS; robust preprocessing and feature selection
	[46]	IoMT-driven early diabetes diagnosis with lightweight ML	Hyper AdaBoost + SMOTE + RFE	Accuracy: 92% ; Supports remote, continuous monitoring	Uses PIMA dataset; optimized for edge deployment
	[47]	IoMT-based DR detection via ensemble DL on fundus images	EfficientNet-B0-B7 + threshold segmentation	Accuracy: 99.18%; Enables early remote DR diagnosis	Uses DDR and IDRiD; supports scalable IoMT imaging
Neurological & Brain Disorders	[48]	Glaucoma diagnosis via IoMT-integrated lightweight DL	CLAHE + ECNN + EfficientNetB4 + V-Net + Aquila optimization	Accuracy:99.35% ; Low complexity, precise segmentation	Optimized, scalable model for early-stage neuro diagnostics
	[49]	Parkinson's detection via smartphone-based IoMT with sensor fusion	Accelerometer, gyroscope, mic, touchscreen + RF + stacking ensemble	Accuracy:87.7%; Improved remote diagnosis	Uses mPower dataset; fusion outperforms single-sensor models
	[50]	Continuous epilepsy monitoring via UWB brain implant	Smart cap-powered UWB system with wireless energy transfer	Wireless, battery-free monitoring; SAR-safe; Long-term use	Validated on phantom/tissue models; real-world IoMT deployment
Elderly Care & Fall Detection	[51]	Real-time fall risk analysis using IoMT walking stick	Smart stick with sensors + edge node; multimodal gait/grip/TUG analysis	Accuracy:92%; Reduced cost; Real-time feedback; Latency reduction	Small internal trial; KOA-PD-NM used for gait model; scalable for home use
	[52]	Distributed fall detection via federated multimodal IoMT	FL with IMU/EEG/video fusion; Pareto-optimized client selection	Accuracy:96.7%; Energy - efficient; Privacy-preserving	Public UP Fall dataset; cross-subject eval; scalable, privacy-aware
	[53]	Vision-based fall detection via deep feature fusion	DFFCV - FDC with MobileNet, ResNet, DenseNet, autoencoder	Accuracy: 99.68% / 98.34%; Low false positives	Real-time, scalable, privacy-aware; uses MCF/URFD datasets
Infectious Disease Surveillance	[54]	Contagious disease prediction via wearables and XAI	Wearables + mobile app + LightGBM + LIME/SHAP	Accuracy:81.73%; real-time edge monitoring; interpretable	FuXAI fuses vitals/history; efficient for quarantine settings
	[55]	Infectious disease detection via edge-based CDAS	CDAS + edge nodes + multi-source fusion	Fast processing; Low bandwidth; Early alerts	Custom 9-feature dataset; evaluated on errors and edge efficiency
	[56]	Fast POCT infectious disease detection with cloud sync	iPonatic: one-step NA release + real-time cloud reporting	AUC:98%; 30-min test; High sensitivity	Telemedicine - ready, cost-effective PCR alternative

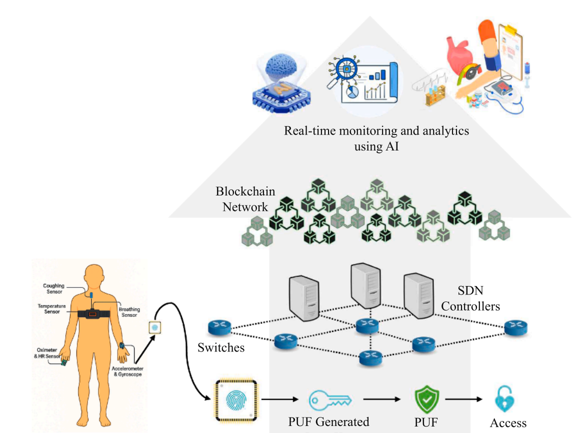

Fig. 6. Conceptual illustration of the integration of PUF, SDN, Blockchain, and AI technologies to enable secure, intelligent, and real-time IoMT-based health monitoring systems.

and wearable technologies to monitor vital parameters, including blood glucose, heart rate, temperature, and oxygen saturation, in real time. As detailed in Section 2.4, recent innovations have further enhanced the capabilities of IoMT systems by integrating advanced tools such as PUFs, SDN, Blockchain, and AI. These integrations address long-standing challenges in healthcare delivery, improving accessibility, personalization, and operational efficiency. Despite these advancements, the full-scale deployment of IoMT remains a notable challenge. Key concerns include data privacy and security, scalable system design, and efficient management of large and heterogeneous datasets. Moreover, ensuring interoperability and long-term reliability of connected devices remains an ongoing technical and regulatory priority. Telehealth has emerged as a transformative application, enabling remote consultations, diagnostics, and treatment, particularly beneficial for underserved and rural populations [18]. Furthermore, AI-driven IoMT solutions have shown promise in improving diagnostic accuracy and optimizing clinical workflows across oncology, diabetes management, cardiovascular health, and robotic-assisted surgery [79]. IoMT systems, when integrated, combine sensors, communication networks, and cloud-based analytics to enable timely and accurate healthcare delivery. Their evolving utility supports both preventive and responsive care models, enabling personalized treatments, early intervention, and improved patient outcomes. An illustrative overview of the IoMT ecosystem and its diverse application domains is provided in Fig. 7. The following subsections present a structured overview of the principal application domains within the IoMT landscape. A consolidated summary of representative technologies and case studies is provided in Tables 3 and 4, covering diverse IoMT applications across major healthcare domains.

3.1.1. Cardiac monitoring & management

Cardiovascular diseases are the leading global cause of death, especially affecting underserved populations [106]. IoMT integration into cardiac care enables early diagnosis, teleconsultations, real-time monitoring, personalized treatment, and emergency alerts [107]. These technologies reduce hospital visits, lower costs, and improve access, espe-

Table 4
Comparative overview of recent IoMT applications in healthcare domains-Part II.

Domain	Ref.	Representative Use Case	Technology Employed	Reported Benefits	Observations
Maternal & Fetal Health	[57]	Neonatal sleep staging via EEG for brain monitoring	1/2-channel EEG + multi-view fusion + cloud-efficient ensemble	Accuracy:82.79% ; 153.6× data cut; NICU / remote use	Lightweight; preserves key signals; fits neonatal cloud setups
	[58]	Fetal monitoring via wearable IoMT device	Accelerometer/gyroscope sensor + real-time processing + mobile annotation	Accuracy:96.4% ; Non-invasive remote prenatal care	Data from 35 subjects; no public dataset; strong IoT prenatal use case
	[59]	Maternal mortality prediction using IoMT data	CNN-GRU with SHAP-based XAI	Accuracy:97.9% ; Early risk detection; Scalable remote monitoring	Combines physiological / demographic data; SHAP interpretability; Public datasets
Mental Health & Emotion Recognition	[60]	EEG-based emotion recognition via domain-invariant learning	DCDA with multi-source fusion, contrastive loss	Accuracy:90.58% ; Cross-subject/session robustness	SEED, SEED-IV EEG; Entropy features; Mitigated domain shift
	[61]	Facial emotion tracking for remote therapy via IoMT	Web UI with TinyFaceDetector, FaceExpressionNet, WebRTC	Enables tele - consultation, feedback, trend tracking	Validated in real sessions; full IoMT stack; wearable-ready
	[62]	Contactless emotion sensing via BCG IoMT sensor	SE-CNN + wavelet-filtered BCG	Accuracy:97.2% (K-Fold), 94.7% (K-Session); robust, real-time	Internal BCG+ECG data (93 subjects); No public set
Emergency & Critical Response	[63]	IoT-based hospital evacuation support	IoT tracking, ARIMA, GA-based dispatch	Evacuation time cut; Higher efficiency	Real NSW flood scenario; No public dataset
	[64]	Smart ambulance detection and traffic control	ResNet18 + LSTM, dual-modal input	Accuracy:98.95%, fewer false alarms	Public Kaggle datasets, real-time inference
	[65]	Urgent care triage and edge offloading via IoMT	Decision Tree (LOADTME) + RADOTOD, biosensors	Performance gain:88%, Offloading: <5.13s	PIMA + synthetic hospital data, edge-deployable
Wellness & Preventive Health Monitoring	[66]	Real-time health tracking via wearable IoMT + cloud analytics	ZigBee - based wearables; fuzzy fusion + Grubbs; Node-RED + MQTT alerts	Accuracy:91.68% (anomaly detection); real - time dashboards; multi - patient support	8-month trial (5 subjects); validated for telemedicine and rural IoMT deployment
	[67]	Continuous Tc monitoring via dual-sensor wearable + ML	Skin + ambient sensors; LR/XGBoost/RF models; real-time, low-power	MAE 0.15°C, RMSE 0.17°C; accurate across rest/motion/cooling	Data from 72 subjects; no public set; validated in controlled/real trials
	[68]	Noncontact glucose monitoring via microwave sensor + ANN	CSRR patch sensor; S11/Fr signals; MLP + K-means classification	Accuracy:100% ; Compact, low-cost	No public data; validated on 0-200 mg/dL glucose samples using ANN/PCA
Remote Rehabilitation & Physical Therapy	[69]	Movement recognition for elderly in AAL via deep learning	CAE + WRRNN with RSO/COA optimization	Accuracy:94.08% ; Supports real-time, personalized elderly care	Public HAR dataset (15 classes); efficient, privacy-aware IoMT-AAL solution
	[70]	IoMT-assisted AAL with DNN for healthcare monitoring	3-layer IoMT-AAL (wearables, edge, cloud) + DNN prediction	Accuracy:88.68%;Privacy:94.3%; Supports secure, independent living	Private dataset (10 patients); Scalable for smart homes and rehab
	[71]	OmniRehab: IoT-based home rehab system with VR and remote control	Omnidirectional platform, IPSMC - LESO control, MQTT + VR games	Max Error: 2.3 mm ; Real-time clinician control; Enhances neuroplasticity	No public dataset; Tested with healthy users; Onboard sensor + VR data

Table 5
Overview of IoMT datasets categorized by architectural Layer, data type, modality, and use cases.

IoMT Layer	Ref.	Dataset Name	Data Type	Records	Public	Multimodal	Use Cases	Limitations
Medical Things	[80]	HLPPDat	Images	1280 images	Yes	No	Posture detection	Static only;lack modalities
	[81]	DAPPER	Signals	142 subjects	Yes	Yes	Emotion modeling	Few users; self-report bias
	[82]	MIT-BIH	Signals	47 subjects	Yes	No	ECG analysis	Small; single-channel
	[83]	mPower	Sensors	1K+ subjects	Yes	Yes	Parkinson's monitoring	Self-report; iOS-only
	[84]	OxMat	Signals, EHR	177k CTGs	No	Yes	Fetal monitoring	Restricted; no real-time
	[85]	w-HAR	Multisensor	4740 samples	Yes	Yes	Wearable HAR	Limited users; fixed setup
	[86]	KU-HAR	Signals	1945 samples	Yes	Yes	HAR via phone sensors	Young cohort; Imbalanced
	[87]	UP-Fall	Multisensor	561 trials	Yes	Yes	Fall detection, HAR	Simulated; lab-only
Communication	[88]	Bot-IoT	Flows, PCAP	72M+ entries	Yes	Yes	Botnet detection	Virtual testbed
	[89]	BODMAS	PE, Features	134K binaries	Yes	Yes	Malware detection	No benign binaries
	[90]	MedBIoT	PCAP, Features	17.8M entries	Yes	No	IoT botnet detection	Lab-based; Limited types
	[91]	ECU-IoHT	Network Traffic	8.9K flows	Yes	No	IoHT attack detection	Simulated; Low realism
	[92]	IoMT-TrafficData	Packets, Flows	18M+ entries	Yes	No	IoMT intrusion detection	Few attacks, narrow scope
Platform	[93]	MIMIC-IV	EHR	60k+ stays	Yes	Yes	Clinical Modeling	Anonymized; Retrospective
	[94]	MIMIC-III	EHR	53K stays	Yes	Yes	Clinical Modeling	Unprocessed, raw text
	[95]	eICU	EHR	200K stays	Yes	Yes	ICU scoring, monitoring	Static, sparse docs
	[96]	HiRID	EHR	33K stays	Yes	Yes	Phenotyping, Mortality	Sparse; Imbalanced
	[97]	UK Biobank	EHR, Images	500K subjects	No	Yes	Disease modeling	Restricted access
	[98]	SICdb	EHR	27K stays	Yes	Yes	Critical care modeling	Single-center; Austria-only
Application	[99]	AMIGOS	Signals, Video	40 subjects	Yes	Yes	Emotion Analysis	Long video group only
	[100]	CASE	Signals, Labels	30 subjects	Yes	Yes	Emotion Analysis	Limited scale
	[101]	CholecInstanceSeg	Video, Labels	41.9K frames	Yes	No	Tool segmentation	Imbalance, 7 tools only
	[102]	BreaKHis	Images	7.9K Images	Yes	No	BC binary class	Image-only; manual ROI
	[103]	NCH Sleep DB	Signals, EHR	3.9K subjects	Yes	Yes	Sleep stages, diagnosis	Pediatric only
	[104]	IDRiD	Images, CSV	516 Images	Yes	Yes	Lesion segmentation	Limited to 81 segments
	[105]	MUVIM	Video	400 trials	No	Yes	Visual fall detection	Some missing/corrupt data

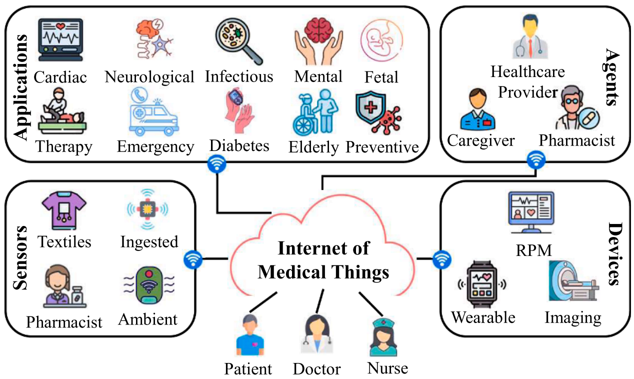

Fig. 7. IoMT ecosystem, illustrating key healthcare applications alongside corresponding agents, devices, sensors, and clinical stakeholders.

cially in low-resource settings. Continuous data collection via IoMT devices also supports research, advancing understanding and treatment of cardiac conditions. These systems offer a scalable, data-driven approach to improving cardiovascular care and outcomes.

3.1.2. Diabetes management

Diabetes mellitus, a group of metabolic disorders marked by chronic hyperglycemia, affects an estimated 1.31 billion individuals by 2050 [108,109]. IoMT integration in diabetes care transforms traditional monitoring into a real-time, data-driven paradigm, enabling early detection and personalized management [110]. Wearable IoMT devices support continuous glucose monitoring, especially critical for Type 1 diabetes patients, where accurate glycemic trend forecasting remains challenging [111]. These systems enable early alerts and therapeutic guidance, supporting earlier diagnosis and improved long-term outcomes.

3.1.3. Neurological & brain disorders

Neurological disorders are among the leading causes of disability and mortality globally, with rising incidence, especially in low and middle-income countries [112]. These conditions involve diverse pathologies, including disrupted blood-brain barriers, amyloid accumulation, and impaired synaptic transmission [113]. IoMT technologies, such as Electroencephalogram (EEG) monitors and wearable motion sensors, enable real-time tracking of neurological activity, thereby supporting early detection and timely intervention. Furthermore, continuous acquisition of neural activity data improves understanding of disease mechanisms and facilitates the design of personalized therapeutic strategies.

3.1.4. Elderly care & fall detection

The growing elderly population poses increasing economic and healthcare challenges, particularly in resource-limited settings [114]. IoMT-enabled systems offer scalable solutions for continuous geriatric care through smart wearable devices embedded with sensors and computational intelligence [72]. These systems enable real-time monitoring of critical vitals, such as heart rate and blood pressure, supporting early detection of anomalies. The generation of timely alerts is crucial for enabling prompt clinical interventions, which are essential for mitigating fall risk, preventing acute health deterioration, and ensuring the overall safety and well-being of elderly patients in both home-based and institutional care settings.

3.1.5. Infectious disease surveillance

Infectious disease surveillance is vital for early outbreak detection and timely public health response. Point-of-Care Testing (PoCT) has become central to this effort by enabling rapid diagnostics directly at or near the patient site [72]. Recent advances in biosensors, such as textile, nanomaterial, chip, and paper-based platforms, offer portable, wireless capabilities and are easily integrated into IoMT infrastructure [72]. These IoMT-enabled PoCT systems support real-time data transmission, rapid disease identification, and prompt intervention, collectively improving epidemic preparedness and strengthening public health resilience.

3.1.6. Maternal & fetal health

Fetal monitoring is essential for maternal and neonatal outcomes. IoMT-enabled Magnetic Resonance Imaging (MRI) systems, coupled with Deep Learning (DL), particularly Convolutional Neural Networks (CNNs), enable automated segmentation and classification of fetal brain structures, aiding early detection of abnormalities [115,116]. Multiple frameworks integrate IoT-based data acquisition with CNN pipelines for preprocessing, model training, and evaluation, using metrics such as accuracy and F1-score [117]. This convergence improves diagnostic speed, accuracy, and resource efficiency in prenatal care.

3.1.7. Mental health & emotion recognition

IoMT-based emotion-aware systems are advancing mental health monitoring through edge AI and wireless BANs. Using speech inputs from various sources, deep models that combine CNN and bidirectional Long Short-Term Memory (BiLSTM) architectures predict emotional states in real time [118]. Optimization techniques reduce latency, power, and memory demands, enabling scalable, energy-efficient emotion recognition for continuous therapeutic evaluation [119].

3.1.8. Emergency & critical response

The COVID-19 crisis highlighted the need for IoMT-enabled infrastructures in emergency care [120]. Smart homes, Accident and Emergency Informatics (A&EI) frameworks, and Open Data Hub (ODH) models promote early detection and rapid response to health events [121]. Wearable sensors that integrate acceleration, temperature, and humidity modules enable real-time monitoring and wireless transmission, thereby supporting timely intervention for vulnerable patients [122].

3.1.9. Wellness & preventive health monitoring

Proactive healthcare has led to the rise of mHealth and IoMT systems that support continuous monitoring, real-time analytics, and personalized feedback [123,124]. These platforms integrate wearable sensors and home devices using technologies such as Wi-Fi, 5G, and NFC to enable secure, reliable exchange of health data [125,126]. Improved connectivity facilitates teleconsultations, access to Electronic Health Records (EHRs), and coordinated care. In preventive cardiovascular monitoring, IoT-enabled Photoplethysmography (PPG) and Electrocardiogram (ECG) devices, often integrated with low-cost computing platforms such as the Raspberry Pi, facilitate continuous, non-invasive, real-time tracking of vital parameters, including heart rate and blood pressure. This capability not only supports the early detection of physiological anomalies, but also promotes a paradigm shift from reactive to proactive and preventive healthcare practices [127,128].

3.1.10. Remote rehabilitation & physical therapy

IoMT integration in rehabilitation enables continuous, remote monitoring of health and mobility. A radar-based ultra-wideband IoMT system combines edge and cloud computing to track vital signs and detect high-risk events in activity classification [18,129,130]. Similarly, wearable triboelectric sensor systems embedded in smart bracelets have been deployed to monitor motor function in Parkinson's disease. Supported by DL, these systems track fine motor skills, identify, and trajectories with high precision, offering cost-effective, sensitive tools for remote rehabilitation aligned with Health 4.0 goals [131,132].

3.2. IoMT datasets

Datasets are a foundational component of innovation in IoMT. From wearable biosensors to cloud-integrated hospital infrastructures, data generated, transmitted, and analyzed through these systems support

Table 6
Overview of LLM-driven applications in healthcare: Roles, case studies, and limitations.

Domain	Role of LLMs	Case Studies	Limitations
Medical Testing & Reasoning	Exhibit reasoning ability by completing clinical exams and tasks.	ChatGPT [133], Bing Chat [134]	Specialty-specific variability;Requires clinical validation
Diagnostic Decision Support	Aid clinical diagnosis and triage across specialties.	GPT-4 [135], SkinGPT-4 [136], RareDx [137], PharmaLLM [138], Oph/Rad LLMs [139,140], OncoLLM [141]	Human oversight necessary; Risk of misdiagnosis in rare/complex cases; Patient perception gap; Variable consistency across specialties
Patient Communication & Engagement	Provide personalized responses and enhance education.	Kidney stones [142], Heart failure [143], Readability [144], Multilingual/Autism [145], Dermatology [146], PsyChat [147]	Complex language; Ethical/privacy concerns; Gaps in completeness
Clinical Documentation & EHR Analysis	Summarize and structure clinical text and imaging reports	Breast cancer [148], EHR triage [135], Lung cancer PACS [149], Glioblastoma [150]	Expert validation needed; Privacy and compliance constraints

the delivery of intelligent, patient-centric healthcare services [151,153]. The performance of any IoMT-based application is functionally associated with the accessibility, structure, and quality of the dataset it uses. With the evolving IoMT ecosystem, researchers are increasingly encountering a heterogeneous spectrum of datasets that are distinct in format, modality, and origin, each presenting unique challenges and opportunities for implementation. To facilitate a structured understanding of this landscape, this study presents a unified taxonomy of representative IoMT datasets based on the canonical four-layer architecture described in Section 2.2. The classification is based on both the source of data and its operational role within biomedical and clinical workflows. More precisely, datasets derived from wearable devices, physiological sensors, or medical imaging devices are mapped to the Medical things layer. Those capturing network flows or packet traces are assigned to the Communication layer. Those performing data aggregation and storage, such as EHRs, are assigned to the Platform layer. Datasets used in diagnostic reasoning, predictive modeling, or supporting higher-level services are categorized within the Application layer. To maintain consistency and reduce ambiguity, each dataset is assigned exclusively to the layer that best reflects its primary function at the point of data acquisition. Although some datasets may conceptually span multiple layers, such as physiological signals that feed into downstream decision-support models, this classification emphasizes their immediate context of generation. For example, biosignals collected from wearable sensors are categorized under the Medical things layer, even if they are later used in inference-driven applications. Each dataset is further annotated with standardized metadata, including the dataset name, data type (e.g., signals, images, EHR), record volume, public accessibility (Yes/No), modality (unimodal or multimodal), primary use cases, and known limitations. This consistent representation enables researchers and developers to evaluate dataset suitability in light of technical requirements, regulatory constraints, and specific research objectives.

Table 5 consolidates these datasets into a single reference table, presenting a comprehensive layer-wise taxonomy of publicly available and relevant IoMT datasets. This classification facilitates a structured perspective on data distribution across the IoMT pipeline and supports targeted integration of LLM and XAI techniques at appropriate architectural levels. To the best of our knowledge, this is the first structured effort to explicitly categorize IoMT datasets according to the canonical four-layer model, offering a novel lens for examining dataset roles, readiness, and convergence potential within the broader IoMT-LLM-XAI convergence framework. Beyond layer-wise classification, several cross-cutting data quality challenges affect the practical utility of IoMT datasets for AI model development. Cross-dataset generalization remains problematic: models trained on MIT-BIH ECG waveforms (47 subjects, single-channel) may degrade when applied to multi-lead hospital monitors or consumer-grade wearables with different sampling rates and noise profiles. Missing data handling is particularly acute in EHR-derived datasets such as MIMIC-III and eICU, where unprocessed clinical notes and sparse documentation introduce gaps that propagate through downstream LLM reasoning pipelines. Data leakage prevention is another critical consideration when temporal patient records are split into training and test sets without accounting for longitudinal dependencies, or when multimodal datasets align patient samples across modalities with insufficient temporal window controls. These challenges underscore that dataset selection in IoMT research requires not only architectural alignment but also rigorous scrutiny of data quality, representativeness, and preprocessing transparency.

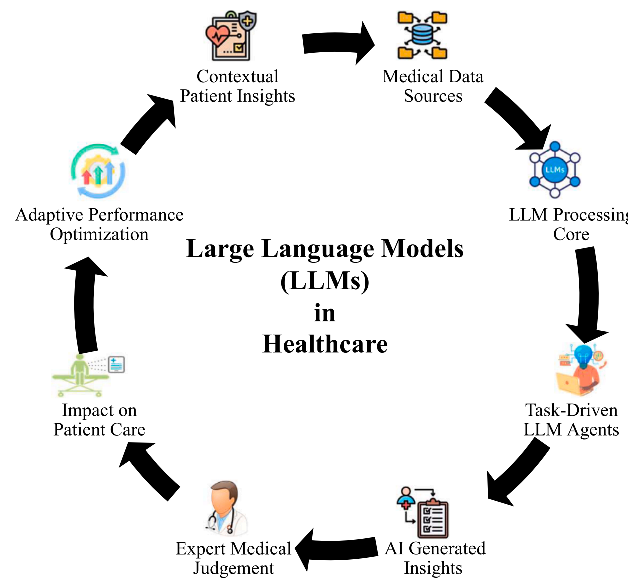

Fig. 8. Role of LLMs in healthcare, illustrating the cyclic transformation of medical data into contextual insights and clinical decisions through AI-driven processing, expert judgment, and performance optimization.

4. Integration of LLMs with IoMT for intelligent healthcare applications

LLMs represent a significant leap in the evolution of NLP, underpinned by advances in DL and centered on the Transformer architecture [154]. This architecture leverages self-attention mechanisms to efficiently model both short and long-range dependencies in textual data. Unlike Recurrent Neural Networks (RNNs), Transformers allow for parallel computation, which enhances training efficiency and scalability, and is critical for deploying high-capacity models across massive corpora [155]. The remarkable capabilities of LLMs stem from three foundational elements: (i) sophisticated language modeling that enables contextual prediction and generation of coherent text; (ii) pre-training on

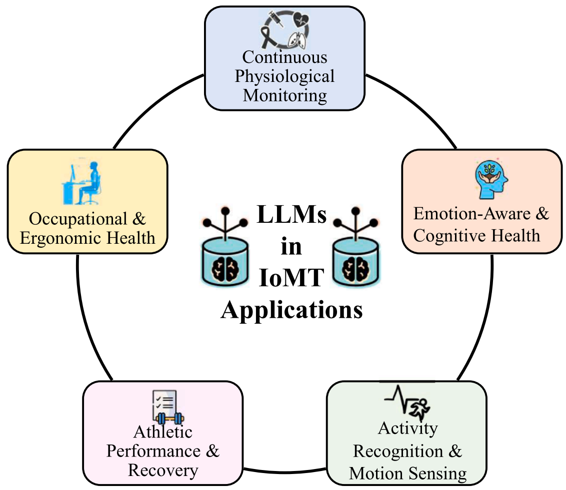

Fig. 9. Categorization of key application domains for LLMs in IoMT-enabled healthcare systems.

large and diverse datasets such as Common Crawl, Wikipedia, and open-access books that endow the model with broad linguistic and factual knowledge; and (iii) the Transformer backbone that excels at capturing nuanced contextual relationships [156].

These models operate probabilistically, learning to estimate the likelihood of token sequences, including words, subwords, or morphemes, given the surrounding context [157]. Training strategies such as Masked Language Modeling (MLM) and Next-Token Prediction (NTP) equip LLMs to learn complex grammar, semantics, and discourse structures. An important insight in LLM development is the concept of scaling laws, which empirically demonstrate that performance improves with larger model sizes and more extensive training data [158]. This has been validated in state-of-the-art models, such as DeepSeek, PaLM, GPT-5 and its predecessors, which exhibit emergent capabilities across a wide range of NLP tasks [159–161]. In parallel, the healthcare domain has witnessed growing interest in integrating LLMs with IoMT. While LLMs have shown promise in tasks such as clinical documentation, decision support, and patient communication, their convergence with IoMT introduces a new paradigm of intelligent, context-aware healthcare. This integration enables real-time interpretation of heterogeneous medical data streams generated by connected devices, thereby facilitating scalable, personalized, and interactive healthcare delivery. Despite their potential, LLMs introduce important clinical risks, particularly hallucinated, unsupported, or clinically misleading outputs. In IoMT-enabled healthcare, these risks may be amplified because LLMs may interpret continuous sensor streams, patient histories, and clinical notes in real-time. Therefore, LLM outputs should not be treated as autonomous clinical decisions. Instead, they should be grounded through retrieval-augmented generation, constrained by verified medical knowledge bases, supported by uncertainty estimation, and validated by clinicians before being used in patient care. This section explores this convergence in three parts. First, it clarifies the evolution from specialized medical models to LLM-enabled healthcare. Second, we examine standalone applications of LLMs in traditional healthcare contexts. Third, we explore how LLMs can be embedded in IoMT systems to enable intelligent data fusion, ambient monitoring, and natural language interaction across the edge, fog, and cloud layers.

4.1. Evolution from specialized medical models to LLM-enabled healthcare applications

To better understand the role of LLMs in healthcare, it is important to distinguish them from the specialized medical models that have traditionally dominated healthcare AI. Before the emergence of LLMs, healthcare AI was largely driven by specialized medical models designed for narrow and task-specific objectives, such as disease classification, image segmentation, lesion detection, physiological signal analysis, and risk prediction [107,115,116]. These models, including CNNs, RNNs, transformers and other DL architectures, have achieved strong performance in well-defined clinical applications involving structured data, medical imaging, and biosignals. However, despite their effectiveness, such models are generally limited in their ability to process unstructured clinical narratives, synthesize heterogeneous information across modalities, support contextual reasoning, and interact through natural language within clinical workflows. In this context, LLMs have emerged as a complementary paradigm that extends healthcare AI beyond narrow prediction tasks toward language-based reasoning, multimodal knowledge synthesis, report generation, question answering, and clinician-patient interaction. Therefore, LLMs should be viewed not as replacements for specialized medical models, but as complementary intelligence layers that enhance the usability, interactivity and contextual adaptability of healthcare systems.

4.2. Applications of LLMs in healthcare

The integration of LLMs into healthcare has progressed rapidly, driven by breakthroughs in DL, growing access to specialized medical datasets, and improvements in domain-adaptive fine-tuning techniques. Early work focused on adapting general-purpose language models for biomedical contexts through targeted pre-training. This led to models such as BioBERT and ClinicalBERT, which demonstrated improved performance on foundational tasks such as named entity recognition and relation extraction [162,163]. Subsequent advances have led to the development of LLMs designed specifically for healthcare, trained from scratch using large-scale clinical corpora and biomedical literature. These purpose-built models, such as GatorTron and MEDITRON [164], embed medical reasoning and clinical vocabulary directly into their internal representations, allowing deeper contextual understanding and alignment with domain-specific knowledge. Concurrently, the emergence of multimodal LLMs has opened new avenues in medical AI. These models integrate textual and visual modalities such as radiology images, pathology slides, or dermatological scans, enabling richer inference and decision-making. Notably, Med-PaLM [157] exemplifies this trend by supporting visual question answering and diagnostic support tasks, demonstrating strong performance in clinically relevant scenarios. Recent efforts have also focused on enhancing model capabilities through advanced prompting strategies, task-specific tuning, and alignment with professional medical standards. Models such as Med-Gemini illustrate this evolution, achieving state-of-the-art results on complex challenges, including clinical reasoning, medical question answering, and licensing examination benchmarks [165]. Table 6 presents key LLM applications in healthcare.

4.2.1. Medical testing & reasoning

LLMs have demonstrated considerable promise in medical knowledge assessments, with several models achieving results comparable to or exceeding those of human candidates. For example, ChatGPT was shown to surpass the passing threshold of the United States Medical Licensing Examination (USMLE), indicating proficiency levels comparable to those of recent medical graduates [133]. Similarly, Bing Chat achieved top-tier scores in the Multi-Specialty Recruitment Assessment (MSRA), outperforming LLaMA-2, ChatGPT-3.5, and even select human test-takers [134]. Beyond general assessments, LLMs have also shown effectiveness in specialized domains. In the Japanese Orthopaedic Association Board Examination, GPT-4 outperformed its predecessors, suggesting improved domain adaptation and conceptual understanding [183]. Dermatology evaluations show that LLM performance varies with question complexity and clinical nuance, emphasizing the need for context-aware assessment before clinical deployment [184].

Table 7
Overview of LLM applications in IoMT and healthcare domains: Roles, use cases, and limitations.

Domain	Role of LLMs	Case Studies	Limitations
Continuous Physiological Monitoring	Interpret multimodal physiological and contextual data from wearables	PhysioLLM [166], Health-LLM [167], LLM for BP [168], Remote health [169]	Data sparsity in biosignals; Need for continuous fine-tuning; Privacy and deployment validation
Activity Recognition & Motion Sensing	Classify human activities and optimize sensing infrastructure	HARGPT [170], LLaSA [171], ChatGPT for sensor design [172], Semantic HAR [173]	Variability in motion patterns; Ambiguity in overlapping tasks; Limited scalability across environments
Emotion-Aware & Cognitive Health Support	Map biometric patterns to emotional and cognitive states	Health-LLM [167], TILES datasets [174,175], MindShift [176]	Ambiguity in signal interpretation; Context drift; Risks in mental health personalization
Athletic Performance & Recovery Analytics	Support athlete training and recovery with personalized feedback	LLM coaching [177], Behavioral coaching [178], physiotherapist agent [179], LLaSA training [171]	Delay in real-time feedback; Limited task generalization; Model-resource tradeoffs
Occupational Health & Ergonomic Monitoring	Provide ergonomic feedback and workplace health insights	Worker-centric LLMs [180], Ergonomic ChatGPT [181], Posture tracking wearables [182]	Cultural/workflow bias; Workplace data sensitivity; Risk of overdependence on automation

4.2.2. Diagnostic decision support

Beyond standardized testing, LLMs are increasingly applied to real-world clinical reasoning and diagnostic support. Fig. 8 presents a streamlined framework for integrating LLMs into the clinical workflow. Central to this architecture is the pathway from the “LLM Processing Core” to “Expert Medical Judgment”, which facilitates evidence-based decision-making. The pipeline begins with diverse structured (e.g., EHRs, lab reports) and unstructured (e.g., imaging, clinical notes) “Medical Data Sources” augmented by “Contextual Patient Insights” such as comorbidities and medication histories. The “LLM Processing Core” handles language understanding, multimodal data fusion, and biomedical retrieval, enabling advanced reasoning. This is further executed by “Task-Oriented Agents”, which automate clinical tasks, shifting AI from passive support to active workflow augmentation. The resulting “AI-Generated Insights”, including diagnoses, treatment options, or documentation are reviewed by clinicians, preserving expert oversight. These outputs inform “Patient Care” and feed into “Adaptive Performance Optimization”, allowing continuous refinement via real-world outcomes and feedback loops. GPT-4 has demonstrated triage performance on par with that of emergency physicians [135], while specialized models support rare-disease diagnostics [137] and pharmacy counseling [138]. In dermatology, SkinGPT-4 matched expert-level accuracy [136], and domain-tuned LLMs have been effective in ophthalmology and radiology [139,140]. However, evaluations reveal a gap between patients’ perceptions and expert-rated accuracy [185], underscoring the need for rigorous validation. Enhancing LLMs with structured knowledge, such as medical ontologies and knowledge graphs, has been shown to improve both accuracy and interpretability [186]. In oncology queries, advanced LLMs have even outperformed junior clinicians [141]. Despite these advances, LLM reliability in complex or rare cases remains variable, necessitating clinician-AI collaboration, robust validation, and adaptive feedback mechanisms for responsible deployment in healthcare settings, as shown in Fig. 11.

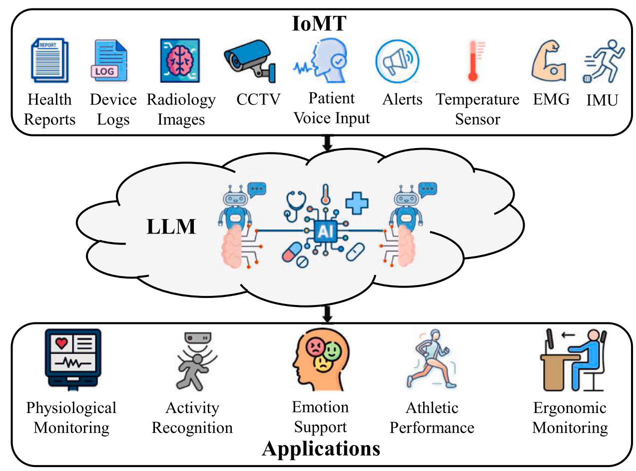

Fig. 10. Conceptual architecture illustrating the integration of LLMs within IoMT-based healthcare systems, depicting the flow from sensor-driven data acquisition to downstream clinical applications.

4.2.3. Patient communication & engagement

LLMs are increasingly employed to enhance patient communication and health education. Studies indicate that LLM-generated responses are generally accurate and comprehensible. For instance, content on kidney stones generated by LLMs was found to be both readable and consistent with urological guidelines, although with occasional gaps in completeness [142]. Similarly, responses to heart failure-related questions were rated satisfactory in terms of informational quality [143]. Despite these strengths, concerns persist regarding accessibility, as many LLM-generated texts exceed recommended readability thresholds, potentially limiting utility for individuals with low health literacy [144]. One key advantage of LLMs lies in their multilingual capabilities, which enable culturally sensitive communication across diverse populations. For example, LLMs effectively addressed health-related inquiries from autistic individuals in Chinese, demonstrating adaptability to linguistic and cognitive needs [145]. Models such as MMedC have been developed to bridge language gaps in healthcare delivery, thereby improving access for underserved language groups [147,187]. Specialized applications are also emerging. In dermatology, LLMs have been used to deliver patient education for managing atopic dermatitis, improving satisfaction, and disease understanding [146]. In mental health, platforms such as PsyChat leverage LLMs to offer conversational support, expanding access to psychological care [147]. As these systems enter clinical workflows, ethical, privacy, and accuracy concerns require continued attention [188].

4.2.4. Clinical documentation & EHR analysis

LLMs are increasingly applied to extract structured insights from unstructured clinical text, offering substantial improvements in medical data analysis and utilization. Their ability to process EHRs, clinical notes, and biomedical literature enables faster decision-making and reduces the documentation burden on clinicians. By integrating capabilities across diagnostics, research, and workflow automation, LLMs contribute to improved patient care and operational efficiency. Recent studies underscore their practical utility. For example, [148] demonstrated that zero-shot inference with LLMs can accurately extract key information from breast cancer pathology reports, thereby minimizing the need for manual annotation. Similarly, GPT-4 was evaluated for its ability to assess patient acuity in emergency departments by analyzing EHR data, with results indicating effective triage support [135]. In radiology, [149]

Table 8
Comparative overview of XAI applications in healthcare: tasks, input domains, and interpretability methods.

XAI Application	Ref.	Clinical Focus	Anatomical Region	Input Domain	XAI Method
Clinical Text/ EHR	[189]	Readmission Prediction	Kidney	Structured EHR	SHAP, LIME
	[190]	UTI Risk Prediction	Urinary Tract	Clinical/EHR	SHAP
	[191]	Diabetes Risk Prediction	Endocrine System	EHR	SHAP, LIME, EBM, etc
	[192]	Cancer Survival Prediction	Bladder/Breast/Prostate	Cancer Registry Data	SHAP, LIME
	[193]	Pulmonary-Embolism-Prediction	Pulmonary Vasculature	Clinical/EHR	SHAP
	[194]	Breast Cancer Detection	Breast	Cancer Registry Data	SHAP
	[195]	Breast Cancer Detection	Breast	Breast Cancer Wisconsin	SHAP
	[196]	Lung Cancer Risk Prediction	Thorax	Structured Survey Data	SHAP
	[197]	Type-2 diabetes diagnosis	Endocrine system	Structured Survey Data	SHAP/ CNN-XGBoost
	[198]	Cardiac Risk Prediction	Heart	Structured Survey Data	SHAP
Medical Imaging & Signal	[199]	Cervical Cancer Screening	Cervical Epithelium	Cervical Cell Images	Grad-CAM++,LRP, etc
	[200]	Skin Disease Prediction	Skin	Skin Lesion Images	LRP
	[201]	Glaucoma Diagnosis & Staging	Eyes	OCT Images	SHAP, PDA
	[202]	Brain Tumor & AD Diagnosis	Brain	MRI	Grad-SHAP
	[203]	Glioma Diagnosis	Brain	PET	SHAP, Anchor, LIME
	[204]	sMCI vs. pMCI Classification	Brain (GM, WM, CSF)	MRI	Grad-CAM
Biomedical Audio	[205]	Parkinson's Disease Diagnosis	Vocal Tract	Voice Recordings	SHAP
	[206]	Respiratory Sound Detection	Lungs	Respiratory Recordings	Intrinsic, Visual, etc
	[207]	COVID-19 detection	Lungs	Respiratory Recordings	SHAP
	[208]	Voice disorders diagnosis	Vocal Tract	Voice Recordings	Occlusion Sensitivity
	[209]	Alzheimer's Disease Detection	Brain	Voice Recordings	SHAP
Multimodal XAI	[210]	Parkinson's Disease Diagnosis	Brain, Vocal Tract	Voice Recordings, Scans	LIME
	[211]	Cancer-Treatment-Outcome-Prediction	Multiple (Pan-cancer)	Clinical/EHR, Genomics, Images	LRP
	[212]	ICU Outcome Prediction	Whole-body (systemic)	Clinical/EHR, Images	SHAP
	[213]	Glioma segmentation	Brain	Multimodal Images	Grad-CAM/Saliency Maps
	[214]	Breast Cancer Detection	Breast	Multimodal Images	Grad-CAM

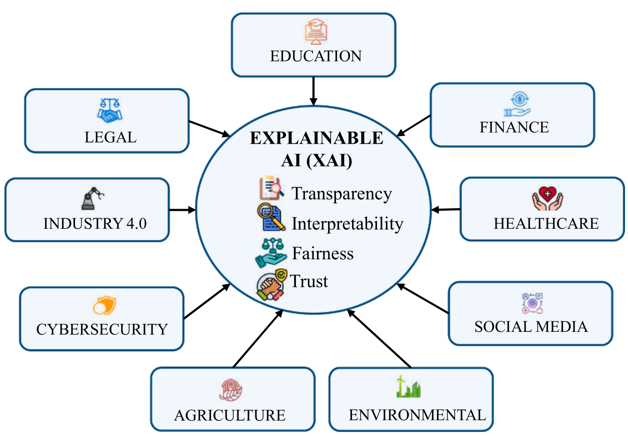

Fig. 11. Cross-domain applications of XAI, highlighting its roles in enhancing transparency, interpretability, and trust across various sectors including healthcare.

fine-tuned an LLM to retrieve pretreatment data for lung cancer cases directly from the Picture Archiving and Communication System (PACS), significantly reducing reliance on manual chart review. Furthermore, [150] used GPT-4 to generate structured summaries from glioblastoma imaging reports, achieving consistent extraction of clinically relevant information. These applications illustrate how LLMs streamline clinical documentation, support real-time decision-making, and enhance healthcare delivery by improving data accessibility, accuracy, and processing speed.

4.3. LLM-enabled applications within IoMT systems

IoMT comprises interconnected, implantable devices designed for continuous monitoring, early diagnosis, and proactive management of health conditions. These systems generate heterogeneous multimodal data, including physiological, motion, and contextual streams that reflect real-time changes in an individual's health status. Integrating LLMs into IoMT platforms adds a transformative layer of intelligence that extends well beyond conventional analytics. By leveraging their capacity to process high-dimensional, unstructured, and multimodal data, LLMs can extract latent patterns, derive clinical insights, and enable context-aware decision support directly from raw sensor inputs. This integration enables adaptive systems to align with diverse clinical and wellness goals. Beyond their foundational role in pattern recognition, LLMs also introduce advanced reasoning capabilities into IoMT environments. These models facilitate a wide range of tasks, including activity classification, health forecasting, personalized alerting, and natural-language interaction. The convergence of LLMs with IoMT marks a paradigm shift toward intelligent, autonomous, and patient-centric healthcare delivery that is proactive and responsive to contextual needs. This section explores key application domains where LLMs augment the utility of IoMT systems, ranging from physiological signal interpretation and behavioral monitoring to emotion-aware cognitive support, physical performance optimization, and adaptive workplace ergonomics. Each use case demonstrates how LLMs transform low-level sensor data into actionable, personalized interventions that drive real-time, context-sensitive care. Table 7 provides an overview of representative LLM applications in IoMT and healthcare domains, together with their corresponding roles, example case studies, and major limitations. Fig. 9 offers a conceptual overview of these application areas, while Fig. 10 presents the architectural integration pipeline, depicting the flow from diverse IoMT data sources through LLM-based processing to intelligent healthcare applications. The upper panel of Fig. 10 illustrates a broad spectrum of input modalities, including structured logs, radiology images, surveillance footage, patient-generated voice input, biosignals such as EMG, IMU, and contextual sensors. The LLM engine, situated centrally, serves as the cognitive core that ingests and interprets these streams through semantic understanding, pattern recognition, and generative reasoning. The outputs support continuous monitoring, motion recognition, cognitive health, athletic performance, and ergonomic applications, enabling adaptive decision-making in IoMT healthcare systems.

4.3.1. Continuous physiological monitoring

Continuous physiological monitoring has advanced significantly with the integration of LLMs into IoMT frameworks. By interpreting both raw sensor data and contextual signals, LLMs deliver real-time, personalized health insights that improve disease management and early intervention. PhysioLLM, for example, merges wearable sensor data with

Table 9
Comparative overview of XAI methods applied in IoMT-based healthcare domains: sources, use cases, and representative studies.

IoMT Domain	IoMT Source	Use Cases	XAI Method	Case Studies
Cardiovascular & Chronic Disease Monitoring	Wearable ECG sensors, Smart diagnostic devices, EHR	Heart disease diagnosis, ECG wave detection, CKD, stroke, diabetes prediction	Decision Trees, LIME, SHAP, Counterfactuals, Bayesian Rules, Neurosymbolic causal rules	[215–224]
Neurological, Psychiatric & Genetic Disorders	EEG, Brain MRI, Neuro-sensing devices, bio-IoT	Brain tumor classification, insomnia prediction, autism gene analysis, glioblastoma detection	Feature Relevance, LIME, FI Scores	[225–228]
Oncological & Dermatological Diagnostics	Dermoscopy, MRI, Ultrasound, Pathology imaging	Skin cancer, melanoma, breast cancer, prostate cancer classification and risk prediction	Grad-CAM, SHAP, LIME, PDP, CAM, HistoMapr, Heatmaps, CatBoost + LIME	[229–235]
Respiratory and Infectious Disease Detection	Chest X-ray, Smart stethoscope	COVID-19 and pneumonia detection, mortality prediction	SHAP, Grad-CAM++, Ensemble XAI, CAM, VBP, LRP, GSInquire	[236–238]
Public & Population Health Risk Assessment	Distributed IoMT sensor networks, EHR cloud systems	Recovery outcome prediction, liver cirrhosis evaluation, large-scale health risk analysis	LIME, SHAP, Agreement-based feature attribution	[239–242]

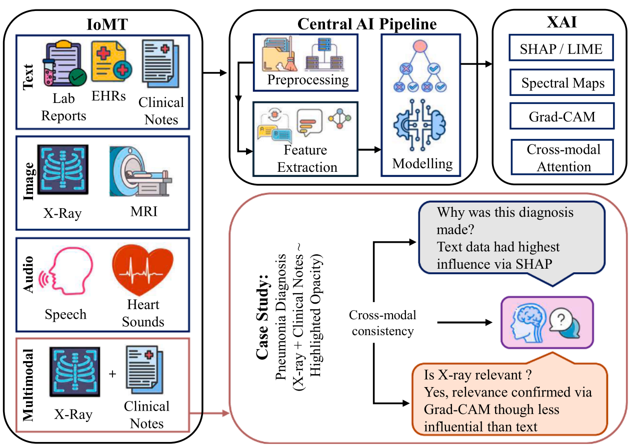

Fig. 12. Multimodal XAI framework illustrating how heterogeneous data from IoMT sources are preprocessed, modeled, and interpreted using various XAI techniques to enable cross-modal, transparent clinical decision support.

user context to provide adaptive sleep and wellness feedback [166]. Health-LLM further demonstrates the utility of LLMs for estimating metrics such as heart rate variability and stress by aligning general-purpose models with physiological tasks through fine-tuning [167]. In the context of blood pressure monitoring, LLMs adapted with domain-specific features have shown promise in enabling cuffless measurement from ECG and PPG inputs [168]. Similarly, hybrid LLM frameworks enable sensor data interpretation, continuous remote monitoring, and real-time feedback [169].

4.3.2. Activity recognition & motion sensing

Activity recognition and motion sensing are central to IoMT-enabled healthcare, enabling continuous monitoring through smartwatches, fitness trackers, and Inertial Measurement Units (IMUs). These systems support diverse applications, from chronic disease management to elderly care and athletic recovery. Recent work has shown that LLMs can enhance activity recognition by interpreting raw sensor data without extensive training. HARGPT, for instance, applies zero-shot prompting with GPT-4 to classify IMU-based activities, outperforming traditional models even on unseen tasks without task-specific fine-tuning [170]. Similarly, LLaSA fuses LIMU-BERT with LLaMA to integrate sensor data and natural language, thereby improving recognition and safety monitoring in real-world settings such as elderly care [171]. LLMs also assist in optimizing the design of HAR systems. ChatGPT has been used to identify optimal sensor placements and extract features, reducing hardware complexity while maintaining accuracy [172]. In smart home environments, LLM-augmented models further mitigate misclassification by leveraging semantic embeddings for context-aware activity interpretation [173].

4.3.3. Emotion aware & cognitive health support

Emotion-aware and cognitive health support is emerging as a critical application of LLMs within IoMT systems. By interpreting physiological signals such as heart rate variability, movement, and sleep quality from wearable sensors, LLMs can infer mental states and deliver real-time, personalized feedback. The Health-LLM framework [167] exemplifies this by using prompting and fine-tuning to predict stress and sleep disturbances based on biometric data. Complementing this, datasets like TILES-2018 and TILES-2019 [174,175] provide rich multimodal signals from healthcare workers in high-stress settings, enabling cognitive modeling and stress analysis. These resources support the development of LLM-based models for fatigue, emotional strain, and psychological risk detection. A recent example, MindShift [176], uses LLMs to analyze real-time smartphone usage, context, and emotional cues, generating adaptive prompts for digital wellness and emotional regulation. More broadly, LLMs are being leveraged to detect indicators of anxiety and depression by linking sensor patterns to mental state inference. This integration supports continuous, context-aware monitoring and personalized interventions, advancing mental health care in clinical and everyday settings.

4.3.4. Athletic performance & recovery analytics

The convergence of LLMs and IoMT is advancing athlete monitoring by enabling real-time, personalized coaching through wearable sensor integration. LLMs analyze physiological signals such as heart rate and movement to deliver adaptive feedback, reduce injury risk, and optimize recovery. [177] demonstrated automated health coaching using continuous sensor data and LLM-driven behavior tracking. [178] further enhanced coaching by embedding behavioral models via priming and dialogue re-ranking, improving personalization and motivation. [179] evaluated LLMs for biomechanical analysis using virtual physiotherapist agents and found that large models effectively identified motion anomalies using retrieval-augmented methods. LLaSA [171] showcased how multimodal data fusion via LLMs supports tailored training and injury prevention.

4.3.5. Occupational health & ergonomic monitoring

LLMs are increasingly being integrated into IoMT frameworks for workplace wellness and ergonomic assessment [180]. emphasized their potential for worker-centric interventions while raising ethical concerns around bias and data privacy. In practice, prompt-engineered LLMs like ChatGPT have shown effectiveness in delivering personalized ergonomic advice, such as posture correction and workspace setup guidance [181]. Complementing this, wearable IoMT devices, including smart textiles and sensor-embedded garments, enable real-time monitoring of posture, strain, and movement. [182] highlighted the role of these systems in preventing musculoskeletal disorders.

5. Integration of explainable AI with IoMT for trustworthy healthcare applications

Explainable AI has gained traction in numerous domains beyond academic research [243]. In environmental systems, XAI supports energy forecasting and natural disaster modeling by uncovering key contributing factors [244,245]. In Industry 4.0, it enhances intelligent decision-making and transparency in automated workflows [246]. In education, XAI improves adaptive learning by interpreting the clustering of student performance using methods such as PCA [247]. In cybersecurity, techniques such as SHAP, LIME, and Permutation Importance help interpret malware detection and intrusion prevention systems [248–250]. Despite their utility, practical challenges remain, including the limited adoption of complex methods such as TReeSHAP [251]. In social media, XAI enhances moderation and misinformation detection by making content classification decisions explainable and trustworthy [252,253]. Similarly, in legal domains, interpretability is essential for fair and accountable decision-making, with tools like LIME providing localized insights for case-specific applications [254,255]. In finance, SHAP and LIME improve transparency in credit scoring and fraud detection, while integration with federated learning and blockchain reinforces privacy and auditability [256,257]. In agriculture, XAI informs crop decisions through interpretable models that consider environmental and seasonal dynamics [258]. These diverse applications underscore the critical role of XAI in enabling transparent and user-aligned trustworthy AI systems. One of the most influential and rapidly evolving areas for XAI integration is healthcare. This section explores this domain in three parts, first, clarifying the conceptual evolution from traditional interpretability to XAI in healthcare, second, examining XAI applications across clinical modalities, and third, examining how XAI enhances interpretability specifically within IoMT-enabled environments. A comprehensive depiction of cross-domain applications of XAI is illustrated in Fig. 11.

5.1. From traditional interpretability to explainable AI in healthcare

To better understand the role of XAI in healthcare, it is important to distinguish it from traditional interpretability methods that have long been used in medical decision-making. Traditional interpretability is typically associated with inherently transparent models, such as decision trees, rule-based systems, linear models, and Bayesian networks, where the reasoning process can be understood directly from the model structure or explicit feature relationships. Although such approaches remain valuable for clinical transparency and trust, they may face limitations in scalability and predictive flexibility when applied to high-dimensional and multimodal healthcare data. In contrast, XAI has emerged to explain the behavior of more complex black-box systems, including deep learning models and advanced AI pipelines, through post hoc or model-specific explanation mechanisms such as SHAP, LIME, Grad-CAM, saliency analysis, attention visualization, and counterfactual explanations. Accordingly, XAI builds on traditional interpretability by improving transparency and accountability in complex models.

5.2. Applications of explainable AI in healthcare

Explainable AI is increasingly critical in healthcare, where transparency is essential for clinical trust and safety. Techniques like SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) are widely adopted, where SHAP offers granular, consistent attributions but is computationally intensive, while LIME provides flexible, model-agnostic explanations with some trade-offs in consistency, especially for high-dimensional medical data [256,259,260]. In medical imaging, tools like Class Activation Mapping (CAM) and Gradient-weighted CAM (Grad-CAM) visualize key regions in diagnostic scans, aiding disease identification, though they are mainly suited for convolutional architectures and may miss spatial nuances [261,262]. Privacy-preserving approaches such as federated Transfer Learning (TL) allow model training across institutions without exposing patient data, but challenges remain in harmonizing distributed datasets [259]. Interpretable models like decision trees and Bayesian networks are valued for transparent reasoning, particularly in precision medicine, although scalability can be limited [263]. Counterfactual explanations, offering "what-if" scenarios, support causal insights but are complex to implement in multifaceted health data [262,264]. Explanations through attention mechanisms and saliency maps also highlight key features but may oversimplify model behavior [258,265]. In emergency care, XAI has enhanced triage and clinical efficiency by clarifying opaque AI decisions [265]. The effectiveness of XAI in healthcare depends on balancing model interpretability and predictive strength. Simpler models provide clarity but may underperform, while complex models demand more sophisticated explanation methods. XAI adoption should take into account clinical context, data complexity, and computational cost [261,262].

This section analyzes XAI applications in healthcare, grouped by modality, textual, visual, signal, auditory, and multimodal to reflect methodological diversity and practical relevance. A summary of representative studies, categorized by anatomical region and XAI method, is provided in Table 8. The table summarizes XAI in healthcare across different data modalities: (1) clinical text and EHR, (2) medical imaging, (3) biosignals (including audio), and (4) multimodal data. To ensure balanced coverage, selections were based on methodological variety and clinical relevance. For instance, in clinical text analysis, XAI methods (e.g., LIME, SHAP) are used to explain predictions by highlighting which features or words contributed to them. Fig. 12 illustrates a multimodal XAI framework, highlighting how diverse IoMT data streams can be interpreted to support transparent clinical decision-making. It demonstrates how a system integrates diverse IoMT data modalities, such as clinical text, medical images, and physiological audio signals, into a unified AI pipeline. The system performs sequential preprocessing, feature extraction, and model inference, followed by interpretability using XAI techniques such as SHAP, LIME, spectral maps, Grad-CAM, and cross-modal attention. A representative case study illustrates how the framework supports clinical reasoning by quantifying the relative influence of each modality (e.g., text vs. imaging) in diagnostic decision-making. This helps clinicians link model outputs to specific input features, improving transparency, cross-modal consistency, and trust in AI-assisted care.

5.2.1. Clinical text & EHR analysis

Explainable AI is increasingly being used to make predictive models based on clinical text and structured EHR data more transparent and easier for clinicians to trust. Structured EHRs contain clearly defined variables such as vital signs and laboratory values, while unstructured clinical notes capture contextual details that are often missed by purely numerical records. When these two data sources are jointly analyzed and supported by XAI techniques, the resulting models become easier to interpret and more suitable for real clinical decision-making. In this context, [189] applied SHAP and LIME to explain 30-day readmission risk following renal transplantation, and integrated the explanations into a web-based tool that enabled clinicians to better understand and manage patient-specific risks. Likewise, [190] used SHAP to interpret a validated Random Forest model for predicting catheter-associated urinary tract infections, offering insights at both the individual patient and broader population levels, thereby clarifying how different factors influenced the model's predictions. A multi-method ensemble by [191] in diabetes risk prediction, integrating SHAP, LIME, Anchors, Explainable Boosting Machines (EBM), Partial Dependence Plots (PDP), and counterfactuals, was used to evaluate explanation fidelity and sparsity for clinical relevance. In oncology, [192] introduced stage-specific models for cancer survivability using SEER data, combining SHAP, LIME, and fairness-enhancing techniques to align predictive accuracy with equity.

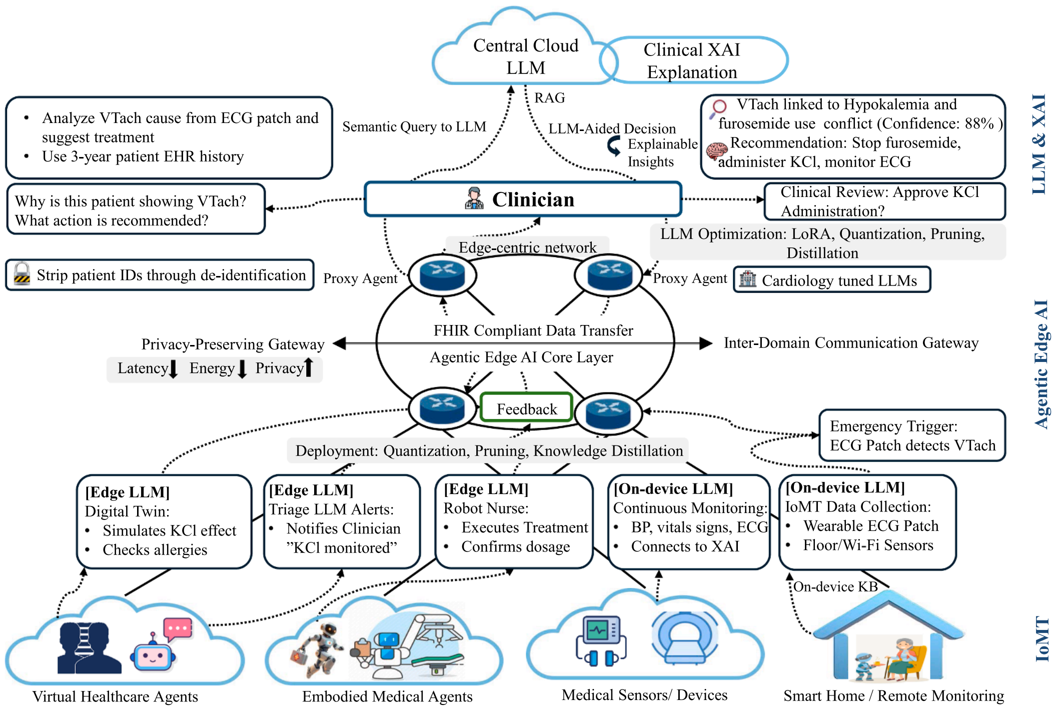

Fig. 13. Case study of agentic edge AI for cardiac emergency response. The framework shows how IoMT devices detect a ventricular tachycardia event, edge agents coordinate triage and intervention, cardiology tuned LLMs perform RAG supported reasoning using patient history and clinical knowledge, and XAI modules provide interpretable evidence for clinician verification.

For pulmonary embolism detection, [193] developed an interpretable model incorporating SHAP, deployed as a clinical decision aid for early risk stratification. Ensemble fusion modeling combined with post-hoc explainability has also been applied to structured cardiovascular risk survey data for cardiac prediction [198], demonstrating that XAI extends across both sensor-driven and registry-driven healthcare analytics. Recent studies highlight the growing role of interpretable fusion models in oncology. For breast cancer, [194] developed a hybrid CNN-LGBM model on structured SEER data and used SHAP for both local and global survival explanations. Similarly, Saharan et al. [195] proposed a CNN-RF hybrid (DXAIB) for the Wisconsin Breast Cancer dataset, with SHAP-based explanations of cytological features. In lung cancer, Deep-Xplainer [196] combined CNN and XGBoost on structured survey data, using SHAP to interpret predictions from lifestyle and symptom-related factors. Together, these works show that ensemble learning on clinical data benefits from post-hoc interpretability to improve transparency, clinical trust, and regulatory readiness. Similar progress has been reported in chronic and cardiac disease prediction. DiaXplain [197] introduced a CNN-XGBoost framework for Type-2 diabetes diagnosis using NHANES survey data, with SHAP explanations for diabetic, borderline, and non-diabetic classes based on demographic, anthropometric, and laboratory features. Likewise, [198] applied ensemble fusion with XAI to structured cardiovascular risk data for cardiac risk prediction. These studies further confirm the importance of explainable ensemble models for trustworthy clinical decision support, even beyond continuous IoMT sensor environments.

5.2.2. Medical imaging & signal interpretation

Explainable AI methods are increasingly applied across imaging and physiological signal domains to enhance transparency in diagnostic workflows. For temporal data, such as ECGs and continuous vital signs, XAI supports time-series interpretation in imaging, thereby improving clinician's understanding of 2D scans (e.g., X-rays, CT, MRI) and 3D volumetric data for tumor analysis and early-stage disease detection. [199] proposed an XAI segmentation framework for cervical cancer using Grad-CAM + +, Layer-wise Relevance Propagation (LRP), and GraphCut, enabling resource-efficient diagnosis [200]. applied LRP to a VGG16-based model for classifying skin conditions, with improved interpretability. Using OCT scans, [201] developed an XAI system for glaucoma diagnosis and staging that outperformed clinicians, with insights derived from SHAP and PDA, and deployed via web and Excel-based tools.[202] combined a vision transformer (EfficientViT), Auto-Canny preprocessing, and Grad-SHAP to detect brain abnormalities from MRI.[203] used SHAP and Anchor explanations in a PET-based glioma classification model, improving diagnostic accuracy and physician confidence.

5.2.3. Biomedical audio analysis

Biomedical audio analysis is gaining traction in healthcare AI due to the diagnostic potential of voice and respiratory signals. While effective in detecting conditions such as cardiovascular disease, depression, Alzheimer's, and COVID-19 [266–269], the explainability of audio-based models remains underdeveloped compared to imaging-based systems. This lack of transparency presents challenges for clinical trust and adoption. Recent efforts have introduced explainability into audio diagnostics.[270] applied Grad-CAM and saliency maps to spectrogram-based CNN models for lung sound classification.[205] used SHAP within a hybrid deep learning model for early Parkinson's detection, combining acoustic features like Mel-Frequency Cepstral Coefficients (MFCC) and jitter.[206] developed a Siamese Neural Network for pediatric respiratory sound analysis with activation maps and Q&A modules for interpretability. For COVID-19 detection, [207] employed an ensemble classifier with SHAP explanations on smartphone-recorded breathing data. In [208], the study examined how model decisions could be better understood by applying Occlusion Sensitivity to fine-tuned OpenL3 audio embeddings for the classification of different voice disorders. By analyzing the effect of selectively masking parts of the audio representations, the authors were able to retain high classification accuracy while also making the underlying decision logic more transparent and easier to interpret. This added interpretability helped clarify which acoustic pat-

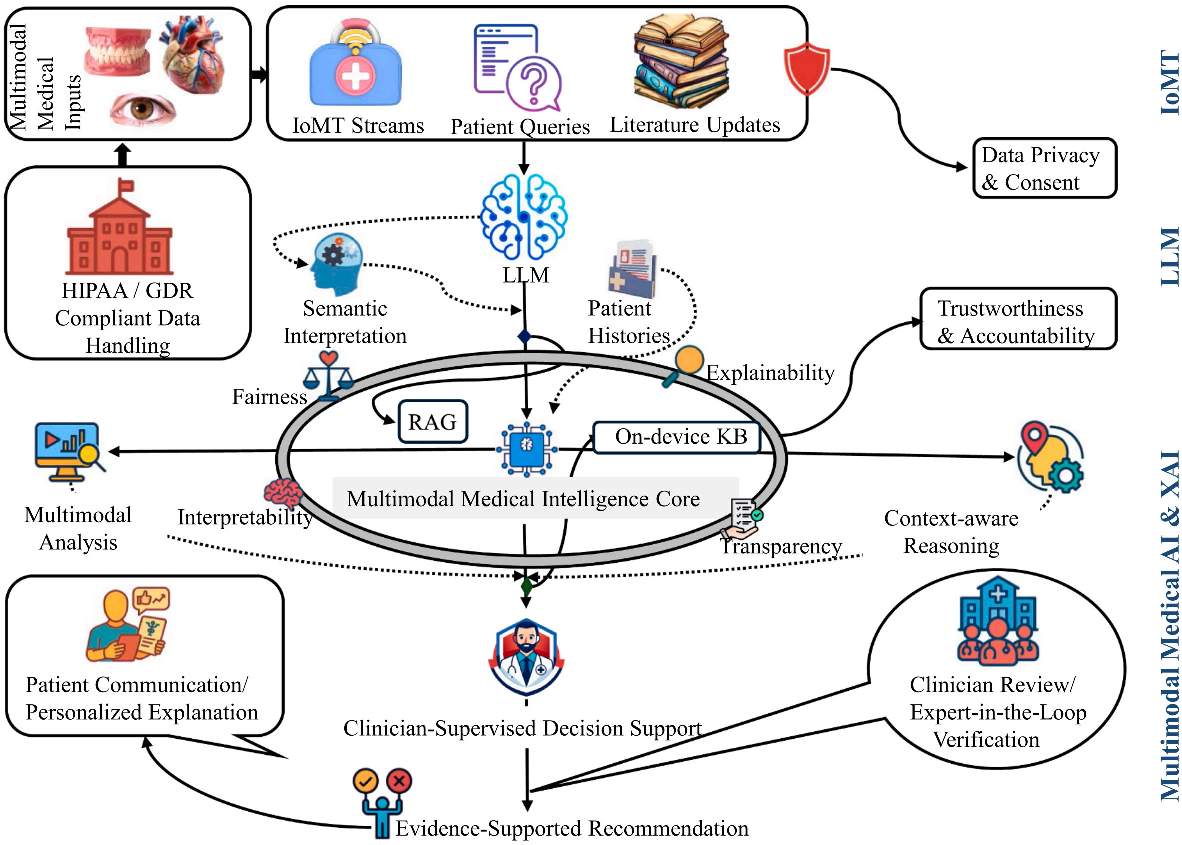

Fig. 14. Case study of generalist multimodal medical intelligence for clinical decision support. The framework integrates IoMT streams, patient queries, patient histories, biomedical literature, RAG, on-device knowledge bases, and XAI mechanisms within a clinician-supervised workflow. The design emphasizes evidence-supported recommendations, privacy and consent, trustworthiness, accountability, and expert verification rather than fully autonomous clinical decision-making.

terns were most influential in distinguishing between voice conditions. In parallel, [209] addressed the early detection of Alzheimer's disease by analyzing speech signals with SHAP-enhanced XGBoost models. Using SHAP-based explanations, the study highlighted the speech features that most strongly influenced the model's predictions, thereby making the results easier to interpret and assess in a clinical context. Explainability linked predictive performance to diagnostic insight, supporting clinically meaningful decisions.

5.2.4. Multimodal XAI in healthcare

Multimodal XAI integrates diverse medical data modalities such as imaging, structured clinical records, and textual inputs to simulate human-like reasoning and provide context-aware clinical support [271]. This convergence enables richer diagnostic insights and improved model interpretability. [272] proposed a co-learning framework for Parkinson's disease that fuses MRI with structured clinical data using DenseNet, ResNet, and Visual Transformer (ViT) backbones. Interpretability is supported by Integrated Gradients and Attention Mapping, which reveal brain regions linked to motor and cognitive decline. Similarly, [211] developed a multimodal system using LRP to analyze real-world data from cancer patients, identifying prognostic markers and offering interpretable treatment guidance. For Parkinson's classification, [210] combined voice, handwriting, and scan data using PSO-based feature selection, hyperparameter tuning, and LIME. In another study, [212] fused clinical time series, chest X-rays, and radiology notes to predict ICU outcomes, leveraging SHAP for transparency. TransXAI [213] used a CNN-Transformer hybrid with Grad-CAM to segment gliomas from multimodal MRI scans, improving both accuracy and interpretability. Similarly, [214] introduced an explainable CAD system for breast cancer that integrates mammography and ultrasound data using YOLOv8 and a ViT-ResNet50 hybrid, supported by Grad-CAM-based visualizations.

After examining XAI techniques and their applications in general healthcare, we now turn to how these methods specifically enhance healthcare applications based on IoMT.

5.3. XAI-driven applications within IoMT systems

The convergence of IoMT and Explainable AI is reshaping intelligent healthcare by pairing data-rich sensing environments with interpretable decision-making. IoMT systems that include interconnected sensors, devices, and platforms generate vast streams of physiological and contextual data. As AI models increasingly underpin clinical decisions in these environments, the need for transparency becomes critical. XAI addresses this by providing interpretable results, supporting trust, accountability, and informed use among clinicians, patients, and regulators. This section examines how XAI techniques are being embedded within IoMT applications, emphasizing their role in improving interpretability and user trust. Table 9 complements the discussion by systematically categorizing representative studies according to application domain, modality, and explanation method.

5.3.1. Cardiovascular & chronic disease monitoring

In cardiovascular and chronic disease monitoring, the integration of XAI into IoMT systems has been instrumental in enabling transparent and reliable diagnostics. [215] employed decision trees to explain clinical reasoning in diagnostic workflows.[216] and [217] proposed data driven frameworks that quantified the impact of key clinical variables in early stage Chronic Kidney Disease (CKD) detection.[218] developed an interpretable cardiac classification model using feature extraction, while [219] applied LIME to explain RNN-based predictions for heart failure outcomes.[220] applied counterfactual explanations for diabetes assessment. SHAP based interpretation for diabetes prediction was demonstrated in [221], and hybrid LIME-SHAP approaches were used by [222] to explain multiple classifiers on diabetes datasets [223]. proposed a 1D U-Net architecture that improved the interpretability and precision of ECG waveform landmark detection by replacing conventional 2D convolutions with temporal 1D layers. Recent neurosymbolic digital twin architectures have integrated wearable ECG/PCG sensing with causal graph reasoning for personalized cardiovascular modeling, using neurosymbolic causal rules for transparent explanations [224].

5.3.2. Neurological, psychiatric & genetic disorders

While binary classification remains prevalent in medical AI, recent research has increasingly addressed more nuanced multiclass challenges. [225] explored multiclass brain tumor classification to enhance differential diagnostic precision.[226] applied feature relevance scoring to identify patterns associated with insomnia, improving interpretability in sleep disorder diagnostics. Although binary classification remains common, recent studies increasingly highlight the need for more nuanced multiclass formulations, particularly in neurological and psychiatric applications. In genomics, [227] used feature importance scores to distinguish between protective and high-risk genes associated with autism spectrum disorder. In another study, the work reported in [228] used LIME-based relevance mapping to analyze glioblastoma classification, where the explanations helped identify tumor-related features relevant to clinical interpretation.

5.3.3. Oncological & dermatological diagnostics

In cancer and dermatological diagnostics, DL models have been widely adopted to improve classification accuracy and clinical utility. Architectures such as VGG16, ResNet50, InceptionV3, and ViT have been evaluated in both standalone and ensemble configurations, with a growing emphasis on explainability. For example, [229] introduced HistoMapr-Breast, a visual explanation tool that highlights clinically significant regions in histopathological images. In dermatology, [230] developed interpretable DL models using dermoscopic and histological inputs, while [231] proposed methods to improve transparency in clinical ML systems. Heatmap-based visualizations for melanoma detection were explored by [232], and LIME-based interpretation of TL models like VGG16 and InceptionV3 was demonstrated by [233] [234]. used CatBoost with LIME for case-specific breast cancer prognosis, while [235] applied LIME to MRI-ultrasound fusion for interpretable prostate cancer diagnosis.

5.3.4. Respiratory & infectious disease detection

In respiratory and infectious disease diagnostics, particularly those amplified by the COVID-19 pandemic, XAI has been instrumental in improving model transparency. [236] introduced an ensemble XAI framework that combines SHAP and Grad-CAM++ to visually interpret mortality-risk predictions for pneumonia and COVID-19 cases. [237] developed VINet, a visual diagnostic system evaluated against CAM and LRP for interpretability.[238] used GSInquire to explain CNN-based COVID-19 detection from chest radiographs, supporting interpretable clinical decision-making.

5.3.5. Public & population health risk assessment

In population health, XAI enhances the transparency of machine learning models used for large-scale risk assessment. [239] used ML with four XAI techniques to predict upper limb recovery during rehabilitation, identifying key predictors and evaluating explanation consistency. [240] applied LIME and SHAP to uncover clinically overlooked factors in liver cirrhosis assessment, aligning AI outputs with clinical insights. Complementing this, [242] benchmarked multiple ML classifiers showing how XAI methods can elucidate decision rationale in complex public health data.

6. System level convergence of IoMT, LLMs, and XAI

The convergence of IoMT, LLMs, and XAI represents an important step toward more intelligent, transparent, and trustworthy healthcare systems. Each technology contributes a distinct capability to this ecosystem. IoMT enables continuous sensing, monitoring, and communication of health related data. LLMs add contextual understanding, reasoning, and natural language interaction. XAI supports interpretability, transparency, and accountability throughout the decision-making process. When combined, these technologies can support healthcare systems that are not only data driven, but also adaptive, interactive, and capable of assisting personalized care in real-time. As this convergence advances, it is also shaping new system paradigms such as the Internet of Agents, edge-centric architecture networks, and autonomous healthcare intelligence. In these settings, healthcare services can move beyond conventional decision support toward coordinated agent based ecosystems, where sensing devices, edge nodes, cloud platforms, clinical knowledge bases, and intelligent agents work together. Such systems can support continuous observation, context-aware reasoning, explainable recommendations, and timely responses across distributed healthcare environments. Building on the architectural and analytical foundations discussed in the previous sections, this section presents system-level models that show how IoMT, LLMs, and XAI can be integrated within unified healthcare frameworks. These models explain how medical sensing, language-based intelligence, knowledge grounding, and explainability can be jointly organized to support transparent, collaborative, and autonomous healthcare services.

Recent HealthCare 5.0 studies have shown that case based analysis can help connect converging technologies such as IoT, AI, and next generation communication networks with practical healthcare scenarios [273]. Building on this direction, the following case studies frame the convergence of IoMT, LLMs, and XAI through two clinically grounded examples. The first case study examines Agentic Edge AI for cardiac emergency response, where edge based agents, wearable sensors, and explainable reasoning can support timely clinician supervised intervention. The second case study considers generalist multimodal medical intelligence for clinical decision support, focusing on how IoMT data, EHRs, patient queries, laboratory findings, and biomedical knowledge can be combined within an explainable decision support workflow. These examples are intended to illustrate possible system designs and research directions, rather than claim the deployment of fully autonomous clinical intelligence.

6.1. Case study 1: Agentic edge AI for cardiac emergency response

This case study illustrates Agentic Edge AI for rapid, explainable cardiac emergency response through IoMT, LLM, and XAI integration within a decentralized agentic ecosystem [274]. Distributed agentic architecture extends conventional IoT by enabling autonomous agents to reason, communicate, and coordinate across distributed environments, with LLMs providing language understanding and adaptive decision-making [275]. Cardiac emergency care demands fast response and clinically understandable reasoning [276], making it a high impact scenario for this convergence. Fig. 13 presents the proposed framework. The system adopts a multi layered cloud edge local model supporting edge centric communication networks. Rather than centralized cloud processing, intelligence shifts closer to the patient to address latency, privacy, and energy constraints [277,278]. At the IoMT layer, wearable devices including ECG patches and physiological trackers continuously collect data and detect cardiac risk indicators. Local on device LLM modules perform early processing and interact with Knowledge Bases for privacy preserving, low latency inference. At the edge layer, lightweight LLMs optimized through LoRA, quantization, pruning, and knowledge distillation enable reasoning on resource-constrained devices [279,280]. Specialized edge agents handle triage, digital twin simulation, and clinical assistance for dosage and contraindication checking, reducing cloud dependence while improving real-time responsiveness. The agentic edge AI core coordinates secure communication and collaboration among healthcare agents through FHIR compliant exchange, with proxy agents managing anonymization, task routing, and module interaction. Inter domain gateways connect wearables, edge nodes, hospital systems, and embodied agents, while feedback loops enable adaptive response to changing patient conditions. Domain specialized LLMs with knowledge representation modules interpret cardiac events using patient history and clinical evidence. RAG dynamically integrates guidelines, records, medication history, and biomedical literature to support grounded diagnostic reasoning [281]. Local KBs keep cardiology knowledge near the point of care for faster, privacy preserving decisions. As shown in Fig. 13, a wearable ECG device detects ventricular tachycardia (VTach). The system formulates a semantic query forwarded to a cardiology specific LLM, which uses RAG and local KBs to review medication history and laboratory results. It identifies hypokalemia from furosemide use and recommends discontinuation with potassium chloride administration, accompanied by confidence scores and interpretable rationale for clinician review rather than autonomous execution. XAI modules generate attention heatmaps, highlight contributing ECG segments and clinical factors, and present relevant EHR excerpts for auditable, verifiable recommendations [282]. Clinician in the loop verification remains essential, with patient facing interfaces translating alerts into personalized explanations. The cloud layer supports large-scale LLM and XAI services through edge centric communication networks, enabling ultra reliable, low latency semantic communication. This framework advances cardiac emergency care from passive monitoring toward proactive, coordinated, explainable response by combining IoMT sensing, LLM reasoning, and XAI transparency within a distributed agentic ecosystem aligned with edge centric communication networks, providing a pathway to trustworthy, autonomous, secure, and ethically grounded emergency response systems.

From a system design perspective, several technical choices underpin this framework. Edge-deployed LLMs use quantization and LoRA fine-tuning to reduce memory footprint while preserving clinical reasoning quality on resource-constrained IoMT devices. RAG modules retrieve from locally cached clinical knowledge bases to minimize network latency and ensure outputs remain grounded in verified medical evidence, directly mitigating hallucination risks identified in Section 4. XAI modules employ attention heatmaps and lightweight feature attribution selected over computationally intensive alternatives to remain feasible within real-time edge inference constraints. FHIR compliant protocols ensure interoperability across heterogeneous IoMT devices, hospital systems, and edge nodes. These design choices balance interpretability, latency, privacy, and clinical reliability within IoMT operational constraints, serving as concrete specifications for future implementations.

6.2. Case study 2: Generalist multimodal medical intelligence for clinical decision support

This case study presents a grounded view of generalist multimodal medical intelligence for clinical decision support, integrating IoMT, LLMs, and XAI within a human supervised workflow. Generalist systems that integrate heterogeneous clinical evidence and reasoning capabilities are increasingly viewed as a foundational step toward broader medical intelligence, including the long-term vision of AGI [283,284]. However, AGI should not be treated as an immediate clinical outcome, and this case study does not claim its deployment. Instead, it focuses on generalized multimodal medical intelligence that combines heterogeneous clinical evidence, supports contextual reasoning, and provides explainable recommendations under clinician oversight. Generalist medical AI systems process diverse information sources including physiological signals, clinical records, patient queries, imaging reports, laboratory results, and biomedical literature [285–287]. Such multimodal reasoning is essential in healthcare, where decisions depend on integrating multiple evidence types. Advanced multimodal systems nonetheless face challenges in interpretability, contextual understanding, ethical accountability, and regulatory compliance. Recent studies show early progress. The MOTOR framework [288] uses knowledge enhanced multimodal pretraining for clinical reasoning, while MedAGI [289] integrates specialized LLMs for cross domain medical queries. These demonstrate broader reasoning potential but highlight the need for safeguards before clinical deployment. Fig. 14 presents a human centric framework integrating IoMT, LLMs, knowledge guided reasoning, and XAI into a trust oriented clinical support pipeline. In this scenario, a patient interacts with a multimodal system receiving real-time physiological streams from IoMT devices, patient generated questions, EHRs, laboratory reports, imaging findings, and biomedical literature. An LLM-driven semantic interpretation module extracts clinical meaning from symptoms, sensor readings, and medical text, converting them into structured representations for downstream reasoning. The reasoning core combines multimodal understanding with knowledge representation for context-aware decision-making. Rather than isolated source recommendations, the framework evaluates the patient's current condition against clinical history, real-time measurements, prior diagnoses, medication records, and relevant medical knowledge. RAG dynamically retrieves external medical knowledge bases, clinical guidelines, and patient specific histories during inference, improving diagnostic precision and adaptability [290]. On device KBs store frequently accessed domain-specific facts locally, enabling privacy preserving and low latency reasoning without continuous network dependence [291]. For example, a patient reports persistent fatigue, shortness of breath, and dizziness through a conversational interface, while IoMT devices simultaneously record abnormal heart rate variability and reduced oxygen saturation. The semantic interpretation layer identifies relevant symptoms and physiological abnormalities. The reasoning module compares these findings with the patient's EHR, medication profile, recent laboratory values, imaging summaries, and retrieved clinical guidelines. Based on combined evidence, the system generates a preliminary risk assessment, suggests possible clinical explanations, and recommends next steps such as urgent clinician review, additional diagnostic testing, or continued monitoring. The output is not an autonomous diagnosis but an evidence supported recommendation requiring clinician review and verification. XAI mechanisms are embedded throughout to ensure transparent and auditable reasoning. Explainability modules identify which symptoms, sensor readings, laboratory values, medical records, or guideline passages contributed to the recommendation, allowing clinicians to examine the evidence and assess clinical appropriateness. The clinician in the loop verification layer remains central, preserving expert judgment in all critical decisions. The framework includes trust and governance components. A data privacy and consent module ensures HIPAA and GDPR compliance through patient authorization, secure data handling, and responsible information sharing. A patient communication interface translates technical recommendations into clear personalized explanations, helping patients understand the reasoning behind suggested actions. These components ensure the system remains transparent, privacy aware, and ethically aligned. At the system-level, this case study demonstrates trustworthy clinical decision support without presenting AGI as a realized technology. As illustrated in Fig. 14, the design combines IoMT enabled real-time sensing, LLM-driven semantic interpretation, knowledge guided reasoning, RAG supported evidence retrieval, and XAI based interpretability within a clinician supervised workflow. This provides a credible pathway toward adaptive, patient centric, explainable, and reliable healthcare systems grounded in current limitations, regulatory requirements, and human oversight.

These case studies clarify the intended scope of the proposed convergence framework. Rather than presenting fully autonomous or fully realized future intelligence as an immediate clinical outcome, they illustrate how IoMT, LLMs, and XAI can be organized into human supervised healthcare workflows. The first case study emphasizes low latency and explainable response in cardiac emergencies, while the second highlights broader multimodal reasoning for clinical decision support. In both cases, clinician oversight, evidence grounding, privacy preservation, and interpretability remain central. This framing supports a credible pathway for future research and system development while maintaining alignment with current clinical, ethical, and regulatory constraints.

7. Limitations and future research opportunities

Although prominent advances have been made in the exploration of either individual technologies or partial integration of IoMT, LLM, and XAI in healthcare, the full convergence of these technologies remains in its developmental stage. Several limitations and research opportunities are outlined in the following subsections.

7.1. Unified IoMT-LLM-XAI frameworks for end-to-end clinical pipelines

We identified that several studies have explored these technologies individually and have only recently begun to examine them in limited pairwise configurations. There is a significant gap in unified frameworks that integrate all three domains and can be used in a transformative manner in healthcare [19,20]. Future systems should prioritize system-level integration to enable automated, transparent, and reliable healthcare workflows in which IoMT-based data are collected and utilized for AI-driven inference, XAI-enabled interpretability, and LLM-powered reasoning and documentation [292]. These fusion systems can be guided by the conceptual frameworks discussed in Section 6.

7.2. Lightweight, edge-deployable models for IoMT devices

The computational overhead of conventional LLMs and XAI techniques restricts their use on resource-constrained IoMT devices [278, 280]. Triadic convergence requires lightweight, low-latency, edge-deployable models and explainability techniques for wearables and mobile health sensors. Deploying these frameworks warrants explicit analysis. Large-scale LLMs are prohibitive for direct edge deployment [277], yet quantization, pruning, knowledge distillation, and LoRA-based fine-tuning reduce model size substantially while preserving clinical reasoning [279]. Full SHAP scales exponentially with feature dimensionality and is impractical for real-time IoMT inference [251]; approximate SHAP, LIME, and attention-based visualization provide lower overhead for latency-sensitive applications [260]. Federated learning distributes training across devices without centralizing sensitive data, improving privacy and scalability [259].

7.3. Personalized and context-aware explainability models

Most current XAI techniques are generic and lack personalization. These techniques are inadequately adapted to individual patient contexts. Studies such as [19] emphasize the need to align explainability outputs with clinical workflows and user expectations to improve transparency and trust in decision-making. Future approaches should develop personalized explainability techniques tailored to individual patients. Personalized explainability models can fuse real-time signals, longitudinal records, and LLM-generated insights to support context-aware healthcare decisions.

7.4. Standardized benchmarks, datasets, and evaluation protocols

Fusion systems require standardized datasets and metrics for effective benchmarking. Future efforts should develop cross-domain, multimodal repositories to enable reproducibility and comparative analysis. Beyond dataset standardization, model generalization across clinical populations remains a fundamental limitation. AI models trained on specific IoMT datasets frequently degrade when deployed across different demographics, clinical settings, or geographic regions [152]. The absence of cross-domain benchmarks evaluating transferability rather than isolated accuracy compounds this challenge. Future benchmarks should validate models across sites, devices, and populations to ensure clinical generalizability.

7.5. Edge-centric architectures with knowledge-enhanced reasoning

Healthcare AI deployments often rely on centralized cloud processing, causing high latency, energy consumption, and privacy concerns with large-scale models and continuous IoMT streams. This is especially critical in time-sensitive scenarios, where delayed inference reduces monitoring, diagnosis, and intervention effectiveness. Real-time IoMT systems therefore require edge-centric or cloud-edge-local strategies that reduce communication delays while preserving efficiency, privacy, and clinical reliability [291]. Future research should explore edge-centric communication architectures with multi-layered cloud-edge-local transformations, as envisioned in Section 6. Lightweight, edge-deployable LLMs enhanced with RAG and on-device KBs enable context-aware reasoning while supporting regulatory compliance and ethical alignment. Real-world IoMT deployments must also contend with temporal distribution shifts from disease progression, seasonal variation, sensor degradation, and evolving patient behaviors. These shifts silently compromise model reliability and degrade edge-based inference validity. Trustworthy convergence systems therefore require uncertainty quantification, continual model adaptation, and proactive input monitoring to ensure sustained performance in dynamic clinical environments. This paradigm enables decentralized intelligence and supports autonomous, trustworthy clinical decision support [277,290,291,293].

7.6. Data security and privacy in handling sensitive patient information

Data quality fundamentally impacts IoMT-LLM-XAI safety and reliability. Sensor noise, missing measurements, calibration drift, annotation inconsistencies, and systematic biases in training data can propagate through LLM pipelines to produce clinically misleading outputs. These quality deficiencies introduce subtle errors that undermine diagnostic validity without detection. Addressing them requires rigorous preprocessing standards, automated data validation, and explicit quality assurance protocols at the sensing layer prior to analytical or generative processing. In IoMT-LLM-XAI systems, patient data traverse wearable sensors, communication networks, edge and cloud platforms, LLM modules, and clinical interfaces. Each layer introduces security and privacy risks during real-time collection, transmission, storage, and analysis of sensitive health information. Threats include data leakage, unauthorized access, data manipulation, denial of service attacks, and misuse of patient information. Expanding connectivity widens the attack surface, making end to end security a mandatory design requirement. Protecting patient confidentiality while enabling meaningful clinical insights is therefore a key challenge [259]. Privacy preserving methods including federated learning, differential privacy, homomorphic encryption, and secure multi party computation offer promising directions for reducing privacy risks. However, these methods require further refinement for efficient, large-scale deployment in IoMT-LLM-XAI environments. Future systems should balance data utility, efficiency, performance, and patient privacy [273].

7.7. Hallucination risks and human-in-the-loop systems for clinical oversight

LLMs offer strong potential for clinical reasoning, diagnostic support, and multimodal integration, yet introduce critical risks. Hallucination generates fluent but incorrect, unsupported, or unsafe medical information. In diagnosis, treatment recommendation, or prescription support, such errors threaten patient safety without expert supervision [273]. Human-in-the-loop mechanisms are therefore essential. Clinicians must verify LLM-generated insights, review uncertain or high-risk outputs, and refine XAI-based explanations prior to clinical decision-making [292,294]. LLM outputs may be hallucinated, incomplete, or clinically misleading, eroding trust and creating safety concerns without proper validation. Human oversight combined with external knowledge grounding and explainability support bridges automation and expert clinical judgment. The case studies in Section 6 further reinforce this need through case studies that emphasize clinician validation for safe and accountable LLM-enabled IoMT adoption.

7.8. Ethical, legal, and regulatory frameworks

The fusion of multiple technologies raises significant ethical and regulatory concerns, including privacy protection, algorithmic bias, explainability mandates, and traceability of decisions. Future research should focus on regulatory-compliant frameworks guided by standards such as HIPAA and GDPR. As noted in [292], embedding ethical design principles within IoMT-enabled pipelines remains a largely unaddressed challenge. Our proposed frameworks, detailed in Section 6, further highlight regulatory alignment as a core design principle to ensure safe, ethical, secure, and compliant integration of IoMT, LLM, and XAI.

By systematically addressing these directions, future studies can unlock the full potential of the convergence of IoMT, LLMs, and XAI, thereby enabling the development of transparent, personalized, scalable, and trustworthy clinical decision support systems.

8. Conclusion

This study presented a structured analytical examination of IoMT, LLMs, and XAI, with a particular focus on their underexplored convergence in healthcare systems. Rather than treating these domains in isolation, the analysis emphasized their complementary roles in supporting adaptive, intelligent, transparent, and clinically accountable healthcare infrastructures. By positioning IoMT as the foundational communication and sensing backbone, LLMs as the contextual reasoning layer, and XAI as the trust enabling layer, this work highlighted how these technologies can be systematically integrated to support trustworthy medical decision-making. The study first established a system-level understanding of IoMT by examining its architecture, foundational pillars, and emerging technologies. Building on this foundation, healthcare applications and representative datasets were analyzed and organized according to IoMT architectural layers. This layered view supports model design, benchmarking, deployment, and reproducibility in diverse healthcare environments.

The convergence of IoMT with LLM-driven intelligence was then examined, focusing on how language-based reasoning and contextualization can enhance clinical workflows when integrated with continuous sensing infrastructures. While existing systems demonstrate promising diagnostic and analytical capabilities, the analysis showed that real-world deployment of LLMs within IoMT ecosystems remains limited. Current efforts often emphasize model development and knowledge engineering, highlighting the need for deeper integration strategies that address operational, clinical, and infrastructural constraints. The integration of XAI within IoMT-based systems was also examined, underscoring its essential role in supporting interpretability, accountability, and clinical trust. Through the analysis of representative applications, this study showed how XAI mechanisms can mitigate the black box nature of advanced AI models and enable transparent reasoning within medical decision pipelines. Such capabilities are particularly critical in healthcare settings, where explainability is closely tied to ethical responsibility, clinician confidence, patient safety, and regulatory compliance.

To strengthen the practical relevance of the proposed convergence, this work also reframed system-level integration through two clinically grounded case studies. The first case study examined Agentic Edge AI for cardiac emergency response, showing how wearable IoMT devices, edge based agents, cardiology-tuned LLMs, RAG, and XAI can support rapid and explainable clinician supervised intervention during a ventricular tachycardia event. The second case study presented generalist multimodal medical intelligence for clinical decision support, illustrating how IoMT streams, patient queries, EHR history, laboratory findings, biomedical literature, and explainability mechanisms can be organized within a human supervised decision support workflow. These case studies demonstrate possible system designs while avoiding claims of fully autonomous clinical deployment. This study synthesized architectural principles, integration strategies, and trust-related considerations across sensing, reasoning, and interpretation layers. The triadic convergence of IoMT, LLMs, and XAI provides a promising pathway toward healthcare systems that are more connected, explainable, privacy-aware, and clinically accountable. Future research should focus on validating these integration models in real-world clinical settings, developing lightweight and trustworthy edge deployable models, strengthening privacy-preserving knowledge grounding, and establishing regulatory and ethical safeguards for human supervised medical AI. Through this grounded perspective, IoMT, LLMs, and XAI can contribute to the development of trustworthy digital healthcare systems that support clinicians, empower patients, and improve the reliability of intelligent medical services.

CRediT authorship contribution statement

Maria Bashir: Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Formal analysis, Conceptualization, Methodology,; **Shaker El-Sappagh:** Writing – review & editing, Validation, Methodology, Formal analysis, Conceptualization; **Simon S. Woo:** Visualization, Validation, Methodology, Formal analysis; **Dong In Kim:** Validation, Methodology, Formal analysis, Conceptualization; **Tamer Abuhmed:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Conceptualization.

Data availability

No data was used for the research described in the article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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