IoT for Next-Generation Smart Healthcare: A Comprehensive Survey

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***Abstract*—The integration of emerging technologies such as the Internet of Things (IoT), artificial intelligence (AI), cloud computing, and blockchain is transforming the landscape of modern healthcare. These technologies enable real-time monitoring, data-driven diagnostics, personalized treatment, and remote patient care, leading to more efficient and accessible healthcare delivery. This article presents a comprehensive review of smart and advanced healthcare solutions driven by these technologies, exploring their architecture, applications, benefits, and limitations. It categorizes healthcare use cases into critical domains, including wearable health devices, intelligent diagnostics, telemedicine, and emergency response systems. Furthermore, this article critically examines key challenges such as interoperability, energy efficiency, data quality, security, and ethical concerns. To address these issues, it discusses current solutions and highlights future research directions essential for scalable and sustainable healthcare innovation.**

***Index Terms*—Activity monitoring, actuators, architecture, connectivity, emerging technologies, healthcare, IEEE Standards, Internet of Things (IoT), sensors.**

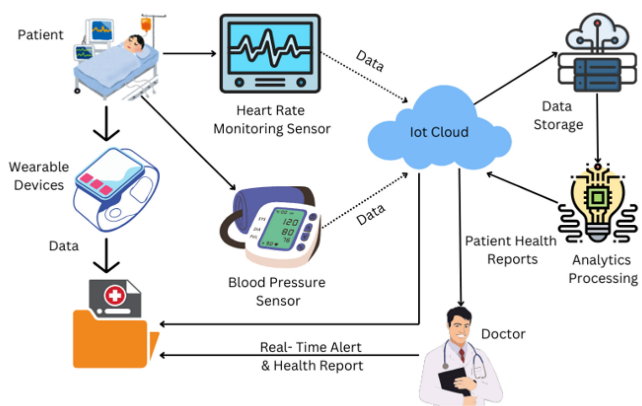

Fig. 1. Illustration of IoT for next-generation smart healthcare.

I. Introduction

INTERNET of Things (IoT) has brought lots of changes in healthcare through remote patient monitoring [1]. This technology helps in keeping patients safe and healthy while doctors provide better care. Better communication between patients and doctors facilitates easier interactions which has resulted in increasing patient satisfaction. The implementation of IoT in healthcare reduces hospital stays and minimizes possible readmissions, further leading to better overall patient care [2]. In addition, healthcare costs decreased, and treatment became more effective. IoT also transforms the healthcare industry by enabling optimal collaboration between devices and people to benefit patients, families, care providers, and insurance companies.

Devices such as wearables, fitness trackers, and other wireless health monitoring tools such as blood pressure cuffs, heart rate monitors, and glucometers offer personalized care to patients, as shown in Fig. 1. These devices provide reminders for activities such as tracking calorie intake, monitoring exercise routines, scheduling medical appointments, and managing fluctuations in blood pressure [3]. IoT has profoundly impacted daily life, particularly for elderly individuals, by enabling continuous health monitoring. This technology is especially beneficial for those who live alone and their families. Alert systems integrated into IoT devices notify family members and healthcare professionals about irregularities or disruptions in the individual's daily patterns. Through wearables and other IoT-powered home monitoring technologies, physicians can monitor patient health more efficiently, ensuring compliance with treatment plans and identifying when urgent medical attention is required [4]. IoT facilitates a more proactive and attentive approach by healthcare providers. The data collected through these devices supports physicians in formulating effective treatment plans and achieving desired patient outcomes.

IoT plays a significant role in hospital environments, serving various purposes beyond individual health monitoring [4]. Fig. 2 presents a timeline of important technologies developed within the healthcare sector from initial research into machine learning during the 1950s to latest achievements in federated learning and AI-based generative systems and emphasizes their radical implications for the healthcare sector. IoT sensors can track the real-time locations of medical equipment such as wheelchairs, defibrillators, nebulizers, oxygen pumps, and diagnostic tools [5]. They also enable hospitals to monitor and analyze staff deployment across various departments. Infection prevention, a key priority in healthcare facilities, is supported

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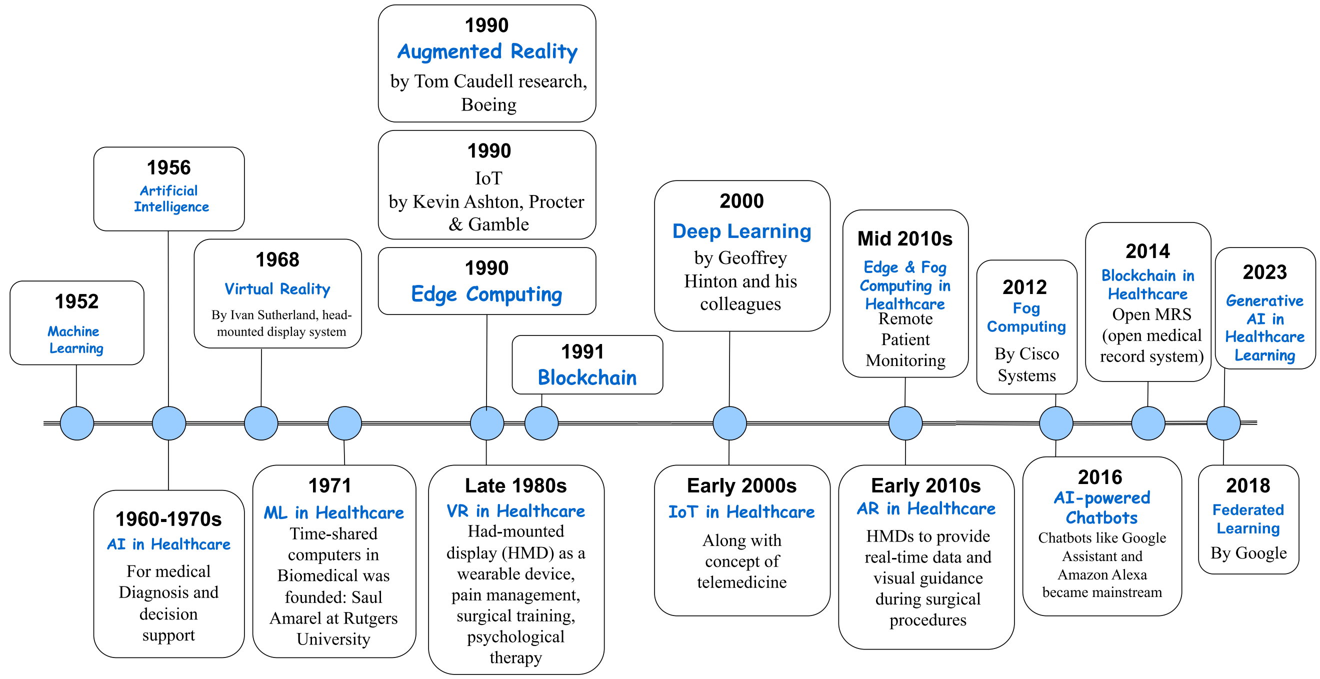

Fig. 2. Timeline of the technologies development and implementation in healthcare.

by IoT-based hygiene monitoring systems, which help reduce the risk of hospital-acquired infections. Furthermore, IoT aids in asset management tasks such as pharmacy inventory control and environmental monitoring, including regulation of temperature and humidity within hospital storage areas, ensuring that medications and medical supplies are optimally stored to maintain efficacy and safety. IoT also offers valuable benefits to the health insurance sector. Insurers can improve underwriting and claims management by utilizing data from IoT-enabled health monitoring devices. The data helps detect fraudulent claims and identify potential candidates for underwriting [6]. IoT fosters greater transparency between insurers and customers by clarifying the decision-making process for pricing, claims handling, and risk assessments. IoT-captured data ensures that customers better understand the reasoning behind operational decisions and outcomes, promoting trust and accountability. IoT revolutionises healthcare by transforming patient care, clinical practices, and health management. By enabling remote monitoring, it enhances patient safety, strengthens healthcare providers' ability to deliver quality care, and improves treatment outcomes, reshaping the future of healthcare delivery.

A. Survey Scope

Several top journals have published articles on IoT in healthcare, including IoT architecture, applications, and enabling technologies. Alam et al. [7] have contributed a review on IoT frameworks for healthcare, reporting current technological application scenarios and emerging trends. Khan et al. have also considered how IoT can better use hospital resources and improve patient care through real-time analytics. The recent work by Goyal et al. [8] elucidated the challenges and future directions of IoT-enabled healthcare wearable devices. This article aims to bridge a critical gap by providing an exhaustive review of IoT architecture, emerging technologies and the latest sensors, which fills the gap between these existing survey articles. In addition, three primary research focuses are on the following research trends in IoT for healthcare, IoT architecture and standards, and key enabling sensors and devices in the IoT-based healthcare ecosystem [9]. Additionally, primary research questions regarding IoT in next-generation healthcare are as follows.

1) Discuss how IoT can be utilized in real-time patient surveillance and diagnosis in actual use cases.
2) Discuss what IoT offers regarding decreased healthcare expenses and better patient outcomes.
3) Do IoT-based solutions for healthcare benefit the efficient management of hospital resources?
4) How might the implementation of advanced sensor and IoT devices promote personalized patient care?

The current research papers and articles cannot answer questions like these, thereby setting the trend of this article, which focuses on open-source works and real-world applications to study IoT-enabled healthcare systems. By conducting our survey, we answer the above-posed questions and develop a constructive direction for future research into including IoT in healthcare.

B. Motivation

The motivation for this survey directly relate to the fast-paced increase in IoT technology in the healthcare industry. The awareness among individuals about the frequent occurrence of chronic diseases and the ageing population has contributed more funds than ever to the healthcare system. Consequently, IoT-related solutions are available in hospitals, clinics, and patients' homes. Integrating connected devices and real-time data collection provides great potential for improving healthcare delivery, quality of care and resource utilization. IoT supports patient engagement through wearables and remote monitoring solutions [10]. Learning how IoT can shorten hospital stays, prevent readmission and ensure continued care would be important in building smart healthcare solutions that respond to new challenges. However, there are still issues, such as the case of health information's sensitivity, which thus raises questions on data security and protection. Also important would be interoperability among various types of IoT and systems in healthcare, all while adhering to even stricter regulations, like HIPAA and GDPR. This article aims to document such trends in sensor technology, cloud computing, and AI-driven data analytics related to the IoT for an efficient, scalable and robust healthcare ecosystem. The survey will provide a comprehensive review of the present state of IoT in healthcare, identify ongoing trends and propose future research directions to guide stakeholders toward innovative strategies for improving health outcomes.

C. Justification for Doing This Survey

While the application of IoT in healthcare has been rapidly advancing, there remains a noticeable lack of comprehensive, up-to-date surveys that consolidate current trends, technologies and challenges under a unified framework. Existing studies often focus on isolated components such as sensor devices, emerging technologies and security protocols but do not provide a holistic view that spans across architecture, standards, AI integration and practical use-case scenarios. This survey is justified by the need for a systematic review that connects multiple domains to present an integrated vision of the IoT-facilitated health ecosystem. By filling gaps in fragmented insights between technical and practical areas this survey provides researchers, developers and policymakers, a unified resource that not only captures the state of the field but also identifies key areas for future research and development.

D. Contribution

As the evolution of healthcare technology continues, introducing IoT into healthcare systems has gained much momentum, few systematic review articles have been reported so far about the potential function of future emerging technologies such as AI, blockchain, cloud computing and the use of sensors and wearable devices in the context of forming Healthcare IoT (HIoT). Motivated by such a gap, this article aims to examine the latest development of IoT-based healthcare systems and key applications, obstacles and future research avenues in this area. The contributions from this work are as follows.

1) First, we describe IoT architecture with major components such as sensors, wearable actuators and connectivity protocols, for instance, Bluetooth, ZigBee and Wi-Fi in the healthcare environment. The review of such composition gives a glimpse into the communication of these components in intelligent healthcare.
2) We are discussing the potential of AI in HIoT, which explores the use of real-time machine and deep learning (DL) algorithms for health monitoring, analytics toward prediction and medicine designed for an individual's needs. The direction will be discussing healthcare in terms of revolution provided by diagnostics in AI-led procedures.
3) This article examines the adoption of emerging technologies, such as blockchain for secure data sharing and cloud computing for storing and processing data within a healthcare system to address some of the major concerns concerning data privacy, scalability, and interoperability.
4) We will discuss promising smart healthcare applications such as remote patient monitoring, chronic disease management and continuous data collection using wearable health sensors. It also discuss the current situation of policies and regulations on IoT healthcare worldwide.
5) Eventually, we conclude the significant issues in research and derive promising future directions on standardized protocolization, wearables low power, data interoperability, and security protection measures for patients' data in IoT health ecosystems.

E. Article Organization

The remainder of this article is structured as follows. Section II highlights the research methodology involving literature classification and existing tutorials on HIoT. Section III offers a detailed view of the IoT-enabled architecture and standards. Section IV explores sensors and devices, which detail different types. Section V discusses the dataset for smart healthcare that entails types of datasets and sources of datasets. Similarly, Section VI provides a discussion on software platforms and protocols in healthcare. In Section VII, we briefly outline the capable applications of AI in healthcare. Section VIII discusses the emerging technologies to support healthcare applications. Section IX highlights the use-case scenario. Section X discusses challenges for designing healthcare solutions. Finally, future opportunities in the context of HIoT.

II. RESEARCH METHODOLOGY AND RELATED SURVEY

HIoT has fully changed the personalization of medicine with real-time patient monitoring, data acquisition and analysis through advanced sensors, wearables and local data processing technologies. Smartwatches and medical wearables sensors monitor critical health indicators such as heart rate, blood pressure and glucose levels [20]. All the processing is done locally, which minimizes latency and bandwidth consumption while maintaining the user's privacy. Wearables, such as BLE and Zigbee, with low-energy communication protocols combined with AI for on-device analysis, are the bases for the early detection of health anomalies [21], [22]. AI with edge computing has greatly enhanced HIoT efficiency in performing the correct action at the right moment through data processing near the generation source. Lightweight protocols, such as MQTT and CoAP further support low-latency data exchange, enabling real-time health monitoring as required in healthcare [23]. This HIoT advance remains an indispensable tool in modern medicine as it advances patient outcomes and decision-making. We discuss some literature classification,

TABLE I
COMPARISON OF RECENT AND RELEVANT SURVEYS ON HIoT

Author & Year	Literature Summary	Architecture	Sensors	IoT Platform	Survey Scope	Technologies	Standards	Challenges	Use-case
Warsi *et al.* [1], 2019	IoT-powered remote health monitoring system for patients for Industry 4.0	✓	✗	✗	✓	✗	✗	✗	✗
Krishnan *et al.* [2], 2018	An IoT enabled patient health surveillance system	✓	✓	✓	✓	✗	✗	✗	✗
Qadri *et al.* [11], 2020	A summary of emerging technologies in the future of healthcare IoT	✗	✓	✗	✗	✗	✓	✗	✗
Mamdiwar *et al.* [12], 2021	Developments in IoT-enabled sensor systems for healthcare monitoring	✗	✓	✗	✗	✗	✗	✓	✗
Le *et al.* [13], 2018	Emerging technologies for health and medicine	✗	✗	✗	✗	✓	✗	✗	✗
Gargrish *et al.* [14], 2023	6G-powered IoT wearable devices for healthcare of the elderly	✗	✗	✗	✗	✗	✓	✗	✗
Al-Sarawi *et al.* [15], 2017	IoT communication protocols	✗	✗	✗	✗	✓	✓	✓	✓
Gopalan *et al.* [16], 2021	A survey on IoT security in healthcare using AI	✗	✓	✗	✗	✓	✗	✗	✗
Kothamali *et al.* [17], 2023	Improving remote patient monitoring through the use of AI and IoT for industrial environment	✗	✗	✗	✗	✗	✓	✓	✗
Karunarathne *et al.* [6], 2021	Ensuring security and privacy in IoT-enabled smart healthcare for Industry 4.0	✗	✓	✗	✗	✓	✗	✗	✓
Supriya *et al.* [18], 2016	Challenges in data security and privacy when adopting IoT solutions	✓	✓	✗	✗	✗	✓	✓	✗
Mavrogiorgou *et al.* [19], 2019	Ensuring interoperability of high-quality data gathered frommedical devices of IoT	✗	✓	✗	✗	✗	✓	✗	✗
Yew *et al.* [4], 2020	IoT-enabled real-time system for monitoring patients remotely	✓	✓	✗	✗	✗	✓	✓	✗
Our Work	**A thorough review of emerging technologies, data challenges and future prospects in H-IoT environment**	✓	✓	✓	✓	✓	✓	✓	✓

"✓" Indicates that the features are either fully or partially addressed in the research study.
"✗" Indicates that the features are not addressed in the research study.

existing tutorials, and surveys on HIoT in the subsequent sections.

A. Literature Classification

A comprehensive literature review was conducted using prominent databases such as IEEE Xplore and DPI, focusing on keywords like HIoT, wearable devices, AI, data security, and emerging technologies. This resulted in over 160 relevant research articles published between 2014 and 2024, with 120 core publications from 2015 to 2023. Among these, 32% (46 papers) focused on HIoT system design and architecture, 58% (52 papers) addressed wearable technologies, sensors, and AI integration, while 47% (34 papers) explored privacy, data protection, and security mechanisms. The majority of contributions came from IEEE (84) and Elsevier (28) journals, indicating strong academic and technical interest. This classification also aligns with global initiatives such as IEEE P2413 (IoT Architecture Standards), the FDA's Digital Health Innovation Action Plan, Europe's Horizon 2020, and India's National Digital Health Mission (NDHM), all emphasizing interoperability, privacy, and secure digital health systems. The review particularly emphasizes literature from 2019 to 2024 to highlight recent advancements and future directions in secure, intelligent, and scalable HIoT systems.

B. Existing Tutorial and Surveys on Healthcare

Several research papers have appeared recently on HIoT to integrate cutting-edge technologies such as IoT, AI, and data analytics into a deep understanding of medical resources along with expert clinical knowledge to optimize personalized medicine, remote patient monitoring and healthcare delivery with safety, privacy and sound well-being in mind [6]. According to the latest survey, HIoT is a strategic approach that can remodel healthcare systems, inspire collaboration among healthcare providers, and set the way for an efficient, accessible and patient-centred future [24]. Similarly, Rejeb et al. discuss the possible applications of HIoT to be a seminal change in how healthcare services are offered and combined with high-tech thought. However, Gandhi et al. have presented a study on intelligent healthcare networks to provide highly customized, patient-specific care solutions by combining medical knowledge and innovative technologies like AI-driven wearables and IoT systems [17]. Nayak et al. have made efforts to make 6G connectivity usable in the healthcare sector and explored challenges and opportunities about seamless real-time monitoring and remote care that are expected to be deployed between 2027 and 2030 [25]. A synopsis of the focus and key contributions of the prior systematic HIoT reviews is presented in Table I.

III. HIoT-ENABLED ARCHITECTURE AND STANDARDS

The integration of the IoT into healthcare has significantly advanced patient care by enabling real-time monitoring, personalized treatment, and data-driven clinical decision-making [20]. Through wearable sensors and smart medical devices, critical physiological parameters can be continuously monitored, facilitating timely interventions and improving overall patient outcomes. In addition to enhancing clinical care, IoT also contributes to operational efficiency by enabling automated patient tracking, asset management, and inventory control, thereby reducing operational costs and streamlining service delivery. Realizing these benefits on a larger scale, however, necessitates a robust and scalable architecture that ensures reliable data acquisition, secure communication, and intelligent data processing, while remaining compliant with established healthcare standards such as HL7, FHIR, and HIPAA. Notably, architecture, standardization, and AI-based analytics are interdependent components that collectively support intelligent, patient-centric care by leveraging real-time data for predictive modeling and system-wide optimization. Despite these advancements, real-world deployments continue

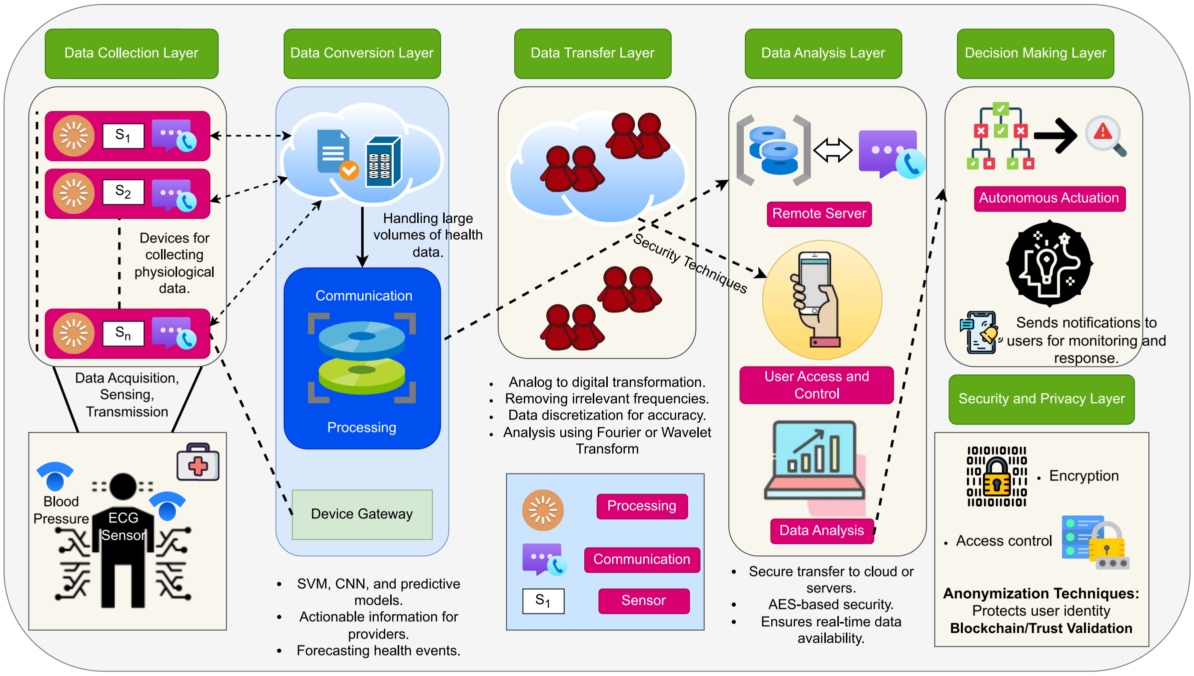

Fig. 3. IoT-driven architecture for smarter health solutions.

to face key challenges, including interoperability, scalability, energy efficiency, and data privacy, which must be systematically addressed during the design and implementation phases [6].

A. Architecture

IoT-enabled healthcare follows a six-layered architecture as illustrated in Fig. 3. These layers represent a comprehensive flow from sensing and processing to action and protection, ensuring smart healthcare systems are both responsive and secure. First, data collection through interconnected devices like sensors and actuators. Secondly, aggregation and conversion of analogue data to digital form [26]. The process involves important tasks such as preprocessing and data transfer to the respective data centre or cloud storage and advancing analytics for actionable insights. This is followed by intelligent decision making and actuation, where insights trigger alerts, enable autonomous interventions (e.g., smart drug delivery), or provide feedback to caregivers. Finally, security, privacy, and trust management mechanisms, such as encryption, access control, and trust evaluation are applied to safeguard sensitive healthcare data and ensure regulatory compliance. Huge opportunities arise at each point in various domains like patient care, hospital management and insurance.

1) Data Collection: The basis of IoT-based healthcare is the constant collection of physiological signals by wearable, implantable, and ambient devices. The most widely measured parameters are heart rate, oxygen saturation, glucose, temperature, and blood pressure. These are time-varying signals that need to be sampled precisely. Based on the Nyquist–Shannon Sampling Theorem

$$f_s \geq 2 \times f_{\max}. \tag{1}$$

Here, f_s is the sampling rate, and $f_{\max}$ is the highest frequency component, ensuring signal reconstruction without aliasing. An ECG signal, $S(t)$, comprising various physiological waveforms, can be represented as

$$S(t) = \{s_1(t), s_2(t), \ldots, s_n(t)\}. \tag{2}$$

However, real-world environments introduce noise and signal degradation. This is typically modelled as

$$S_{\text{measured}}(t) = S(t) + N(t), \quad N(t) \sim \mathcal{N}\left(0, \sigma^2\right) \tag{3}$$

where $N(t)$ is Gaussian noise with zero mean and variance σ^2. In real-time monitoring scenarios, noise suppression and sensor fusion are critical to maintaining accuracy. Kalman filtering is widely employed for this purpose. It iteratively estimates a patient's actual physiological state from noisy measurements

$$\hat{x}_k = \hat{x}_{k-1} + K_k\left(z_k - H\hat{x}_{k-1}\right). \tag{4}$$

Here, $\hat{x}_k$ is the estimated state at time k, z_k is the measurement, and K_k is the Kalman gain, dynamically adjusting predictions for improved accuracy in systems like ECG tracking or glucose monitoring. Most off-the-shelf sensors show drift, calibration problems, or compromised battery life, constraining long-term deployment reliability in outpatient situations

2) Data Conversion: After acquisition, analog signals must be converted into a digital format for computational processing. analog-to-digital converters (ADCs) perform this transformation via sampling and quantization, represented as

$$S_d[k] = Q(S(t)) \tag{5}$$

where $Q(\Delta)$ is the quantization function. The bit depth (e.g., 8-bit = 256 levels) determines fidelity. During this phase, preprocessing techniques such as Fourier transform (FT) or Wavelet Transform are applied to extract significant features and suppress high-frequency noise. The FT decomposes the signal into its frequency components

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft} dt. \tag{6}$$

This is particularly useful in medical signal analysis like EEG/ECG, where distinguishing normal versus abnormal rhythms hinges on identifying specific frequency bands. Additionally, digital low-pass filters with transfer functions

$$H(z) = \frac{b_0 + b_1 z^{-1} + \cdots + b_m z^{-m}}{1 + a_1 z^{-1} + \cdots + a_n z^{-n}}. \tag{7}$$

It eliminates irrelevant or artifact-induced signal spikes, ensuring reliable data for downstream AI processing. Real time preprocessing requires considerable onboard processing capacity, typically not present on low-power wearable devices, resulting in offloading difficulties.

3) Data Transfer: This information is transferred into central systems, like servers in a hospital, cloud platforms or hospital information systems (HIS). Data transfer ensures that real-time updates are given to healthcare providers while keeping patients' medical data safe. Data transfer can be modelled as the time taken to transfer data via a communication channel

$$T_d = \frac{D}{B}. \tag{8}$$

Here, T_d refers to transmission time, D is denoted as data size in bits, and B refers to the channel's bandwidth. In the case of real-time monitoring, T_d must be minimized since delay can occur for data transmission, affecting the outcome in the patient case. Its confidentiality can be assured using encryption algorithms like advanced encryption standard (AES). For example, AES-256 uses an encryption key of 256 bits for the encryption of data

$$C = E_k(P) \tag{9}$$

where C is the ciphertext, P is the plaintext, and E_k represents the encryption function with key k. Protocols like message queuing telemetry transport (MQTT) and constrained application protocol (CoAP) are used for efficient, secure data transfer. Most healthcare centers employ legacy infrastructure with minimal bandwidth and unstable connectivity, making smooth data transfer and secure integration with HIS challenging.

4) Data Analysis: Advanced techniques like big data analytics, AI, and ML analyze healthcare data to provide actionable insights. support vector machines (SVM) classify patient data to identify disease patterns

$$f(x) = \text{sign}\left(\mathbf{w}^T \mathbf{x} + b\right) \tag{10}$$

where $\mathbf{w}$ is the weight vector, $\mathbf{x}$ is the input feature vector, and b is the bias term. convolutional neural networks (CNN), are used to analyze X-rays, MRIs or CT scans for medical imaging cases. Predictive models forecast patient outcomes, disease progression, and potential readmissions, enabling proactive, personalized care while reducing healthcare costs. Health systems are now enabled to serve patients more proactively and personally through AI and ML algorithms that improve the outcome while reducing overall healthcare costs. Most ML models are trained on clean, well-structured datasets but do not generalize in real-world clinical environments because of missing data, class imbalance, or patient heterogeneity. Interpretability and adherence to medical regulations are also obstacles to clinical adoption.

5) Decision Making and Actuation: Once data is analyzed, decisions are made either autonomously or by healthcare professionals. In IoT-based healthcare systems, this phase involves executing actions based on insights derived from the analysis, typically by sending commands to actuators. For instance, in response to detected anomalies, such as fall detection or cardiac irregularities, alerts are generated and communicated to healthcare providers or caregivers. Autonomous actuation mechanisms, such as smart drug delivery systems (e.g., insulin pumps), enable real-time intervention without manual input. Additionally, feedback is provided to patients or caregivers through mobile or wearable interfaces to ensure ongoing monitoring and support. The integration of robotic systems, like those used in surgical assistance, can further enhance patient care by providing automated or semi-automated responses to evolving conditions. This phase ensures a seamless transition from data acquisition to actionable health interventions.

6) Security, Privacy, and Trust Management: Healthcare data is extremely sensitive, necessitating robust security measures to maintain confidentiality and integrity. In IoT-enabled healthcare, a dedicated phase for security, privacy-preserving mechanisms, and trust management is crucial. Data encryption (e.g., AES-256) ensures the protection of patient data during transmission and storage, while anonymization techniques safeguard personal identifiers. Access control mechanisms, such as role-based access control (RBAC) and multifactor authentication (MFA), prevent unauthorized access to sensitive information. Blockchain or distributed ledger technologies offer decentralized and tamper-proof storage of healthcare data, ensuring transparency and trust in data handling. Trust models, such as edge trust evaluation, assess the reliability of data sources and devices, ensuring that only trusted entities contribute to critical healthcare decisions. This phase is integral to ensuring the overall safety and compliance of the IoT-based healthcare system.

B. Standards

Healthcare took far longer to embrace IoT than other sectors. These problems and challenges are unique since they revolve around direct patient care. Relaxing the limitations of a lack of standardization has become a significant bottleneck for the process. Let us examine some of the core areas where standards are fundamentally essential in HIoT.

1) IoT Standards for Healthcare: The standardization of IoT in healthcare is crucial for ensuring seamless integration, reliability, and patient safety. Key standards include IEEE 11073 for medical device communication, which enables interoperability between diverse healthcare devices by defining protocols for data exchange [27]. Health level seven (HL7) standards enable the sharing of clinical and administrative data across healthcare applications, with HL7 v2 widely used for messages and HL7 v3 introducing a more robust, XML-based approach. ISO/IEC 80001 tackles risk management for IT networks integrating medical devices, helping healthcare organizations maintain network safety and effectiveness while integrating new IoT devices. These standards provide a framework for device manufacturers and healthcare IT teams to ensure IoT solutions can be safely and effectively integrated into existing healthcare ecosystems.

2) AI Standards: As AI becomes more prevalent in HIoT, standards are emerging to guide its development and implementation. ISO/IEC JTC 1/SC 42 is developing standards for AI systems, covering areas such as ML frameworks, AI system trustworthiness and big data analytics [28], [29]. The IEEE P7000 series focuses on ethical considerations in AI design, addressing issues like data privacy, algorithmic bias and transparency. These standards ensure that AI-driven healthcare solutions are reliable, explainable, and free from unintended biases, fostering trust among healthcare providers and patients. By adhering to these standards, developers can create AI systems that enhance patient care while maintaining ethical and safety considerations.

3) Healthcare Data Standards: Effective data management is critical for leveraging the full potential of HIoT. HL7 FHIR (Fast Healthcare Interoperability Resources) specifies how healthcare information can be shared between various computer systems using a RESTful API approach that simplifies implementation. Digital imaging and communications in medicine (DICOM) ensures that medical images from various devices can be stored, retrieved, and shared consistently across different systems [30]. Systematized nomenclature of medicine clinical terms (SNOMED CT) provides comprehensive clinical terminology, ensuring consistent coding of clinical concepts for accurate data analysis and interoperability. These standards enable healthcare providers to integrate data from various sources, including EHRs, imaging systems and IoT devices. This creates a more comprehensive view of patient health and enables data-driven decision-making [31]. By leveraging these standards, healthcare organizations can build robust, interoperable IoT ecosystems that enhance patient care, improve operational efficiency and pave the way for innovative healthcare solutions.

4) Data Security and Privacy Standards: Moving to the digital landscape benefits the medical industry [6]. However, there are also some risks in IoT healthcare devices that hospitals should be aware of. Data privacy and security concerns are paramount, as the collection and transmission of sensitive medical data require stringent safeguards to protect patient privacy. Interoperability issues can arise due to the multitude of vendors and technologies involved in the development of IoT devices, which can lead to data silos and inefficient communication [32]. Standardized protocols and regulations are critical to ensure IoT devices integrate seamlessly with existing healthcare systems and networks.

C. Sensors and Devices

The incorporation of IoT in healthcare enables continuous monitoring through connected sensors and devices that capture and transmit real-time data, allowing healthcare providers to respond promptly to health concerns [33]. By facilitating early detection and timely intervention, IoT has shifted healthcare from reactive to proactive, resulting in improved outcomes, enhanced patient experiences, and reduced costs. At the core of these systems are embedded sensors and intelligent devices designed to collect, analyze, and transmit critical physiological and environmental data [34]. These technologies are capable of tracking vital parameters such as heart rate, blood pressure, glucose levels, oxygen saturation, temperature, and motion, while also monitoring environmental factors like air quality, humidity, and ultraviolet radiation [35], [36], [37], [38].

Advanced sensor modalities, including biosensors, imaging, and wearable technologies, enable noninvasive and continuous health monitoring, providing real-time insights into biological functions [39], [40], [41]. Applications range from glucose sensing for diabetes management and ECG recording for arrhythmia detection to motion tracking and sleep monitoring through accelerometers, bioimpedance sensors, and altimeters [20], [42], [43]. In parallel, ingestible and imaging sensors have expanded the diagnostic capabilities of modern healthcare, enabling internal visualization of the gastrointestinal tract and supporting targeted drug delivery through capsule-based systems [44], [45], [46], [47], [48]. A structured overview of various IoT-enabled sensors and devices with their specific medical applications is presented in Table II, which outlines their respective roles in healthcare scenarios.

In addition to sensing technologies, a wide spectrum of IoT-enabled medical devices plays a crucial role in delivering personalized care. These include wearable and implantable devices such as fitness trackers, smartwatches, pacemakers, insulin pumps, and neurostimulators, which support continuous monitoring, real-time alerts, and therapeutic interventions [41], [49], [50]. Portable systems like handheld ECGs and pulse oximeters extend care beyond clinical settings, while stationary equipment such as smart beds, infusion pumps, and connected inhalers ensure precision treatment and efficient workflow in hospitals [51], [52], [53], [54]. Furthermore, IoT-based emergency response and fall detection systems enhance safety in vulnerable populations by enabling rapid alerts and intervention through integrated sensing and communication frameworks [55], [56]. These sensor-driven devices contribute to the shift toward data-driven, proactive, and personalized healthcare. They empower patients to self-monitor health conditions, enable clinicians to make informed decisions based on continuous data streams, and promote scalable, remote care delivery—thereby addressing the growing demand for efficient, accessible, and patient-centric medical services.

IV. Dataset for Smart Healthcare

Smart healthcare systems rely on diverse datasets that capture critical information related to clinical history, physiological signals, environmental factors, and genomic structures. These datasets serve as the foundation for intelligent decision-making, real-time monitoring, predictive analytics, and personalized care [57]. This section classifies the various

TABLE II
TECHNOLOGICAL CLASSIFICATION OF SENSOR TYPES AND THEIR FUNCTIONAL APPLICATIONS

Sensor Type	Description	Applications	Technology Used	Data Types Captured	Challenges
Biosensors	Devices that measure biological processes and convert them to electrical signals.	Heart rate monitor, Electrocardiogram sensor, glucose monitoring.	Electrochemical transducers, piezoelectric sensors	Electrical signals, biochemical data	Calibration issues, short lifespan
Wearable Sensors	Sensors integrated into wearable devices for diagnostics and monitoring.	Fitness trackers, smartwatches, accelerometers, altimeters.	MEMS (Micro-electromechanical systems), optical sensors	motion data, physiological data (e.g., heart rate)	Battery life, data accuracy during motion
Environmental Sensors	Sensors that measure environmental parameters such as air quality, radiation, and weather.	Air quality sensors, radiation detectors, solar radiation meters, PAR sensors.	Chemical sensors, photodiodes, thermistors	Air quality indices, radiation levels	Sensitivity to environmental noise, maintenance needs
Imaging Sensors	Sensors that detect and convey information to form images using light or other electromagnetic waves.	X-ray sensors, CT sensors, optical sensors.	Photodiodes, CCD (charge-coupled device), CMOS sensors	Image data, radiation levels	High power consumption, image noise
Ingestible Sensors	Small sensors ingested to monitor internal body conditions or deliver drugs.	Smart pills, capsule endoscopy.	pH sensors, radio frequency transmitters	Physiological data (e.g., pH, temperature)	Biocompatibility, power supply

TABLE III
IoT-INTEGRATED HEALTHCARE CLASSIFICATION OF DATA SOURCES AND APPLICATIONS ADVANCED HEALTH MONITORING PERSONALIZED CARE

Dataset Type	Description	Sources	Data Types	Typical Use Cases in IoT Healthcare
Clinical IoT Dataset [1]	Patient health data collected through IoT devices such as vital sign monitoring in real-time, remote diagnostics, etc.	IoT-enabled hospital systems, telemedicine platforms, Electronic Health Record (EHR) systems, wearable health devices.	Structured (vital sign data, medical records), Unstructured (real-time sensor feeds, physician notes).	Remote patient monitoring, and chronic disease management, predictive analytics for early diagnosis, and telehealth services.
Imaging Dataset[2]	Medical images integrated with IoT-enabled imaging devices, allowing real-time diagnostic feedback.	IoT-integrated MRI/CT machines, mobile radiology devices, cloud-based imaging platforms.	DICOM, PNG, JPEG, 3D medical imaging formats	AI-driven radiology, tumor detection, image-guided surgeries, continuous diagnostic feedback from remote locations.
Sensor and Wearable Dataset [3]	Continuous data from wearable sensors that track essential parameters like heart rate, blood pressure, and physical activity in real-time.	IoT wearable devices (smartwatches, fitness trackers), in-home IoT monitoring systems, smart health sensors.	Time-series data, numerical (vital signs, step counts), accelerometer and gyroscope data	Remote health monitoring, post-surgery rehabilitation tracking, real-time health analytics, personalized health insights.
Genomic and Proteomic IoT Dataset[4]	Integration of genomic and proteomic data for personalized healthcare via IoT devices, enabling remote analysis of genetic information.	Cloud genomics platforms, connected biobanks, research databases accessible via IoT systems.	DNA/RNA sequence data, protein structures, gene expression profiles	Precision medicine, genetic predisposition tracking, IoT-driven drug development, personalized therapeutic monitoring.
Environmental and Contextual Dataset[5]	Environmental sensor data coupled with patient health metrics to analyze the effect of external factors on health.	IoT environmental sensors (air quality, temperature, humidity), GPS, smart home IoT systems.	Geospatial data, temporal data, environmental indices (pollution, temperature)	Environmental health analysis, pollution exposure studies, location-based disease risk assessment, contextualized patient health monitoring.
real-time Emergency Dataset[6]	Data from emergency response IoT systems, capturing patient conditions during critical events for immediate intervention.	IoT-enabled ambulances, smart emergency wearables, remote monitoring systems, real-time hospital ER systems.	real-time vital signs, GPS location, emergency response indicators	real-time emergency care, automated alerts to healthcare providers, continuous monitoring during patient transport, faster ER response times.

types of datasets used in IoT-based healthcare environments, presents common data sources, and outlines taxonomies and benchmarking strategies that distinguish dataset utility and relevance. Table III provides an illustrative summary of these datasets, their formats, and use cases.

A. Types of Dataset

1) Clinical Datasets: Clinical datasets consist of detailed patient information recorded during hospital visits, ongoing treatments, and diagnostic assessments [58]. These include structured data such as medical codes, treatment protocols, lab results, and vitals, as well as unstructured data like physician notes and clinical narratives. Electronic health records (EHRs) are the principal source of clinical datasets, offering a longitudinal view of patient history. When integrated with IoT-enabled systems, clinical datasets support real-time monitoring and improve clinical workflows by enabling decision-support tools. Laboratory data and device-generated vitals contribute to predictive models that aid in early diagnosis and treatment optimization. Benchmarking for these datasets often focuses on predictive performance, data completeness, and interoperability across institutions.

2) Imaging Datasets: Imaging datasets include diagnostic scans from modalities such as magnetic resonance imaging (MRI), computed tomography (CT), X-rays, and ultrasound. These datasets play a critical role in the identification and analysis of various conditions including cancer, neurological disorders, and cardiovascular anomalies [59]. With advancements in machine learning and computer vision, imaging datasets have become fundamental in the development of computer-aided diagnosis (CAD) systems. Data formats typically include DICOM, along with other formats like PNG or other for preprocessing. Benchmarking of imaging datasets often uses metrics such as accuracy, Dice coefficient, and Intersection over Union (IoU) to evaluate image segmentation and classification models.

3) Sensor and Wearable Datasets: Data from wearable sensors and mobile health devices are increasingly integrated into smart healthcare systems to monitor physiological signals in real time. Devices such as smartwatches, fitness trackers, and implantables record parameters like heart rate, blood pressure, sleep cycles, and glucose levels [60]. These datasets, often in time-series format, are essential for chronic disease management, fitness tracking, and real-time health anomaly detection. Taxonomically, they can be organized by sensor type, sampling frequency, and health metric. Common evaluation criteria include signal quality, continuity, and model performance in detecting anomalies or predicting health trends[61].

4) Genomic and Proteomic Datasets: Genomic and proteomic datasets capture molecular-level information including DNA sequences, RNA transcripts, and protein expression profiles. These datasets are instrumental in precision medicine, helping to identify genetic predispositions and tailoring treatments based on individual biological markers [62]. Such datasets are commonly sourced from biobanks and genomic platforms. With the integration of IoT, remote collection and cloud-based analysis of these datasets have become feasible. Benchmarking focuses on variant detection accuracy, sequence alignment performance, and the reliability of models used in predicting treatment responses.

5) Environmental and Contextual Datasets: Environmental datasets include air quality indices, weather conditions, and geolocation data, while contextual datasets cover lifestyle behaviors, socioeconomic indicators, and mobility patterns. These datasets are critical in assessing external influences on patient health and are often collected using IoT sensors, GPS modules, and smart home systems [63]. When combined with clinical or wearable data, environmental datasets help in predicting disease outbreaks and understanding triggers for conditions like asthma or heat-related illnesses [37]. Benchmarking in this domain evaluates correlation strength with health events, data resolution, and context-aware model performance.

B. Sources of Dataset

The advancement of intelligent healthcare systems, particularly those involving IoT and AI integration, depends significantly on the availability, diversity, and quality of datasets. These datasets originate from various sources, which can be broadly categorized into publicly available, proprietary, and synthetic datasets. Each category presents distinct characteristics, challenges, and performance benchmarks that support the development of data-driven healthcare innovations.

1) Publicly Available Datasets: Public datasets are essential for promoting transparency, reproducibility, and collaborative research in smart healthcare systems [64]. These datasets are generally curated and maintained by government agencies, academic institutions, or open-source communities and offer accessibility without the barriers of licensing or commercial restrictions. Notable sources include PhysioNet, which provides open access to physiological signal data such as ECG and EEG, the U.K. Biobank, a comprehensive biomedical database comprising genetic, clinical, and lifestyle information, and the cancer imaging archive (TCIA), which supplies annotated medical imaging datasets for oncology research [65]. These datasets span various modalities, including genomic sequences, imaging data (e.g., DICOM), and time-series physiological signals, offering a holistic resource base for algorithm training and validation. Public datasets are commonly used to benchmark machine learning models in terms of classification accuracy, model generalizability, and bias detection across demographic subgroups [66]. The availability of standardized benchmarks also enables comparative evaluations across studies, enhancing reproducibility and peer validation.

2) Proprietary Datasets: Proprietary datasets are exclusive resources compiled by hospitals, pharmaceutical companies, and technology firms. These datasets are typically high-resolution, longitudinal, and multidimensional, encompassing EHRs, continuous monitoring from IoT devices, medical imaging archives, drug response profiles, and genomic sequencing data [65]. Examples include collaborations such as the Mayo Clinic and Google partnership to develop AI-driven diagnostic models, and pharmaceutical initiatives like Pfizer's clinical trial registries, which incorporate patient genetics, therapeutic responses, and side-effect profiles. Companies, such as Medtronic, Apple, and Fitbit also generate large-scale wearable data for use in predictive health analytics and lifestyle-based interventions [11]. While access to these datasets is restricted due to commercial and ethical constraints, they play a vital role in personalized care delivery, disease progression modeling, and real-world validation of clinical AI systems. Performance evaluations in proprietary settings typically emphasize clinical applicability, inference latency, interoperability with healthcare workflows, and patient safety outcomes, rather than public leaderboard metrics [67].

TABLE IV
COMPARISON OF IoT COMMUNICATION PROTOCOLS: RANGE, FEATURES, APPLICATIONS, AND DATA RATES FOR HIoT

Protocol Category	Protocol	Range	Key Features	Common Applications	Data Rate
Short-range Communication	Bluetooth	Up to 100m	Supports IPv4, IPv6, IPX, low overhead	Networking peripherals, wearables	Up to 3 Mbps
Short-range Communication	BLE (Bluetooth Low Energy)	Up to 100m	Point-to-point, automatic connection, low energy	Smartphone-device connections, IoT device setup	125 kbps to 2 Mbps
Short-range Communication	Zigbee	< 100m	2.4 GHz band, low latency	Industry, consumer electronics, remote controls	250 kbps
Medium-range Communication	Wi-Fi	Up to 300m	High-speed data transfer, uses IP protocols	LAN, home/business networks	Up to 9.6 Gbps
Medium-range Communication	Z-Wave	Up to 100m	Low-power RF, mesh network	Smart home products, security systems	100 kbps
Long-range Communication	Cellular (5G, LTE, NB-IoT)	Global coverage	High-speed, SIM-based, supports mobility	IoT, mobile communications, real-time tracking	Up to 10 Gbps (5G)
Long-range Communication	LTE-M	Global coverage	Supports mobility, low latency	real-time vehicle tracking, mobile IoT devices	Up to 1 Mbps
Long-range Communication	NB-IoT	Global coverage	Better coverage, supports GSM, 4G, 5G	Fixed IoT devices, smart metering	200 kbps
Low Power Wide Area Network	Sigfox	2 km to 1,000km	Low power consumption, long range	Remote IoT devices, long battery life applications	Up to 100 bps
Low Power Wide Area Network	LoRaWAN	2km to 15km	Broad-coverage, low power	M2M applications, IoT deployments	Up to 27 kbps
Application Layer Protocols	MQTT	N/A	Publish-subscribe model, low bandwidth usage	M2M communication, IoT sensors	Varies based on implementation

3) Synthetic Datasets: Synthetic datasets are computationally generated to replicate the statistical distributions and patterns observed in real-world healthcare data. These datasets address key limitations such as data privacy, access restrictions, and class imbalance in rare disease modeling. Advanced methods such as generative adversarial networks (GANs), variational autoencoders (VAEs), and domain-specific simulation frameworks are commonly used to synthesize high-fidelity clinical, genomic, and imaging data [66]. Organizations like Syntegra and MDClone specialize in producing synthetic EHRs and other healthcare datasets that preserve analytic utility while eliminating patient-identifiable information. These synthetic datasets facilitate open experimentation, model testing, and cross-institutional collaboration without legal or ethical complications. Benchmarking of synthetic datasets involves multiple criteria which includes statistical similarity to original data (e.g., distributional alignment), fidelity of downstream model performance, and reidentification risk scores, which evaluate the dataset's ability to protect individual privacy [68].

V. SOFTWARE PLATFORMS AND PROTOCOLS

The successful implementation of smart healthcare solutions relies on robust software platforms and protocols that facilitate data integration, processing, and communication across various healthcare systems. A comprehensive comparison of IoT communication protocols, including their range, features, applications, and data rates, is provided in Table IV to highlight their suitability for HIoT scenarios.

A. Platforms

Platforms for the healthcare system can be broadly categorized into open-source and commercial solutions, each offering unique advantages and catering to different needs within the healthcare ecosystem.

1) Open-Source Platforms: Open-source platforms, with freely accessible source code, offer significant benefits for smart healthcare, particularly regarding flexibility, transparency, and cost-effectiveness. These platforms empower healthcare developers to modify and extend the software for specific needs, facilitating the integration of unique features and alignment with specialized workflows [69]. Open-source software promotes transparency, allowing for easier identification and resolution of security vulnerabilities, while a collaborative developer community continuously enhances the platform's functionality, security, and efficiency [70]. Open-source platforms in healthcare include tools for managing EHRs, patient monitoring systems, and data analytics frameworks, each contributing to a more accessible and adaptable healthcare ecosystem. Open-source platforms in smart healthcare include open medical record system (OpenMRS), observational health data sciences and informatics (OHDSI), and OpenEHR, each offering unique capabilities for managing and analyzing health data. OpenMRS is a flexible, modular system for managing electronic medical records. OHDSI provides tools and resources to analyze large-scale observational health data, supporting research initiatives and advanced healthcare data analytics. These platforms enhance healthcare delivery and research by providing robust, adaptable, and cost-effective solutions.

2) Commercial Platforms: Commercial platforms are proprietary software solutions developed and maintained by private companies. They often offer comprehensive features, dedicated support, and integration capabilities tailored to meet healthcare organizations' needs. While these platforms typically involve licensing fees, they provide robust, enterprise-grade solutions focusing on reliability and scalability [71]. Many commercial platforms offer integrated, end-to-end solutions that unify aspects like EHRs, patient management systems, and analytics tools, which streamline workflows and enhance operational efficiency. Designed for large-scale deployments, commercial platforms ensure scalability to support growing healthcare demands and reliable performance in critical situations. Commercial platforms in smart healthcare include Epic Systems, a leading provider of EHR systems, offering extensive solutions for patient management, clinical documentation, and data analytics [72]. Cerner provides EHR systems, population health management, and interoperability tools to enhance care coordination across healthcare organizations. All scripts is recognized for its EHR and electronic prescribing solutions, and it is known for its strong integration capabilities and support for value-based care initiatives, assisting providers in improving patient outcomes [73]. McKesson is a well-established platform that provides comprehensive supply chain, EHR, and pharmacy management solutions tailored to large healthcare systems.

B. Protocols

This section offers a detailed explanation of the various protocols employed in smart healthcare, covering a wide spectrum that includes communication, low-power networking, application, and security protocols. These protocols are essential for ensuring seamless connectivity, efficient data transmission, and secure interactions across devices and systems in the healthcare ecosystem.

1) Short-Range Communication: Short-range communication protocols enable devices to transmit data over several hundred meters, often using direct Internet connections or gateways [74]. These protocols are commonly found in applications such as industrial automation, home automation, and healthcare systems, where devices must communicate over limited distances. They offer low-power and efficient data transmission, making them appropriate for a variety of IoT devices requiring connectivity without extensive infrastructure. Bluetooth, one of the most widely used short-range communication protocols, supports common networking protocols such as IPv4, IPv6, and IPX [75]. It allows for the connection of various computer peripherals and is widely adopted for its low overhead and support for different networking needs. Bluetooth low energy (BLE) is an optimized version of Bluetooth, designed for energy efficiency and ideal for applications that require intermittent data transmission, such as healthcare devices connecting to smartphones or tablets [22]. BLE operates directly through smartphone apps, enabling easy device connections without requiring an operating system menu interface, and offers lower energy consumption compared to classic Bluetooth. ZigBee, operating in the 2.4 GHz frequency band, is another limited-range protocol widely used for applications requiring low-latency communication and minimal energy consumption for remote controls. It is particularly useful in environments with restricted areas and when small amounts of data must be transmitted efficiently.

2) Medium-Range Communication: Medium-range communication refers to wireless technologies that enable connectivity over distances varying from a few meters up to several hundred meters. These protocols balance range and data transfer speeds, making them ideal for a range of IoT applications, including home automation, industrial monitoring, and healthcare systems [76]. Wi-Fi and Z-Wave provide robust communication options for devices requiring reliable connectivity without extensive power consumption or long-range connectivity. Wi-Fi, a widely adopted communication protocol, is most suitable for local area networks (LANs) within limited areas, offering high-speed data transfer. It uses standard Internet protocols (IP) to communicate between devices, making it ideal for environments requiring fast data exchange. However, Wi-Fi's high power consumption and relatively limited range make it less suitable for low-power or battery-operated IoT devices. Additionally, the scalability of Wi-Fi can be a limitation in large IoT deployments. In contrast, based on low-power radio frequency technology, Z-Wave is particularly favored for smart healthcare applications for remote control and energy management systems. On a mesh network, Z-Wave offers secure communication with encryption and operates on a 908.42 MHz frequency in the U.S., though it varies by region. Supported by the Z-Wave Alliance, this protocol ensures interoperability and provides a reliable solution for healthcare systems.

3) Long-Range Communication: These communication protocols play a vital role in H-IoT systems, allowing devices to transmit data over extensive distances to the cloud or through gateways, enabling remote monitoring and managing patient health. These protocols are crucial for telemedicine, remote patient monitoring, and smart health management systems, where healthcare data from patients in rural or remote locations needs to be transmitted reliably to healthcare providers [77]. They ensure that healthcare providers can track patient conditions in real-time, even when patients are not on-site, thereby improving care delivery and accessibility. Cellular networks, including 5G and beyond, have evolved from traditional mobile telephony to reliable communication channels for IoT [78]. These networks require access through telecom infrastructure and third-party service providers, involving SIM cards for connected devices and subscription costs. Choosing a network requires considering prices and checking coverage, which becomes complex for international projects where devices operate in different countries. LTE-M, an evolution of the LTE network (4G), supports uplink speeds up to 7 Mb/s and downlink speeds up to 4 Mb/s in the Cat-M2 version. Its support for mobility, including seamless handovers between cells, makes it suitable for applications like real-time vehicle tracking for ambulance services. LTE-M includes power-saving features like power saving mode (PSM) and extended discontinuous reception (eDRX), which extend battery life for IoT devices, such as wearable health monitors.

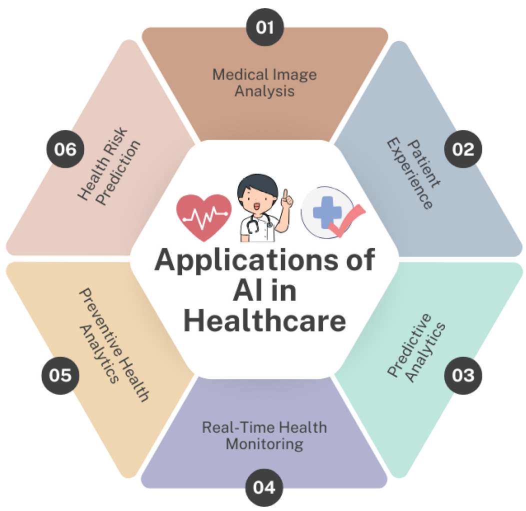

Fig. 4. Illustration of AI advancements in healthcare.

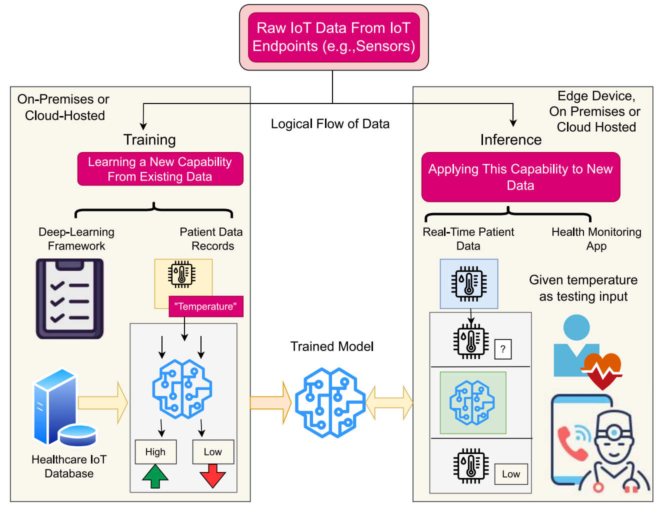

Fig. 5. IoT data input to ML models (training versus inference).

While these features extend battery life, they limit network performance during low activity, making LTE-M suitable for healthcare use cases where frequent live data transmission is not crucial.

4) Low Power Wide Area Network Protocols (LPWAN): LPWAN protocols are designed to interconnect low-bandwidth, battery-operated devices over extended distances with minimal energy consumption [79]. Designed for Machine-to-Machine (M2M) and IoT networks, LPWANs offer lower costs and enhanced power efficiency compared to traditional mobile networks. They also support a larger number of connected devices across a wider coverage area. These protocols typically handle packet sizes ranging from 10 to 1000 bytes and can achieve uplink speeds of up to 200 Kb/s, with operational ranges varying from 2 km in urban areas to over 1000 km in rural or remote regions, depending on the specific technology used. Among the popular LPWAN protocols are Sigfox, LoRaWAN, and NB-IoT, each offering distinct advantages for IoT healthcare applications. Sigfox is a low-power, long-range network ideal for connecting remote healthcare devices that require long-term operations without recharging, such as wearables for chronic disease monitoring or environmental sensors in rural clinics [80]. LoRaWAN, alternatively, is a noncellular wireless technology that provides secure, long-range communication for IoT deployments. It is particularly beneficial in healthcare for applications like patient tracking, hospital asset management, and remote health monitoring, where secure and low-power communication is essential. NB-IoT provides lower data speeds and higher latency than other LPWAN protocols.

5) Application Layer Protocols: In IoT architecture, the application layer is positioned above the service discovery layer [81]. As the topmost layer, it extends from the client side and serves as the interface between the end devices and the network. This layer is responsible for data formatting and presentation which is particularly crucial in healthcare as it enables the interaction between medical devices (e.g., heart rate monitors and glucose sensors) and healthcare applications, allowing for real-time patient monitoring, diagnostics, and alerts. MQTT is a widely used protocol in HIoT applications, particularly for remote patient monitoring and telemedicine [82]. It employs a publish-subscribe architecture to facilitate M2M communication. Its light-weight messaging protocol is compatible with constrained devices enabling communication between multiple devices. Designed for low-bandwidth environments, it is ideal for sensors and mobile devices operating on unreliable networks. Another important protocol in the HIoT space is the CoAP, designed for low-bandwidth and resource-constrained networks. CoAP uses a client-server architecture similar to HTTP but operates over UDP instead of TCP, providing lower communication overhead and faster message delivery [83]. This makes CoAP an excellent choice for healthcare applications like smart medical devices and remote patient monitoring, where devices may be intermittently connected or have limited power resources.

VI. AI IN HEALTHCARE

AI drives transformative changes across the healthcare sector, enabling more efficient, accurate, personalized care solutions. By leveraging data-driven approaches and advanced computational techniques, AI supports tasks ranging from diagnostics and treatment planning to drug discovery and patient monitoring [16]. The foundation of these advancements lies in various machine learning paradigms, including supervised, unsupervised, reinforcement, and DL. These methodologies empower healthcare systems to harness complex datasets and provide actionable insights, ultimately revolutionizing medical practices and improving patient outcomes [84]. Fig. 4 illustrates the broad spectrum of AI advancements being integrated into healthcare, spanning diagnostics, patient monitoring, and treatment optimization. Integration of IoT and AI within healthcare takes raw data from IoT sensors and deploys them toward intelligent patient-monitoring systems with decision-making intelligence as illustrated in Fig. 5. Inference feeds real-time patient data into the trained model via edge devices or cloud-hosted platforms, enabling health monitoring applications to provide actionable insights and support personalized care, such as alerting physicians or suggesting interventions.

A. Supervised Learning

Supervised learning is pivotal in healthcare for predictive modelling and disease classification. By training algorithms on labelled datasets, supervised learning techniques, such as SVMs and random forests provide precise predictions about patient outcomes, treatment responses, and potential complications [85]. These models are essential for cancer detection, patient risk stratification, and personalized medicine, enabling clinicians to make data-driven decisions confidently. Additionally, these techniques are now being applied in the early detection of chronic diseases such as diabetes and cardiovascular conditions, where timely interventions can significantly improve patient prognosis [86]. Supervised learning models also perform critical tasks in optimizing healthcare operations, like predicting patient admission rates and managing hospital resource allocation. Despite these advancements, Gu et al. [87] have discussed the reliance of supervised learning on the strictly fully supervised learning paradigm and its empirical risk minimization theory poses significant challenges in real-world healthcare monitoring. Issues such as limited labeled data, label quality, data heterogeneity, and poor generalization of computational models to new environments hinder their effectiveness. Tackling these challenges requires advanced techniques, including data augmentation, sampling strategies, loss engineering, supplemental tasks, adaptive strategies, and combining multiple models to integrate domain knowledge. By addressing these limitations, supervised learning models can further enhance their potential to transform healthcare analytics and decision-making. The supervised learning algorithms have been extensively used in various tasks in healthcare and have proven their versatility and potential. For instance, Sun et al. [88] have utilized SVMs to predict breast cancer recurrence with clinical and genomic data, thus obtaining robust accuracy in stratifying the patient's risk. Similarly, Kumar et al. [89] have used logistic regression models to predict inpatient mortality, hospital readmissions, and prolonged stays. These studies emphasize the pivotal role of supervised learning in advancing predictive analytics and personalized medicine within healthcare.

B. Unsupervised Learning

Unsupervised learning uncovers hidden patterns within healthcare datasets without relying on labelled data [90]. Techniques like k-means and hierarchical clustering facilitate the segmentation of patient cohorts, the identification of rare diseases, and the analysis of unstructured data such as genomics or EHRs. This approach is particularly useful for exploratory analysis, anomaly detection, and understanding relationships within complex biological systems [91]. Moreover, unsupervised learning helps drug discovery by clustering molecular compounds concerning their chemical properties and biological activities, accelerating the identification of potential drug candidates. It also enhances personalized medicine by identifying novel patient subgroups that may respond differently to specific treatments, thus making it possible for more targeted interventions. Therefore, unsupervised learning can significantly facilitate research and clinical applications in medicine [92]. These advancements have also facilitated targeted public health interventions and enhanced diagnostics, as seen in cancer classification, where ML models address the complexity of vast datasets to improve classification accuracy [93]. The unsupervised learning algorithms, including k-means clustering, hierarchical clustering, and DBSCAN, have stood out in healthcare. For example, Priyadarshi et al. [94] have used k-means clustering to better sense some latent patterns of cardiovascular disorders in cardiac imaging and improve diagnostic precision. Self-organizing maps (SOM) have also been applied to analyze complex patient data, including genomics and EHRs, uncovering relationships that are not immediately apparent. These algorithms allow healthcare professionals to uncover hidden patterns, identify at-risk populations, and optimize treatment strategies without relying on labelled datasets, making them essential for medical research and clinical applications.

C. Reinforcement Learning

Reinforcement learning (RL) introduces adaptive decision making capabilities in dynamic healthcare settings [95]. By modelling healthcare processes as Markov decision processes (MDPs), RL optimizes sequential decision-making tasks such as drug dosage determination and adaptive therapy design. RL's iterative learning framework allows healthcare systems to continually improve outcomes, especially in personalized medicine and robotic surgery, by balancing immediate benefits with long-term goals. For instance, Kalusivalingam et al. [96] have discuss about the potential area of healthcare technology is demonstrated by the investigation into improving remote patient monitoring systems by combining RL algorithms. The algorithms, particularly recurrent neural networks (RNNs) and CNNs have demonstrated an exceptional ability to manage enormous volumes of diverse data, identifying complex patterns frequently difficult for humans to decipher. Such capabilities make proactive actions essential for controlling chronic illnesses and averting unfavorable health occurrences possible. RL is applied to make clinical decision support systems smarter by learning optimal treatment pathways from historical data and real-time feedback. It is also significant in chronic disease management by optimizing care plans tailored to individual patient needs over time [97]. Finally, it applies to hospital management contexts, optimizing patient flow, resource allocation, and scheduling to increase efficiency in operations. Emerging fields such as automatic diagnostic systems and virtual health assistants employ RL to generate real-time, context-aware recommendations to ensure its impact will persist in the transformation of healthcare delivery.

D. Deep Learning

DL, a subset of machine learning, excels at extracting meaningful insights from large, complex datasets such as medical images, genomic sequences, and time-series data. CNNs are extensively used in imaging diagnostics, identifying radiographic patterns for tumour detection. Similarly, RNNs and their variants, like long short-term memory (LSTM) networks, analyze sequential data, enabling early anomaly detection

TABLE V
EMERGING TECHNOLOGIES SUPPORTING HEALTHCARE APPLICATIONS

Technology	Description	Key Benefits	Applications	Use Cases
Edge and Fog Computing	Decentralizes data processing near the source to improve speed and reduce latency	Faster response, enhanced security, lower costs	real-time patient monitoring, wearable devices	Remote monitoring, predictive analytics, data transfer for emergencies
5G/6G Wireless Communication	High-speed, low-latency wireless tech for data transmission	real-time care, improved connectivity, faster data collection	Telemedicine, remote surgery, large-scale data analysis	Remote consultations, personalized treatments, reduced lag in data transmission
Wearable and Implantable Devices	Continuous health monitoring through wearable/implantable tech	Early disease detection, personalized healthcare	Chronic disease management, clinical trials, patient safety	Fitness trackers, glucose monitors, smart implants, neurostimulation
Advanced Robotics	Automates surgeries and medical tasks for precision	Minimally invasive surgery, reduced errors, quicker recovery	Surgical assistance, diagnostic tasks, disinfection	Robotic surgery, microbots for disease detection/treatment
Telemedicine	Remote delivery of healthcare services via telecommunications	Increased access, cost savings, faster diagnosis	Virtual consultations, remote monitoring, telehealth nursing	Live video consults, mobile telehealth, virtual physical rehab
Blockchain in Healthcare	Decentralized, secure storage of medical data	Secure data sharing, supply chain transparency	Medical record management, drug traceability	Patient EHRs, counterfeit drug prevention, supply chain monitoring
AR/VR	Immersive tech merging digital and real environments	Better training, surgical precision, improved diagnostics	Medical education, surgical planning, remote care	3D surgery models, remote patient diagnostics, medical training
Smart Ambient Assisted Living	Tech supporting elderly independence via smart devices	real-time health alerts, disease management	Elderly care, remote health monitoring, smart home systems	Health sensors, family alerts for critical events, smart care homes

and predictive analytics in patient monitoring. DL enhances precision in diagnostics and supports real-time decision-making in HIoT devices. Furthermore, Hussain et al. [98] have demonstrated that the AI-led diagnostic algorithm significantly affects treatment in patients with Alzheimer's disease. DL revolutionizes drug discovery by using molecular structures and accurately predicting drug-target interactions in ways previously unseen in any development process. Genomics uses DL to find mutations and associations linked with disease, paving the way to targeted therapies. GANs are also applied to augment medical datasets by synthesizing realistic medical images, addressing data scarcity challenges. Natural language processing (NLP) applications in healthcare supported by DL include extracting critical information from clinical notes and streamlining documentation workflows, thereby expanding their influence across the healthcare ecosystem. In Kalusivalingam et al.'s [96] research paper, they used CNNs and RNNs to improve remote patient monitoring systems. RNNs were applied to handle time-series patient data, such as continuous monitoring of vital signs like heart rate and blood pressure. By capturing temporal dependencies in the data, RNNs facilitated predicting potential health events. Integrating these DL algorithms with RL techniques to optimize patient monitoring, improve decision-making, and ultimately enhance healthcare delivery.

VII. EMERGING TECHNOLOGIES TO SUPPORT HEALTHCARE APPLICATIONS

Recently, the growth of the IoT, AI, Blockchain technologies, and many more have been gaining popularity and use in healthcare sectors as illustrated in Fig. 6 and Table V. Recent advancements in healthcare IoT encompass a broad spectrum of technologies—from wearable devices and remote patient

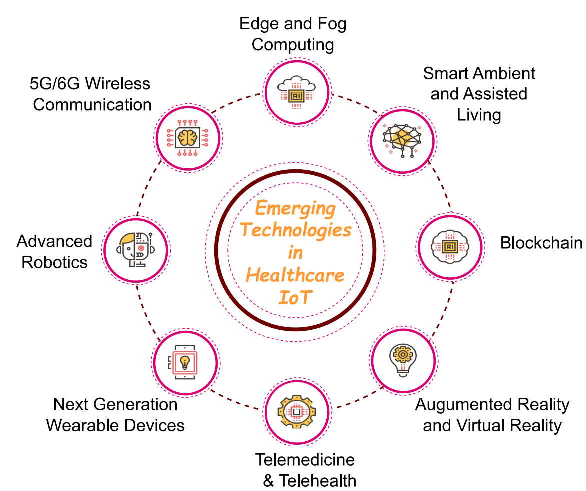

Fig. 6. Emerging technologies in HIoT.

monitoring systems to AI-assisted diagnostics and fog-enabled architectures. A comparative analysis of these solutions in terms of latency, scalability, energy efficiency, and deployment readiness is summarized in Table VI, which highlights their suitability across different healthcare environments. Integrating emerging technologies in healthcare design reshapes the blueprint of patient care environments. From augmented reality assisting in surgical planning to smart hospitals leveraging the IoT for real-time monitoring, the impact of technology on healthcare design is not just revolutionary, it is changing the landscape of how we approach wellness and medical care.

A. Edge and Fog Computing

Edge computing also means providers can rely on AI or IoMT technology to aid in diagnoses and predictive analytics.

Speeding up the transfer of patient information is vital for hospitals in particular, where latency issues, slow processing, and an unreliable network can all impede emergency services [99]. Edge computing is advantageous over other systems because it decentralizes how data is processed. Smaller information centres and networks are more efficient than having one centralized system for storing and transferring patient files, and they can be linked to the burgeoning ranks of remote patient monitoring devices and wearables. That can result in shorter transfer times between devices and data centres [100]. Edge computing advantages include reduced response times, higher security through less sensitive data transmitted over networks, reduced network congestion, increased reliability through offline or low-latency operations, and cost-effectiveness as less power is utilized for local computation [101].

Fog computing in healthcare is a technology that involves processing and analyzing data closer to its source, usually within the health environment itself [102]. It is an intermediary between data-collecting devices, such as medical sensors or wearables, and centralized cloud servers. It allows the data of devices like heart rate monitors, blood pressure sensors, or health trackers to be processed locally rather than sent to distant cloud servers. It means faster processing of time-sensitive information, quicker responses, and reduced load on central cloud systems [103]. Fog computing proves particularly beneficial for applications requiring real-time analysis with prompt action, such as critical health condition monitoring or managing medical emergencies. Fog computing provides several advantages, including reduced latency since the data is computed at or close to the network's edge, enhanced security and privacy as data and applications are closer to users, and increased scalability through the addition of resources at the edge of the network.

B. 5G/6G Wireless Communication

5G, or fifth-generation technology, is the latest advancement in wireless communication systems [104]. It represents a significant leap forward compared to its predecessor, 4G LTE. 5G technology aims to enhance the performance of mobile networks, providing faster speeds, lower latency, and increased capacity to accommodate the increasing need for data-heavy applications and devices [78]. The COVID-19 pandemic has made people more aware of the importance of their health and well-being and has led many to take steps to protect themselves and improve their overall health. 5G is transforming healthcare by enabling real-time video consultations, remote patient monitoring, seamless connectivity, enhanced quality, reliable connectivity and reduced lag time, collection and examination of large volumes of patient data, personalized treatment plans and precision medicine approaches. The transformative potential of 5G and 6G in healthcare, insurance, and life sciences is profound [105]. Embracing 5G's capabilities while prioritizing security, privacy, and investment in training initiatives will empower these industries to unlock unprecedented opportunities and deliver enhanced services to individuals worldwide. Although the commercial deployment of 6G is several years ahead, its ability to mould the trajectory of connectivity and technology holds significant promise [14]. As research and development progress, the industry will be able to refine its vision and unlock even more transformative possibilities with the introduction of 6G.

C. Next-Generation Wearable and Implantable Devices

The next-generation wearable and implantable devices include smart health monitoring devices and smart surveillance hats [106]. These can use wearable sensors for measuring physiological information, sousveillance, navigation, and a smart device to smart device communications over cellular coverage. Wearable devices have many positive benefits, such as continuous health monitoring (e.g., fitness trackers and smartwatches), early identification of health problems (e.g., irregular heart rhythm), improved medication adherence (e.g., smart pill bottles), enhanced data collection for clinical research, personal safety (e.g., fall detection for the elderly), and reducing stress for mental health assistance. These developments lead to better health management, security and well-being. Implantable devices are also advancing rapidly in the next generation of medical technology [107]. These include miniaturized sensors that can be implanted within the body to monitor specific health parameters continuously, such as glucose levels or cardiac function. Benefits and application examples of implantable devices are precise and continuous health data collection (e.g., implantable glucose monitors), targeted drug delivery (e.g., smart drug-release implants), neurostimulation for pain management or treatment of neurological disorders, cardiac monitoring and regulation (e.g., implantable cardioverter-defibrillators), restoration of sensory functions (e.g., cochlear implants) and brain-computer interfaces for assistive technologies. Both wearable and implantable devices contribute to the ongoing digital transformation in healthcare.

D. Advanced Robotics

Robots are designed to carry out a range of essential tasks, such as engaging with patients, assessing their living environments, functioning in hazardous situations and emergencies, analyzing data to enhance pharmacy efficiency, and sanitizing hospital rooms [108]. Advancements in robotics have greatly influenced many medical specialties, which are increasingly making procedures more efficient and providing great benefits. The latest development in robotics healthcare involves using microbots for disease detection and treatment. In this process, a patient swallows a small camera that takes images of the digestive system, based on these images, physicians can identify signs of disease or other conditions. Robotic innovations also advance minimally invasive surgery, as small incisions allow robot-assisted tools to introduce with fewer risks of complications and infections [109]. Incorporating robotics in healthcare frees up staff time for other critical tasks as it automates repetitive, mundane, and administrative processes. Robotics helps reduce surgery times, saves time from time-consuming visits, enables personalized treatments, and increases surgical success rates. In surgical settings, robots offer improved ergonomics and comfort for surgeons, which reduces fatigue and increases procedural volumes. Robots can also reduce human error in high-risk procedures. Future developments in robotics enable robots to perform lab tests independently, remove plaque from arteries, take tissue biopsies, and target cancerous tumours. Robots may also be able to deliver targeted medication, offer care for minor issues, and communicate with patients regarding their symptoms.

E. Blockchain

Blockchain is a novel technology that introduced innovation in various fields, including healthcare. It applies blockchain networks to secure and exchange patient data within hospitals, diagnostic laboratories, pharmacies, and healthcare service providers [110]. Their applications can successfully detect important and potentially harmful errors in the medical field, thereby improving the performance, security, and transparency of healthcare data sharing. Moreover, blockchain helps in keeping track of products used in medicine [110]. In the health and pharmaceutical sectors, this technology can prevent counterfeit medications by allowing the traceability of all pharmaceutical products and tracing the source of falsification. Blockchain also maintains the confidentiality of patient records, as medical histories stored on the blockchain are immutable and cannot be modified. This decentralized network runs on standard hardware used in hospitals. The benefits of blockchain include patient-centric EHRs, with a blockchain-based system integrating existing electronic medical record software to provide a unified view of a patient's medical history. Moreover, blockchain enhances supply chain transparency by enabling tracking items from manufacturing through every stage of the supply chain. This method gives customers complete visibility and transparency of the goods they buy.

F. Augmented Reality and Virtual Reality

Augmented reality (AR) and virtual reality (VR) bring the virtual and real worlds together, enhancing the real one with digital objects. This convergence is transforming medical education and practice. In healthcare education, AR and VR enable students to engage in highly interactive simulations that model complex surgical procedures or diagnose rare medical conditions [111]. This practical, risk-free learning environment enhances the educational experience and better prepares future healthcare professionals. For practising surgeons, VR technology offers powerful tools for surgical preparation. Surgeons can train and improve techniques and enhance personalised surgical approaches by generating 3-D models of a patient's body and modelling surgical procedures in a virtual space. This approach allows for better preparation and potentially improved surgical outcomes. In patient care, AR and VR technologies are improving virtual consultations. These tools allow doctors to retrieve patient data and vital signs instantly, making the experience of both patients and healthcare providers more engaging and insightful. Furthermore, these immersive technologies enable more accurate remote diagnostics and training. Benefits of AR and VR in medical care are enhanced hospital education through immersive, realistic simulations, improved surgical preparation and planning, more effective remote consultations and diagnostics, risk-free environment for medical training and practice, personalized treatment planning, increased accuracy in medical procedures, better patient engagement and understanding of treatments [112].

VIII. Use Case Scenario

The incorporation of IoT in healthcare has brought major progress in the administration of patient care through efficiency, personalization, and accessibility. Indeed, with connected devices, health providers can monitor patients continuously, gather real-time data, and respond more quickly to health concerns. In this respect, IoT solutions have moved healthcare from reactive to proactive healthcare, whereby earlier detections of health conditions lead to timely interventions and, therefore, better outcomes, improved patient experiences, and lower healthcare costs. This range of use-case scenarios illustrates how IoT is applied to different health domains, from elderly care predictive diagnostics to telemedicine and even robotic surgery.

A. Elderly Care and Assisted Living

IoT technologies are revolutionizing elderly care, enhancing safety, independence, and overall quality of life. Smart home devices monitor daily activities, detect falls, and alert caregivers to potential issues. Wearable devices track vital signs, medication adherence, and sleep patterns, while connected mobility aids provide real-time location data and track movements [113]. These solutions enable seniors to age in place, allowing them to continue living in the comfort of their homes while giving families peace of mind, knowing their loved ones are well-monitored and cared for. Additionally, voice-activated assistants can help remind seniors to take their medication, attend appointments, or even guide them through daily routines, promoting a greater sense of control and autonomy. Enhanced safety continuous monitoring helps in the early detection of falls, wandering, or other emergencies, ensuring timely intervention and potentially preventing more serious outcomes. For instance, sensors in beds can detect abnormal sleep patterns that might signal health issues. Devices like smart pill dispensers ensure that medication is taken on time, while smart thermostats allow seniors to easily control their home environment without needing to move around much [45]. Geofencing technology can alert family members if their loved ones wander outside a designated safe area, ensuring a faster response if something goes wrong. These advancements in IoT technology enhance physical safety and promote emotional well-being by allowing seniors to live more independently.

B. Predictive Analytics and Early Diagnosis

By leveraging IoT-generated data and AI algorithms, healthcare providers can identify disease patterns and risk factors earlier. Continuous monitoring through wearables and home sensors allows for detecting subtle changes in patient health, potentially flagging issues before they become critical. This proactive approach can lead to earlier interventions and improved patient outcomes. Early detection allows subtle

TABLE VI
COMPARATIVE ANALYSIS OF HIoT SOLUTIONS

H-IoT Solution	Latency	Scalability	Deployment Readiness	Energy Consumption	Remarks
Wearable Health Devices (e.g., smartwatches, fitness bands)	Low (< 1 sec)	High (consumer-scale)	Commercially deployed	Low (battery-efficient)	Widely used for fitness, basic vitals, and lifestyle monitoring.
Remote Patient Monitoring (RPM)	Medium (1–3 sec)	Moderate (per facility)	Extensively adopted	Medium	Effective for chronic disease care and elderly monitoring.
Body Area Networks (BANs)	Very Low (<500 ms)	Low (personal use)	Pilot/Experimental	Very Low	High responsiveness, ideal for real-time health data.
Smart ICU Systems	Low (<1 sec)	Low–Moderate	Hospital-grade deployments	High	Reliable but infrastructure-heavy and costly.
Fog-enabled H-IoT Architecture	Low–Medium	High (edge-level scaling)	Prototype/Pilot stage	Medium	Latency-sensitive use cases, supports decentralized processing.
Cloud-based IoT Platforms (e.g., AWS HealthLake)	Medium–High	Very High (cloud-native)	Commercial platforms	High	Flexible but reliant on stable network and compute resources.
AI-assisted Diagnostics (e.g., ML models for imaging)	Medium (1–2 sec inference)	Moderate (clinic-level AI)	Partially adopted	High (GPU/compute-intensive)	Enhances accuracy, but requires significant power and integration.
LoRaWAN-based Health Monitoring	High (>5 sec)	Very High (wide-area)	Pilot stage, remote regions	Very Low	Great for rural, low-resource areas, but not real-time capable.

health changes to be identified promptly, leading to earlier diagnosis and treatment [114]. A sudden drop in activity levels detected by wearable devices could indicate the onset of a health issue that might otherwise go unnoticed. With real-time data at their disposal, doctors can adjust treatments based on trends, allowing for more targeted and timely interventions. Personalized risk management involves the development of tailored health plans based on individual risk profiles. Data from IoT devices provides insights into lifestyle factors, genetic predispositions, and environmental influences, allowing healthcare providers to tailor care plans to address the unique needs of each patient. Leveraging predictive analytics in healthcare allows for a shift from reactive to proactive care, ensuring patients receive timely interventions that improve their quality of life and reduce healthcare system burdens. In this section, we examined the various use cases of how IoT can be utilized. Moreover, we addressed the solution to this question "Discuss how IoT can be utilized in real-time patient surveillance and diagnosis in actual use cases." by discussing the role of IoT in monitoring patient in real-time and also the early diagnosis of diseases.

C. Personalized Treatment Planning

IoT devices facilitate the gathering of extensive amounts of patient-specific data, allowing for more tailored treatment plans [115]. By analyzing data from wearables, implantables, and home monitoring systems, clinicians can adjust medications, therapies, and lifestyle recommendations in real-time, optimizing treatment efficacy and minimizing side effects. It reduces the need for generalized treatments that may not suit every patient, providing a more individualized healthcare experience that aligns with each person's unique condition, genetic profile, and lifestyle. By incorporating ML and AI into IoT systems, healthcare providers can predict possible complications before they manifest [116]. For example, data collected from a heart monitor or glucose sensor can flag abnormalities early, allowing doctors to make preemptive adjustments to prevent serious health events. Personalized plans also reduce side effects by minimizing adverse reactions to medications, ensuring that prescribed medications and their dosages are suited to the patient's unique biochemistry [115]. Enhanced patient engagement is another key benefit, as patients are more inclined to follow personalized treatment plans that reflect their specific needs. When healthcare plans are tailored for them, patients are more likely to follow them diligently, resulting in better health outcomes. This engagement is further strengthened by IoT devices that provide reminders and alerts, keeping patients actively involved in their health management.

D. Telemedicine and Virtual Healthcare

The integration of IoT with telemedicine platforms has expanded access to healthcare services. Remote patient monitoring devices transmit vital signs and symptoms to healthcare providers, enabling virtual consultations and reducing the need for in-person visits [117]. With the rise of chronic diseases such as diabetes and hypertension, regular monitoring is essential, and IoT technologies allow this to happen seamlessly without requiring frequent hospital visits. Telemedicine supports preventive care by providing healthcare professionals with a constant data stream [118]. Doctors can monitor patient health daily, intervening when necessary rather than waiting for a routine check-up to identify issues. This model is transforming by enhancing its efficiency and patient-centred approach. Patients save time and resources by receiving care from home, which is especially beneficial for those with busy schedules, mobility limitations, or transportation challenges. Continuous monitoring through real-time data transmission also plays a crucial role in improving the management of chronic conditions. Healthcare providers can track the patient's health 24/7, enabling the early identification of issues before they escalate, greatly enhancing long-term health management. In this section, we examined how IoT has improved patient lives through reduced costs and also we addressed the solution to this question "Discuss what IoT offers regarding decreased healthcare expenses and better patient outcomes."

E. Robotic Surgery and Assisted Devices

IoT-enabled surgical robots and assisted devices enhance precision and reduce invasiveness in medical procedures [109]. These systems provide surgeons with real-time data and haptic feedback, improving outcomes and reducing recovery times. Surgical robotics, which combines IoT with AI, offers unprecedented control and accuracy, allowing surgeons to perform complex procedures that require delicate precision [119]. This improves surgical outcomes and expands the possibilities of what can be treated surgically. Robotic surgeries mean less invasive procedures, fewer complications, and faster recovery times for patients. Minimally invasive techniques, guided by IoT-enabled robots, result in smaller incisions, less blood loss, and a reduced risk of infection. The ability to remotely monitor the patient's condition during surgery also helps in preventing complications during the procedure, as doctors can access real-time data on vital signs and make necessary adjustments to ensure the patient's safety. Patients experience shorter hospital stays and are able to resume daily activities more quickly, reducing overall healthcare costs associated with long recovery periods [108]. Remote expertise is another advantage, as surgeons can operate remotely or consult with specialists in real-time, improving surgical outcomes. This capability is especially valuable when local expertise is unavailable, allowing specialists to assist in surgeries from anywhere in the world.

F. COVID-19 Like Pandemic Management

The COVID-19 pandemic revealed the power of IoT in managing large-scale health crises [37]. Contact tracing applications, thermal imaging cameras, and automated sanitization systems have been deployed to control virus spread. IoT-enabled supply chain management has improved the distribution of critical medical supplies and vaccines. Additionally, wearable devices that monitor symptoms like body temperature and oxygen levels are helping detect early signs of infection, making it easier to prevent outbreaks. The ability to monitor and track individuals and entire populations in real-time allows for a much more agile response to pandemics. Data collected from various IoT devices can be aggregated and analyzed to identify hotspots and predict outbreaks before they happen. This data-driven approach to pandemic management is a crucial tool in reducing the spread of disease and ensuring that medical resources are allocated where they are most needed. Efficient distribution, facilitated by improved supply chain management, ensures the timely delivery of essential medical supplies, helping to prevent shortages and ensuring that critical equipment reaches areas in need. This allows governments to better balance public health needs with economic considerations. In this section, we examined how IoT has revolutionized healthcare through better utilization of resources in hospitals and also we addressed the solution to this question "Do IoT-based solutions for healthcare benefit the efficient management of hospital resources?".

IX. Lessons Learned

This section summarizes the lessons learned from current state-of-the-art studies and summarizes research issues that need to be addressed to ensure an effective H-IoT environment. Section I introduced H-IoT and the revolution it has made in healthcare industry, emphasizing its role in enabling remote patient monitoring, improving treatment outcomes, and enhancing resource utilization. However, despite these benefits, integration of IoT into healthcare is quite challenging. Furthermore, it helps reduce hospital stays, lowers costs, and boosts treatment efficiency. In hospitals, IoT enhances equipment tracking, staff management, and infection control. The tech timeline indicates how rapidly IoT has developed in tandem with AI and other technologies. However, challenges like data privacy and system compatibility remain, highlighting the need for secure and standardized solutions. Section II discussed research methodology, literature classification, and existing tutorials and surveys on healthcare. Section III addressed the IoT-enabled architecture, which follows a layered approach from data acquisition to analysis, ensuring secure, accurate, and efficient handling of health information. It also introduced the decision Making and actuation phase, facilitating real-time interventions, and the security, privacy, and trust management phase, ensuring robust data protection and regulatory compliance.

Section IV outlines the diverse datasets powering smart healthcare. These datasets play a vital role in diagnostics and predictive analytics. The data sources consist of public repositories, proprietary healthcare systems, and synthetic datasets designed to address privacy and availability challenges. Collectively, they enable AI-driven innovation and boost the effectiveness of IoT-enabled health solutions. Later on, in Section V, we discussed the importance of choosing appropriate software platforms and communication protocols in intelligent healthcare systems, highlighting their roles in facilitating secure, scalable, and energy-efficient data exchange among various healthcare applications. In Section VI, we addressed how different AI techniques are being applied across healthcare from analyzing complex medical data to optimizing hospital operations. In Section VII, we addressed emerging technologies like edge computing, 5G, robotics, and blockchain, reshaping healthcare delivery by enabling faster, decentralized, and more secure systems. In Section VIII, we addressed the transformative impact of IoT across healthcare by diving into concrete, real-world scenarios from smart elderly care systems

TABLE VII
CHALLENGES AND POTENTIAL SOLUTIONS FOR ISSUES IN HIoT

Challenge	Impact	Potential Solution	Cost Implication	Complexity Level
Data Privacy & Security	Increased risk of data breaches can lead to significant financial losses, loss of patient trust, and potential legal implications. Protecting sensitive information is crucial in maintaining healthcare integrity.	Implementing strong encryption protocols and real-time monitoring systems can mitigate these risks effectively, ensuring that data is secure during transmission and storage.	High	High
Interoperability	Lack of system compatibility can result in inefficiencies, duplicated efforts, and increased operational costs. This can hinder the overall effectiveness of healthcare delivery.	The use of standard protocols and centralized hubs can facilitate better integration among various systems, leading to improved communication and data sharing across platforms.	Medium	Medium
Algorithm Development	Inaccurate diagnostics can lead to misdiagnoses, inappropriate treatment plans, and ultimately affect patient outcomes. Reliable algorithms are essential for effective healthcare solutions.	Training AI on diverse datasets can enhance the accuracy of diagnostics, ensuring that the algorithms are robust and capable of handling a variety of patient scenarios.	High	High
Connectivity Issues	Loss of critical data due to connectivity problems can have severe consequences in emergency situations, potentially compromising patient care and safety.	Developing offline capabilities and network redundancy can ensure continuous data access, minimizing the risk of data loss during connectivity disruptions.	Medium	Medium-High
Low Energy Consumption	Short device lifespan due to inadequate energy management can lead to increased replacement costs and operational disruptions in healthcare settings.	Designing energy-efficient devices and implementing adaptive sampling techniques can significantly extend device lifespan while maintaining performance.	Medium	High
Integration with Workflow	Disruptions in clinical operations can lead to reduced efficiency, decreased staff productivity, and negatively impact patient care quality.	Tailored user interfaces (UI/UX) and comprehensive staff training programs can improve system integration and ensure smooth workflows in clinical settings.	High	High
Data Quality & Bias	Skewed healthcare outcomes can arise from poor data quality and bias in data collection, resulting in ineffective treatments and disparities in patient care.	Implementing bias detection mechanisms and ensuring diverse data collection strategies can enhance data quality and provide a more accurate representation of patient needs.	Medium	High
Cost & Resource Allocation	Budget overruns can jeopardize projects and lead to inadequate resources for critical healthcare initiatives, affecting service delivery.	Developing scalable and flexible architectural frameworks can help organizations manage costs effectively while adapting to changing healthcare demands.	High	Medium-High

to robotic-assisted surgeries and pandemic control strategies. In Section X, we discussed the major technical and operational challenges in implementing smart and advanced healthcare solutions. Eventually, In Section XI, we addressed the future directions in H-IoT focusing on strategies that aim to overcome current limitations in smart healthcare systems.

X. CHALLENGES IN SMART AND ADVANCED HEALTHCARE SOLUTIONS

Major challenges during the design of smart healthcare solutions include robust data security and privacy, device-to-device interoperability that ensures seamless functionality, developing reliable algorithms for real-time data processing connectivity, and integration complexities in deploying and maintaining IoT healthcare systems as depicted in Table VII.

A. Connectivity and Interoperability

Reliable connectivity forms the backbone of smart healthcare systems, enabling continuous monitoring and timely decision-making. However, ensuring uninterrupted communication between IoT devices and centralized systems is particularly difficult in rural or remote areas with limited network infrastructure. Frequent signal losses or bandwidth limitations can lead to data gaps, delayed alerts, and compromised patient outcomes [19]. In addition, the lack of universal standards for communication protocols and data formats complicates interoperability among heterogeneous devices and platforms. Seamless data exchange across systems developed by different manufacturers remains an unresolved challenge, hindering the creation of unified patient records and coordinated care models [120]. Addressing these issues requires not only the adoption of standardized frameworks but also the development of middleware solutions that can translate and synchronize diverse data streams in real-time. Furthermore, the growing number of connected devices intensifies the risk of network congestion. Without intelligent traffic management, critical medical data may be delayed or lost [20]. Prioritizing urgent health information and implementing dynamic bandwidth allocation strategies are crucial for maintaining system reliability.

B. Energy Efficiency and Sustainability

Many IoT-enabled healthcare devices are designed to operate continuously, often in environments where frequent recharging or battery replacement is impractical [121]. This makes energy efficiency a critical design consideration. Wearable sensors, for instance, must balance low power consumption with accurate sensing, frequent data transmission, and, increasingly, on-device data processing. Advanced energy-saving techniques such as duty cycling, adaptive sampling, and lightweight communication protocols have shown promise but are still limited by hardware constraints and application-specific requirements [12]. Emerging solutions like energy harvesting from body movement or ambient sources can extend device longevity but introduce challenges in power stability, user comfort, and integration complexity. As HIoT systems evolve to include AI capabilities and edge analytics, their energy requirements will grow further [122]. Thus, ongoing research must focus on developing ultralow-power hardware architectures and efficient software models tailored for healthcare use cases.

C. Data Quality, Bias, and Ethical Concerns

High-quality data is essential for the accuracy and reliability of smart healthcare applications. However, in real-world settings, data collected by IoT devices can be inconsistent, noisy, incomplete, or biased. These issues stem from sensor degradation, environmental interference, patient nonadherence, or variations in device calibrationt [123]. Bias in healthcare data and algorithms is particularly troubling, as it can lead to inequitable treatment outcomes. Underrepresented populations may receive inaccurate predictions or suboptimal care if models are not trained on inclusive datasets. This necessitates rigorous validation protocols, real-time anomaly detection, and continuous auditing of model performance across diverse demographic groups. Moreover, the ethical management of patient data—including privacy protection, informed consent, and data ownership—remains a pressing concern. Regulations like GDPR and HIPAA attempt to address these issues, but technical enforcement and patient trust are ongoing challenges [18]. Developing secure, transparent, and patient-centric data governance models will be pivotal to the success of future healthcare systems.

D. Cost Constraints and Resource Management

The high cost of deploying and maintaining smart healthcare infrastructures presents a major barrier to large-scale adoption. These expenses include not only the purchase of IoT devices and networking equipment but also software licensing, data storage, cybersecurity solutions, and the training of personnel [124]. Smaller clinics and healthcare providers in resource-limited regions often lack the financial and technical capacity to adopt such systems, exacerbating existing inequalities in healthcare access. Additionally, the rapid pace of technological advancement creates uncertainty around long-term investment, with solutions potentially becoming outdated before yielding full value. To address these concerns, cost-effective system designs, open-source platforms, and scalable architectures must be prioritized. Public-private partnerships and government-backed incentive programs could also play a key role in making smart healthcare more affordable and accessible [114].

XI. Future Directions

These future directions in IoT healthcare align with current technological trends and address key challenges in the industry. By focusing on interconnectivity, sustainability, privacy, and interoperability, IoT has the potential to significantly transform patient care delivery, improving clinical outcomes while reducing costs and environmental impact.

A. Scalability and System Integration

As HIoT systems transition from small-scale prototypes to full-scale deployments, scalability becomes a significant concern. Managing large volumes of data generated from thousands of interconnected devices across various healthcare settings requires robust system architecture [109]. Future smart healthcare systems must ensure efficient device discovery, data routing, and fault-tolerant communication without compromising real-time responsiveness. Moreover, ensuring compatibility between new-age technologies like 6G, AI accelerators, and distributed ledgers with legacy HIS and medical equipment introduces further complexity [17]. Interoperability across heterogeneous platforms and maintaining performance across varying load conditions will be a key challenge in future deployments.

B. Personalized and Adaptive Healthcare Delivery

The vision of personalized medicine involves tailoring diagnosis and treatment plans based on an individual's genetics, lifestyle, and real-time health indicators. Achieving this requires healthcare systems to be highly adaptive and responsive to changing patient conditions [79]. However, AI models currently face challenges related to data imbalance, generalizability, and explainability. Ensuring that these models can provide equitable and reliable recommendations across diverse populations, including those underrepresented in training datasets, is a critical concern. Additionally, translating complex model outputs into actionable insights for healthcare professionals requires intuitive interfaces and transparent decision-making mechanisms, which remains an ongoing challenge [125].

C. Federated Learning and Intelligent Edge Devices

To preserve data privacy and reduce reliance on cloud infrastructures, federated learning enables training machine learning models directly on edge devices without centralizing sensitive patient data. While promising, implementing federated learning in healthcare environments introduces several technical difficulties. These include handling nonindependent and identically distributed (non-IID) data across clients, ensuring secure model aggregation, and maintaining model accuracy despite limited computational and battery resources at the edge. Moreover, frequent disconnections or device failures can interrupt model updates, impacting learning efficiency. Future research must develop robust, lightweight federated learning frameworks customized for the constraints of HIoT devices.

D. Real-Time Multimodal Data Interpretation

In smart healthcare, devices continuously generate a variety of data streams—including sensor readings, medical imaging, audio inputs, and patient records. Combining these data types (multimodal fusion) in real-time to extract meaningful insights is highly complex due to the temporal, structural, and contextual variations in each modality [126]. For instance, synchronizing heartbeat data from wearables with electrocardiogram reports and historical health data requires precise temporal alignment and intelligent correlation algorithms. The challenge also extends to managing data loss, artifacts, or inconsistent sampling rates [127]. Future systems must develop advanced multimodal analytics that are resilient, efficient, and clinically interpretable.

E. Predictive Analytics for Preventive Care

Smart healthcare systems aim to shift from reactive treatments to proactive, preventive care. Predictive analytics can identify at-risk patients before symptoms become severe [116]. However, developing reliable predictive models that operate in real-time and with high precision remains difficult. These systems must consider not only structured data but also unstructured information such as clinical notes, patient behavior, and environmental conditions. Additionally, models must be able to distinguish between normal variability and early signs of deterioration without generating false positives or negatives [107]. Future research must focus on integrating holistic datasets and developing context-aware models that adapt to individual patient baselines.

F. Advanced Cybersecurity for Distributed Healthcare

The widespread distribution of IoT devices, cloud-based health records, and remote diagnostics increases the surface area for cyberattacks. Healthcare data is a prime target for ransomware, phishing, and unauthorized access. Future smart healthcare systems must go beyond traditional encryption and access controls to implement adaptive, context-aware cybersecurity measures [128]. This includes anomaly detection using AI, dynamic trust management, and blockchain for tamper-proof data logging. However, deploying these techniques within the constrained environment of wearable and implantable devices presents practical difficulties. Ensuring minimal latency, low power consumption, and uninterrupted operation during attacks will be critical for future systems [78].

XII. Conclusion

Governments, organizations, and academic communities are working together to ensure a smooth transition to IoT in the healthcare ecosystem. This study is valuable for readers who want to learn more about the importance of IoT and associated technologies in healthcare applications. This article furnishes a comprehensive summary of the IoT frameworks for healthcare applications and an architecture to simplify medical data transmission between medical devices and fog devices or cloud computing servers. Many concepts and applications are uniformly added to the IoT in the healthcare integration process. Moreover, our survey includes conventional architectures and existing research on fog computing in healthcare applications. Then, we described major successes that indicate the effectiveness of integrating IoT, fog, and cloud computing in healthcare. This article also analyses and summarizes standards and protocols to establish an interoperable healthcare ecosystem. Finally, various research barriers and possible solutions to IoT in healthcare applications are shown, including data security, green IoT, and sensor networks.

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