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IoT and artificial intelligence implementations for remote healthcare monitoring systems: A survey

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ABSTRACT

The Internet of Things (IoT) and artificial intelligence (AI) are two of the fastest-growing technologies in the world. With more people moving to cities, the concept of a smart city is not foreign. The idea of a smart city is based on transforming the healthcare sector by increasing its efficiency, lowering costs, and putting the focus back on a better patient care system. Implementing IoT and AI for remote healthcare monitoring (RHM) systems requires a deep understanding of different frameworks in smart cities. These frameworks occur in the form of underlying technologies, devices, systems, models, designs, use cases, and applications. The IoT-based RHM system mainly employs both AI and machine learning (ML) by gathering different records and datasets. On the other hand, ML methods are broadly used to create analytic representations and are incorporated into clinical decision support systems and diverse healthcare service forms. After carefully examining each factor in clinical decision support systems, a unique treatment, lifestyle advice, and care strategy are proposed to patients. The technology used helps to support healthcare applications and analyze activities, body temperature, heart rate, blood glucose, etcetera. Keeping this in mind, this paper provides a survey that focuses on the identification of the most relevant health Internet of things (H-IoT) applications supported by smart city infrastructure. This study also evaluates related technologies and systems for RHM services by understanding the most pertinent monitoring applications based on several models with different corresponding IoT-based sensors. Finally, this research contributes to scientific knowledge by highlighting the main limitations of the topic and recommending possible opportunities in this research area.

Contents

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1. Introduction

With ongoing population growth, the healthcare sector faces many challenges. A thorough literature review revealed that limited staffing, inefficient patient flow, lengthy hospital stays, and subpar communication methods were common issues related to healthcare. Indeed, there is a need to address these problems, which this paper aims to do. For internet of things (IoT), resource availability, security, and networking are the main priorities for developers. Numerous problems are faced when combining it with potential key barriers (Patel and Shah, 2021). Smart cities generate and utilize smart solutions as populations increase to create a more conducive environment. If we want to ensure productivity, we need a sound healthcare sector so that people can perform their jobs with minimal worries. T. Alizadeh put forward a smart city model that consists of a patient record system integrated with various healthcare applications that is enabled with IoT devices and machine learning (ML) protocols (Alizadeh, 2017). The technology and architecture of remote health monitoring (RHM) consist of a patient record system that integrates well with the appropriate sensing mechanisms and collects structured and unstructured data for ML analysis (Chong et al., 2018). Communication protocols have become essential for transmitting data and signals between IoT devices, systems, and models (Alizadeh, 2017). Smart cities offer quality of life to their residents. Smart cities can benefit from blockchain technology by storing transactions in a safe, open, shared, and immutable ledger (Majeed et al., 2021). The smart city's communication systems are categorized into proximity wireless, personal area networks, wireless local area networks, wireless metropolitan area networks, and wireless wide-area network technologies. They exist in radio-frequency identification (RFID), Bluetooth, near field communication (NFC), 3G, 4G, 5G, Zigbee, etcetera.

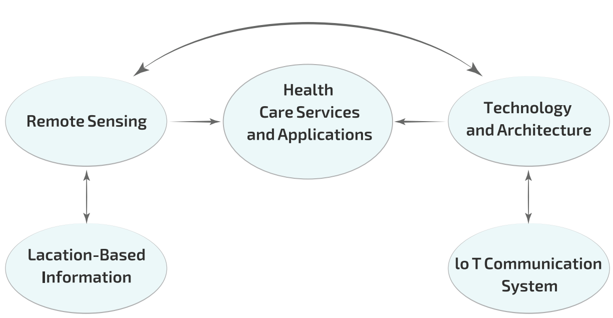

Fig. 1. Basic elements of an IoT-enabled smart city healthcare system.

1.1. Smart city and healthcare services

The concept of smart city healthcare is one that many traditional cities aim to emulate by setting up conventional devices and equipment for integrating healthcare resources with smart solutions. Smart solutions and information and communication technology (ICT) play a crucial role in ensuring smart cities' success in providing citizens with quality healthcare services (Alizadeh, 2017; Urbieta et al., 2017). The smart city's vital goals include making provision for high-quality living, conserving healthcare service quality, and promoting more conducive quality conditions for citizens. There must be a particular model to generate and provide creative and productive healthcare services.

As shown in Fig. 1, different systems, architectures, and frameworks work together for a common purpose, where the essential elements of an IoT-enabled smart city healthcare system are implemented. Smart services can be grouped into six main components: (i) smart economies, (ii) smart environments, (i) smart governments, (iv) smart people, (v) smart mobility, and (vi) smart living. An explicit explanation of services in these various forms has been provided (Mora et al., 2018). A smart city delivers a much better, more comfortable, and luxurious living environment. It also grants citizens the opportunity to be actively involved in actions that benefit their requirements and to be functional members of society. Citizens make use of many smart devices to engage with and utilize these services. Smart service is an explicit, sophisticated network configuration in which a substantial amount of individual data is delivered from citizens using the Internet. In February 2020 (prior to the COVID-19 outbreak), approximately 1000 virtual visits were registered, compared to 3000 to 3500 visits on a peak day during the COVID-19 outbreak in April. By supplying treatment as the patient performs social distancing, such telemedicine facilities may reduce infection risk during the outbreak of infectious diseases (Lee and Lee, 2021).

1.2. Healthcare Services, Applications, and remote sensing

In a smart city, services are delivered to resolve the issues faced by residential surroundings (Aborokbah et al., 2018). The practical systems consist of hospital services and health monitoring services. The concept of remote sensing is commonly used in Healthcare monitoring services with high number of researches and applications (Veenis and Brugts, 2020). Core to the smart city healthcare system is a patient record management center (PRMC) that helps collect, manage, and preserve patients' electronic health records (EHRs) (Deshmukh, 2017). Important indications

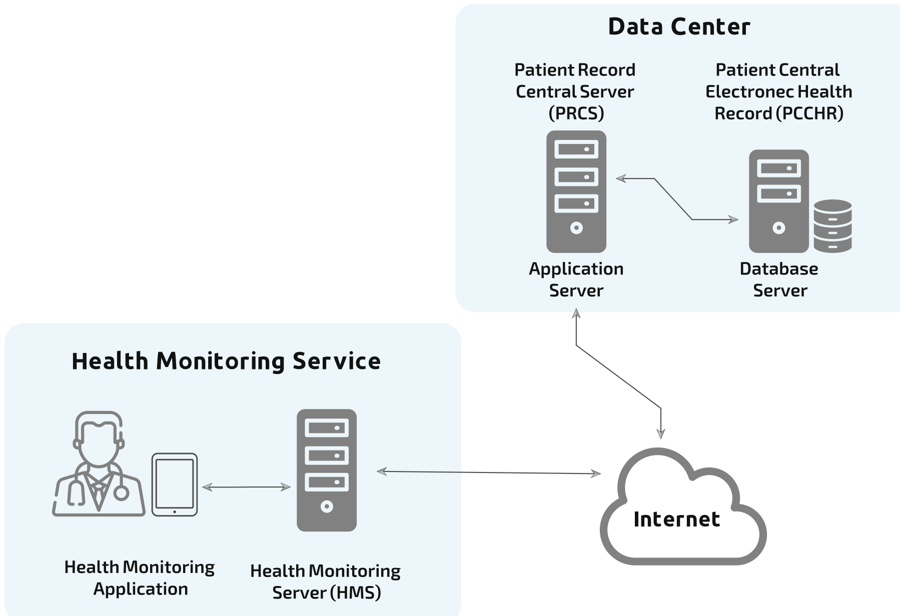

Fig. 2. Simplified technology architecture for smart healthcare services.

internal to the patient, such as an electrocardiogram (ECG), blood pressure, and pulse, are sensed and collected. External indications refer to critical climatic conditions, such as humidity and temperature; they are obtained from the medical sensor connected to the patient and transferred to the health service for further examinations including remote healthcare services (Livingston et al., 2017).

1.3. Technology and architecture of RHM

The health monitoring service is a system that obtains information from both the medical sensors attached to the patient's body and the smart device of the custodian. The health monitoring server (HMS) serves as the controller; it delivers an individualized healthcare plan (IHP) in real time through an analysis of the current health situation and historical records (Alghanim et al., 2017). It also generates signal notifications, warnings, and exceptions during periods involving critical situations. The smart service's essential elements include health monitoring service for evaluation and oversight, hospital service for procuring health problem identification, and instant reaction. At the same time, the PRMC deals with storing and utilizing information. The health monitoring system serves the IHP in real time. The hospital system permits medical specialists to make inferences on the patient's health status concerning the documented report delivered by HMS and the past health records obtained from the PRMC, where all personal records are kept.

The PRMC is a central storehouse in which all the health records and data of patients and the prevailing health conditions in the digital health records of patients are kept (Alghanim et al., 2017). It also delivers the necessary information-carrying headers of constraints and protocols to other systems connected to it. The health monitoring service also has local storage. This storage holds the patient's medical history and health records as the main requirement for a simplified technology architecture for smart healthcare service, as shown in Fig. 2. The patient central electronic health record (PC-EHR) is versatile storage that embodies patients' past health records and their detailed information, such as name, address, phone number, etcetera.

1.4. Sensing, Monitoring, and controlling

Sensors, monitoring, and control are required to make healthcare cities smarter. These sensors' feedback values help healthcare providers conduct monitoring and control through automation. These sensors' feedback values help healthcare providers carry out monitoring and control through a series of automation. The IoT, wireless sensor networks, deep learning, and other technologies can be used successfully to accomplish these goals (Singh et al., 2021). Smart cities can quickly attend to many people's healthcare needs at once by having access to real-time information. Healthcare providers can make quick decisions that yield positive results. IoTs, AI, and computing technology have changed the face of healthcare (Sharma, 2019). Sensors can be implanted in the body or worn on the body's surface, such as smartwatches.

Connections are made to healthcare providers through gateways and wireless networks with data transmitted (Movassaghi and Abolhasan, 2014). The implanted sensors, such as electrochemical glucose sensors, help monitor and control diabetes (Lucisano et al., 2016). Patients also self-manage and personalize their diabetes using AI devices. Sensors can transmit data to smartphones, and patients with DM can use these systems to monitor their blood glucose levels (Chaki et al., 2020). Several other advanced sensors are used to monitor and control sleep apnea, rheumatoid, cranial pressure, and heart arrhythmias (Cook et al., 2018). The main limitations of these devices are in operations and management. The people in charge may not have the required education or may forget to charge the devices. This makes it essential to adopt zero effects technologies (ZETs) to free the user from the tasks needed to operate and manage the sensor devices (Sharma, 2019). Remote sensing helps monitor a variety of diseases, such as cardiovascular diseases and dementia. Behavioral monitoring is an essential process in treating such disease categories. According to one estimation, the number of people affected by dementia in 2017 was a staggering 47 million. This number is projected to increase to 132 million by 2050 (Lucisano et al., 2016). Advanced remote sensing systems with assistance from the IoT and AI would ease the monitoring and control needed to effectively treat these diseases.

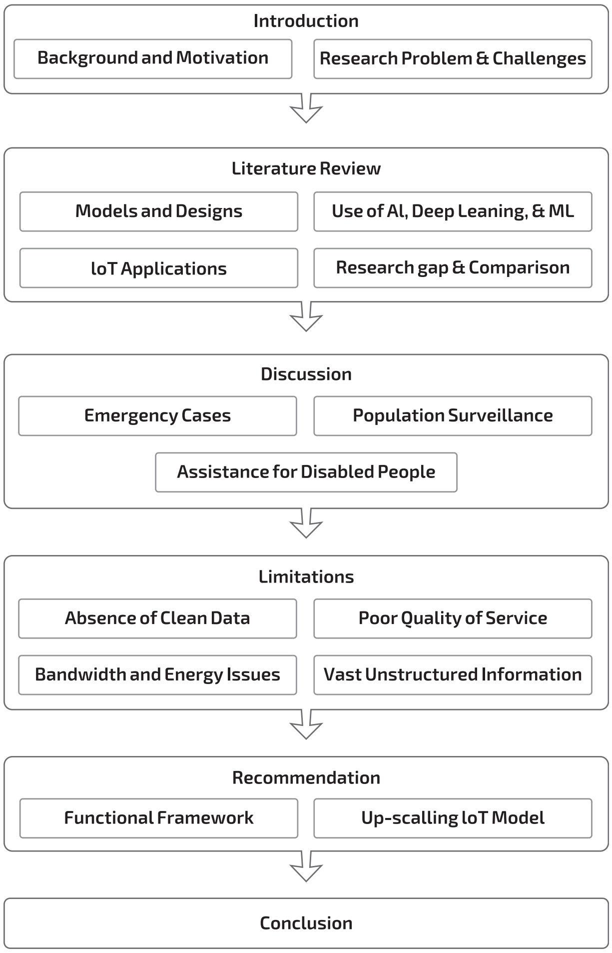

Fig. 3. Organizational structure of the paper.

1.5. Applying location-based information in a smart city environment

Location-based services work best with smart city data analytics systems and implementations. Data, such as demographics and global positioning, are integrated to locate the user. The data collected are integrated and analyzed by the smart city, enabling healthcare providers to offer the best healthcare services at the right time and location. The data are collected through smart devices, smartphones, and watches that have multiple advanced sensors. Longitude and latitude are detected by a location-based information system integrated with a global positioning system (GPS).

1.6. IoT communication systems

Internet protocol version 6 (IPv6) plays a critical role in the transition to the IoT (Kumar et al., 2019) since IPv4 has been depleted. It serves as a strategy for packet-switched networks, delivering end-to-end datagram communication, telecoms, and Internet converged services and protocols for advanced networks (TISPAN) core network, and 3gpp core networks. It functions as a connecting link to other networks, including the roaming service. RFID and near field communication (NFC) (Catarinucci et al., 2015; Kim et al., 2017) are powerful technologies that aid IoT functionality. RFID is a short-range communication technology that uses an electromagnetic field to recognize and follow tags connected to objects spontaneously. RFID and integrating sensor technologies promote several fresh prospects in the IoT paradigm, while supporting computing, sensing, and connectivity abilities in other passive systems. IEEE 802.15.1, which is Bluetooth, functions in the 2.4 GHz globally provided ISM (industrial, scientific, and medical) band and is an essential technology that supports short-range IoT applications. Bluetooth special interest group (SIG) recommended Bluetooth low energy (BLE) in both the Bluetooth 4.0 requirements and Bluetooth 5.

On the other hand, IEEE 802.11 primarily comprises media access control (MAC) and physical layer (PHY) requirements for wireless local area network (WLAN), generally referred to as wireless fidelity (Wi-Fi). This technology's primary challenge is that it consumes tremendous energy, contrasting with Zigbee and Bluetooth (Palattella et al., 2014). Some modifications are needed to enhance its mobile nature, roaming, and quality of service (QoS) executions. Advancements like IEEE 802.11ah low power Wi-Fi work well with wide range of IoT applications. They can deliver QoS, more energy-efficient and productive output, scalability to several devices, and cost-effective remedies (Adame et al., 2014; Kiryanov et al., 2019; Maier et al., 2018). The rest of the paper is organized as follows. In Section II, we overview the related work area, while in Section III, we discuss how smart cities positively influence public health and help in disease prevention. Section IV sheds light on the limitations of the research area, whereas Section V recommends and discusses some possible solutions to these limitations. Finally, Section VI concludes the paper. The entire paper is summarized in Fig. 3.

2. Literature review

Implementing RHM in smart cities requires IoT and ML technologies (Pawar et al., 2018; Qi et al., 2017) These operations are commonly an assemblage of IoT devices connected to execute predictive analysis, prognosis, remote monitoring, surgeries, and preventative analysis, as the case may be (Ermes et al., 2008; Pawar et al., 2018). Remote healthcare monitoring requires specific models and designs to operate by integrating them into the patient record system for efficient data management. RHM aims to create applications such as glucose level sensing, ECG monitoring, blood pressure monitoring, body temperature monitoring, oxygen saturation monitoring, rehabilitation systems, medical management, wheelchair management, and other imminent healthcare solutions. During the COVID-19 Pandemic, IoT introduced medical devices, including linked imaging, hospital procedures, drug distribution, patient care, diagnostic tests, and pharmacy control, as well as the advancement of health safety with smart instruments, such sa blood gas analyzers, thermometers, smart beds, glucose meters, ultrasound, X-rays, and I-patient biological services (Javaid and Khan, 2021).

Some technologies are mainly built to function with IoT or machine-to-machine (M2M) applications, which require a vast regional range, extended battery-consuming lifetime, low-cost devices, and low bandwidth. These technologies are referred to as low power wide-area network (LoPWAN) (Raza et al., 2017). Moreover, the majority of IoT applications cannot function without the transfer of data using cellular technologies, such as 2G (D-AMPS, GSM, and PDC), 2.5G (GPRS), 2.75G (EDGE), 3G (UMTS/WCDMA, EvDO, HSPA, and HSUPA), 4G (LTE, and LTE-A), and 5G. A network connection is denoted with cellular representation or machine-type communication (MTC).

Furthermore, some 3G and 4G technologies like 3GPP LTE cover a vast expanse range and work well with QoS. The technology is enabled with mobile and roaming services, scalability, high-security levels, billing, and organization clarity. Their integration allows for the connection of sensors with the aid of a standardized API (Palattella et al., 2014). Long term evolution advanced (LTE-A),

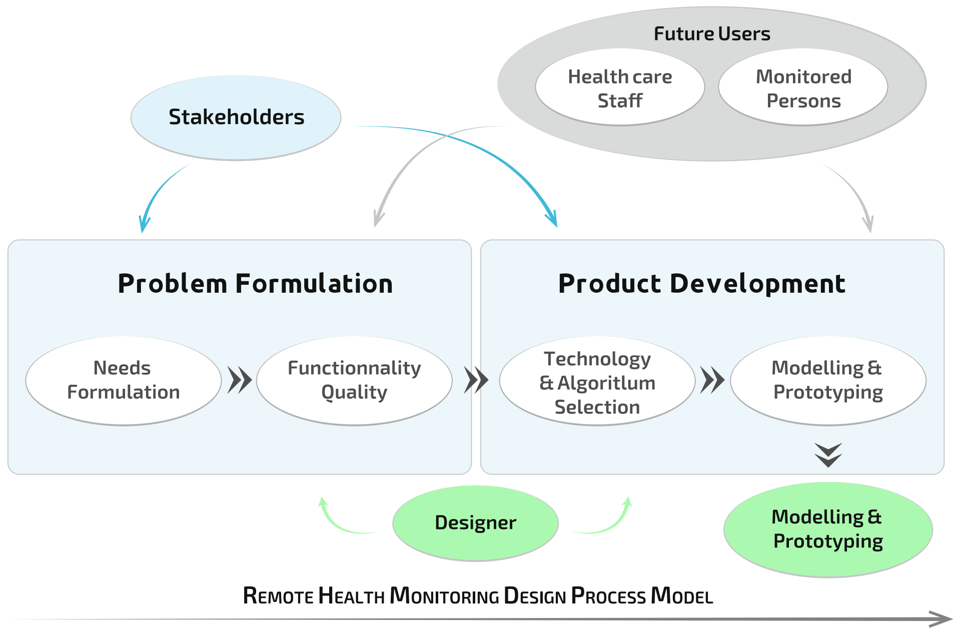

Fig. 4. A simple design of remote healthcare system processes (Dziak et al., 2017).

mobile worldwide interoperability for microwave access (WiMAX) release 2, Wire-less MAN—Advanced or IEEE 802.16 m—aids improvements such as better scalability, higher speeds, and low costs to adapt to future IoT market requirements and also to prevent technology fragmentation. These technologies fulfill part of the prerequisites for IoT. However, they still contain some problems yet to be resolved. For instance, QoS and network congestion prove to be challenging problems due to many nodes or devices connected (Trencher and Karvonen, 2019). A thorough study of the 5G cellular network framework and some other critical developing technologies, like cloud computing, interference management, spectrum distributing with cognitive radio, software-defined network (SDN), etcetera, have been outlined in Gupta and Jha (2018). IoT-based healthcare systems' have an efficient healthcare technologies, such as the IoT-Fog-Cloud continuum, the standard platform that facilitates communication among ifferent layers and types of fog device (Kumar et al., 2019). However, some authors contemplate that there is a considerable extension between 5G and IoT. 5G design undertakings are in motion to aid the use of devices on a larger scale to facilitate universal IoT, and at the same time, also reduce the consumption of energy with reduced costs. A summary of distinct qualities and some comparisons between these technologies have been outlined (Maier et al., 2018).

2.1. Models and designs for remote healthcare monitoring

The system of health monitoring within the smart city framework is problematic. The design of such systems requires problem formulation and product. Stakeholders determine the overall concept and prospects of the new system development (Dziak et al., 2017). This requires incorporating future end users and needs capture for the development of the new system. The focus is more on the smart healthcare system's goal, starting with a proper initial assessment of the problem and evaluating its workability.

Stakeholders define the desired design and functions of the proposed smart healthcare system. The required technology and algorithm choice must be thoroughly undertaken in three steps: selecting algorithms and technology, selecting a model and prototype, and solution validation (Dziak et al., 2017). Appropriate technologies and algorithms are chosen by the designers, which is in tandem with the specified needs and requirements, as stated by the users and the stakeholders at the problem development phase. Therefore, in selecting the right technology and algorithms, environmental considerations are crucial. Some sensors cannot withstand high humid environments, and some energy sources present risks at specific temperatures (Ermes et al., 2008). Within these constraints, the designer develops creative solutions or modifies current ones, as shown in the processes of a simple design for a remote healthcare system in Fig. 4. Examples of technologies and algorithms considered are constrained application protocol (CoAP), support vector machine (SVM), k-means, clinical correlation analysis (CCA), Bluetooth, Wi-Fi, and RFID (Dziak et al., 2017). IoT-based healthcare systems aim to improve patients' well-being and the life quality of smart city dwellers (Peña-Ayala, 2014). There has been tremendous input into developing models and designs for remote healthcare monitoring in the last decade.

2.1.1. mHealth based design

An end-to-end model is needed to integrate the IoT in medical care systems to connect IoT-based sensing devices to clinical care systems (Almotiri et al., 2016). mHealth is an example of such an IoT-based model, created and integrated into the healthcare system. mHealth is designed in three layers. The layer that consists of information gathering includes IoT-based systems that can sense and collect parameters that pertain to health only (Veenis and Brugts, 2020). For instance, a sensor that senses blood sugar level or a sensor that monitors cardiac rate, tracks physical fitness (e.g., Fitbit). The layer for storing information includes keeping medical information on larger scales and speedy storage racks. The layer for processing information involves the analysis of this sensor information with the use of different methods, which include algorithms that are both non-AI and AI based (Dziak et al., 2017). The sensing devices must send the sensed information to the layer where it is stored and the second layer where it is processed. mHealth is not complicated and easy to navigate; it could be used with BLE, ANT, Zigbee, NFC, or Wi-Fi-based interaction protocols.

Table 1
Problem formulation and product development in rhm designs (Dziak et al., 2017; Oussous et al., 2018; Patel et al., 2010).

Problem Formulation			Product Development	References, Year
Functionalities		**Quality**	Possible Technologies and Algorithms	
General	Itemized			
Localization	In apartment	Four room-zones level accuracy	Bluetooth, RFID, Wi-Fi	(Peña-Ayala, 2014)
	In building	Floor level accuracy	RFID/Wi-Fi, Bluetooth	(Peña-Ayala, 2014)
	Outdoor	10 m accuracy	Bluetooth, GPS, Wi-Fi	(Peña-Ayala, 2014)
Activity recognition	Fall Lying Standing Sitting Walking	Validity Reliability	RFID, Wi-Fi, genetic algorithms, neural networks	(Peña-Ayala, 2014)
Vital signs monitoring	Heart rate	Method	Electrocardiogram, infrared	(Alshurafa et al., 2015; Sunhare et al., 2020)
Behavior classification	Normal Suspicious Danger	Validity	Genetic algorithms, anomaly detection, neural networks, support vector machines, K-means	(Peña-Ayala, 2014)
Control	Easy to handle	Speed	Inter-Integrated Circuit, Serial Peripheral Interface, CoAP	(Kang and Larkin, 2017; Oussous et al., 2018; Peña-Ayala, 2014; Sunhare et al., 2020)
Communication	Possible long range up to 40 m	Secure	Bluetooth, Wi-Fi, RFID	(Camps-Valls and Bioucas-Dias, 2016; Kang and Larkin, 2017; Patel et al., 2010; Peña-Ayala, 2014; Sunhare et al., 2020)

2.1.2. 6LoWPAN-Based design

Network systems that based on the Internet protocol (IP) are ubiquitous. Thus, utilizing the IP network systems becomes more compelling as it would ensure the transmission of medical care information that is IoT-based. IPV6 system, however, requires a considerable volume of power to process data and bandwidth. Its expectation is for processing power to have an always-on feature complicated for systems based on the IoT network. Furthermore, 6LoWPAN (Tanaka et al., 2019) has been indicated as the most suitable model for IoT-based network systems.

2.1.3. CoAP-Based design

In Garcia-Carrillo et al. (2017), a description of the CoAP modeled that functions within the medical care systems is presented. CoAP is a layered application system that is mainly structured for sensing devices that experience resource constraints. CoAP application systems aid interactions that can be relied on by utilizing constrained (CON) and acknowledgment (ACK) data and best-effort interaction by utilizing NON-data. Networks in medical care implementing the CoAP protocol could utilize any channel to transfer sensed information to the system. CoAP application system is very identical to HTTP and supports four approaches that transmit sensed information, including POST, DELETE, GET, and PUT.

2.1.4. IEEE 11,073 health standard-based design

The RHM of patients with chronic heart failure has been proven to improve the health of heart failure patients (Veenis and Brugts, 2020), drastically reducing hospitalization rates while improving overall clinical outcomes in communities. Smart devices are becoming routine in RHM as vaults of information exchange with functionalities that include data collector for patient agents (PAs) from onboard sensors, data transmission to a server, collaboration, and data sharing from other devices and feedback to relay information back to the patient. A battery-based system is used for optimization techniques to test the effect of smart devices' battery strength on remote healthcare monitoring system compliance (Sharma, 2019). Decreasing the frequency at which a patient charges their smartphone could increase system compliance. They tested the battery optimization technique in-house and on-field. The trial aimed to develop a framework to understand how technology could reduce cardiovascular disease (CVD) risk. Researchers explored novel and smart biosensing technology using novel nanosystems, bio-active molecules, computational analytics, and hardware integration to achieve the easy operation and performance assessment required for timely therapy decisions (Jain et al., 2021). Another study has developed models and prototypes of carbon nanotubes (CNTs) based on conformal patch antenna arrays (Patel et al., 2010). Their research employed carbon nanotubes that can be ink-jet printed on the fabric's surface to create patch antenna arrays. The transmission design used a radio-frequency (RF) transmitter system schematics and simulation using an agilent advanced design system (ADS). The research proposed the usefulness of random designs in precision and suggested simulation strategies for evaluating their acceptable use and diagnostic tools (Khan and Zubair, 2020). The design reported an investigation on CNT patch antennas, which resulted in the improvement of antenna parameters, such as voltage standing wave ratio (VSWR), return loss, gain, radiation pattern, and efficient energy harvesting (Patel et al., 2010). The research found that CNT, owing to its unique electronic property, had the potential for a less conformable polymer-CNT nanocomposite antenna. Moreover, RF transmitters can help seamlessly transmit ECG signals and be interspersed with comfortable antennas to enhance patients' RHM. Table 1 shows the problem formulation and the possible product.

2.2. AI and deep learning, machine learning and big data for remote sensing, monitoring, and controlling

Using ML-based remote healthcare monitoring services, predictive analysis can help hospitals promptly discharge patients from the hospital. Predictive analysis ensures ease in creating a risk stratification model, whereby additional efforts are committed to managing a set of high-risk factor patients. These models rely on past historical data, applying dynamic data from the patient to predict future contingencies and action plans to reduce possible complications. The success of ML-based applications is confirmed by statistics that support deep learning as an important aspect of ML (Rahman et al., 2020). Studies have show that incorporating clinical variables and vital signs can be valuable in predicting readmissions (Chaki et al., 2020; Raj et al., 2020; Rothman et al., 2013; Uddin and Sensors, 2020). Here, the patient health system can be implemented by providing considerable help. In modern facili-

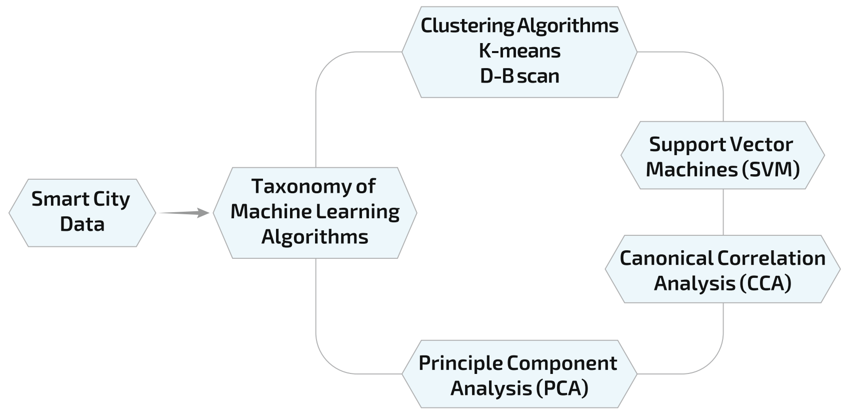

Fig. 5. Machine learning taxonomy over smart-city data.

ties, data collection and examination machines are mobilized to enable data collection and sharing in higher-level information systems (Chaki et al., 2020). Nonetheless, noisy data, data transmission loss, and incomplete data should be considered.

In the last few years, new attention has been paid to the combination of AI and deep learning (DL), ML, and big data in remote sensing and monitoring. Several papers (Chaki et al., 2020; Oussous et al., 2018; Rothman et al., 2013; Uddin and Sensors, 2020) have been published to introduce the necessary and sometimes concrete AI concepts of DL and big data, as well as remote sensing and monitoring communities. Remote sensing (monitoring and control) of the environment is experiencing an explosion in terms of the volume of available information, which presents unprecedented capabilities toward the global-scale monitoring of natural and artificial processes. In this era of AI, DL frameworks consume all viable resources. Meanwhile, the availability of unprecedented volumes of data related to health, such as digital text in EHRs, clinical text on social media, text in electronic medical reports, and medical images, are also highly responsible for DL popularity in the health domain (Pandey et al., 2021). The increase in the volume and variety of knowledge bases has created a situation where data analysis becomes a problem (Mohammadi et al., 2018; Raj et al., 2020) Chaki et al. (2020) discussed both ML and artificial intelligence-based methods in tracking, assessment, self-management, and interactivity. ML has been introduced for automating and processing remote sensing observation to address this problem. AI and DL research has been aggressively pushed by Internet companies, such as Google, Facebook, and Microsoft, for remote sensing, monitoring, and controlling for image analysis, including indexing, segmentation, and object detection. The practical scenario often drawn to this success is the trumping of Lee Sedol, the World Go Champion by Google's AlphaGo AI (Mohammadi et al., 2018).

According Xiao et al. (2018), remote sensing and monitoring data are often multimodal. They may include more than one framework, for example, optical and synthetic aperture radar (SAR) sensors, where both the imaging geometry and their contents may be entirely different. The study also highlighted remote sensing data's naturalness as readily available in the environment, stating it to be geodetic with controlled quality. They also conclude that remote sensing is faced with a major challenges since the current day sensing and monitoring systems deal with enormous data volume that may require much effort to process (Xiao et al., 2018). Researchers have built a generic system for diagnosing diseases, which proposes a system, collects knowledge, processes it, and produces an output outcome focusing on learning from historical evidence (Al-Hawari and Barham, 2019). The diversity of objectives and the data's particular characteristics allow the deployment of ML and signal processing algorithms (Camps-Valls and Bioucas-Dias, 2016). In the deployment of AI in healthcare for remote sensing and monitoring, there is a need to train it through clinical data from clinical activities, such as screening, diagnosis, and treatment, so they can gain acquaintance with features that share similarities and outcomes of interests (Constant et al., 2021; Jiang et al., 2017). This data is often available in several forms, including electronic records, records on medical devices, clinical and laboratory images, and physical examination (Jiang et al., 2017; Khan, 2020). ML algorithms present a considerable advantage in managing healthcare data for smart city healthcare deployments.

2.2.1. Machine learning algorithms

It is necessary to determine what task is to be executed for small data analysis. Selecting or synthesizing the most suitable data mining algorithm is a difficult component of any IoT-powered smart world. Under all constraints, an algorithm should deliver useful analytics, reliably forecast future events, and control the network and resources effectively (Sunhare et al., 2020). We need to optimize processes, such as predicting values, predicting categories, feature extraction, or structured discovery. A general taxonomy for ML over the smart city is represented in Fig. 5. Data to reveal the structure of unlabeled data and clustering algorithms may be the best tool obtainable. K-means are described in Mahdavinejad et al. (2018), as the most popular and commonly applied clustering algorithm. It can accommodate a large volume of data coupled with a wide range of data types. A study by Gil et al. (2019) suggested applying the K-means algorithm to manage smart homes and smart-city data. As described in Mahdavinejad et al. (2018), the D-B scan is another clustering algorithm used in structuring data from unlabeled data. It is also used in Khan et al. (2014) and Ma et al. (2013) to cluster small citizen behavior.

Two important algorithms are used to spot abnormal data points and inconsistencies in smart data. The first is the one-class SVM and PCA-based anomaly detection methods explained in Mahdavinejad et al. (2018), which traces anomalies and noisy data with great precision. One study used a one-class SVM (OCSVMs) to search and find activity anomalies. The linear regression and support vector regression (SVR) methods described in Mahdavinejad et al. (2018) are the two most applied algorithms (Grzelak et al., 2019) to forecast values and group sequenced data. As used in these algorithms, the chosen models' purpose is to process and train data with high-speed characteristics. For instance, Du et al. (2020) used a linear regression algorithm for real-time predictions, which was applied to categorize smart citizen behaviors (Ma et al., 2013). In predicting the categories of data, neural networks are the best learning models for function approximation issues. Moreover, because there is a need for accuracy in smart

Table 2
Machine learning algorithms and use cases in smart city healthcare.

Machine Learning Algorithm	Function	Application and Use Cases for Smart City Healthcare	References, Year
K-means	Reveals the structure of unlabeled data Uses clustering Algorithm to process a large volume of data	Smart home healthcare, Smart City Healthcare	(Gil et al., 2019; Grzelak et al., 2019; Mahdavinejad et al., 2018)
Dbscan	Reveals the structure of unlabeled data Handles a wide range of data types Clustering management of human data	Human Sensor Data Management, e.g., body level temperature providing communication feedback through an M-IoT-based network	(Gil et al., 2019; Khan et al., 2014.; Ma et al., 2013)
Support Vector Machines	Manages large volumes of data and grouping them according to their types. Handles high volumes and various types of data Highly efficient for smart data processing algorithms Processes and train data with high-speed characteristics	Human health pattern, health behavior, and Lifestyle pattern, E.g., Real-time sensing of blood sugar level Forecasting Healthcare Solutions	(Deshmukh, 2017; Du et al., 2020; Khan et al., 2014; Liu et al., 2019; Mahdavinejad et al., 2018)
Clinical Correlation Analysis	Two frequently used algorithms for use in extracting data characteristics. CCA compares and shows the relationship between the two groups of data. An Input to detect anomalies by comparing multiple data sources.	Application in developing healthcare solutions through the interaction and integration of various tools, machines, and cases	(Mahdavinejad et al., 2018)
Neural Networks	Provides an efficient learning model for function approximation issues.	Learning methods are used to improve the functionality of healthcare devices, applications, and tools. Specific use cases are in rehabilitation management	(Deshmukh, 2017; Ma et al., 2013)
Anomaly Detection Algorithms	Normal and abnormal dataset Comparison with strange data sets Binary classifier and construction deductions	Specific applications in monitoring applications, such as blood pressure monitoring and ECG. Automated to help detect abnormalities in the information received	(Gupta and Jha, 2018; Jiao et al., 2019; Mahmoud et al., 2016; Xu et al., 2018)

data, a multi-class neutral network should offer the best solution according to its long training time. Two studies, namely Khan et al. (n.d.) and. Liu et al. (2019), applied the SVM in classifying traffic data. In a study by Mahdavinejad et al. (2018), principle component analysis (PCA) and canonical correlation analysis (CCA), respectively, were the two frequently used algorithms for extracting data characteristics. Moreover, CCA is capable of showing the relationship between the two groups of data. A variant of PCA and CCA can also be used to detect anomalies.

2.2.2. Detecting anomalies

Anomaly detection is defined as recognizing elements or structures in a dataset that are not in harmony with other elements or a regular pattern. These unusual patterns are anomalies, exceptions, outliers, surprises, novelties, noises, or deviations (Xu et al., 2018). However, a study has claimed that identifying anomalies in data becomes more challenging as the scale of the data increases. This is because as the number of anomalous data points to normal data points decreases, the chance of detecting the right anomaly decreases. (Hashmi and Ahmad, 2019). There are many anomaly issues in datasets that lead to cleaning requiring binary classification tasks. For instance, an anomalous group is usually not adequately displayed in the overall training set. They display extensively more dissimilar characteristics than typical structures and may be distinguishable (Milacski et al., 2015). Anomaly detection follows an established procedure depending on the degree to which the tags are available. In standardized anomaly detection procedures, a binary (normal and abnormal) tagged dataset is provided, and after that, a binary classifier is employed. This should handle the issue of uneven datasets arising from data points with abnormal tags. Anomalies are then discovered by constructing the structure's typical character model with the trained model and inferential deduction (Xu et al., 2018). The application of anomaly detection is made in numerous real-world operations of health monitoring. In contrast to manual detection and diagnosis, an automatic system can detect and treat anomalies with much greater ease and reliability (Chaki et al., 2020). Anomaly detection can be utilized as a preprocessing stage.

An algorithm for eliminating noise from a data set can considerably enhance successive ML algorithm execution, particularly in regulated learning functions (Gupta and Jha, 2018; Jiao et al., 2019). One-class SVMs are one of the most prominent procedures for anomaly detection. Mahmoud et al. (2016) designed a novel anomaly detection algorithm that uses statistical methods to indicate anomalies and noise present in power datasets and obtained from smart environments. Table 2 summarizes the ML algorithms and use cases in smart-city healthcare applications and implementation.

2.3. Healthcare monitoring system through Ontology agents

Ontology agents (OA) have become a practical approach in the initiation and management of acquisition, query, and recycling of knowledge in distributed AI (DAI) approaches and applications that include web-based education systems (WBES) and multi-agent systems (MAS) (Raj et al., 2020). In their study focusing on patients' health monitoring, Kokkonis and his team employed the Java agent development (JADE) framework system, an open-source platform famous for its use in providing several APIs for distributed application development and interconnectivity to collect vital signs data in patients (Asiminidis et al., 2018). Researchers built Malavefes, a malaria voice-enabled computational fuzzy expert framework for accurate anti-malarial drug dose prescription, created using Visual Basic.NET and JADE Framework (Oluwagbemi et al., 2018).

2.4. Remote monitoring in home healthcare

The IoT is a class of computers that has remote sensors, microcontrollers, and transceivers. It considers healthcare essential for humans to monitor, manage, detect, and respond to information received from the system and efficiently minimizes healthcare spending (Surantha et al., 2021). Telehealth remote monitoring has been mostly incorporated in progressive countries like the United States over the last 5 years. This trend is due to growing confidence in remote healthcare's effect on bettering patients' health (Avila et al., 2017). Findings revealed that success expectancy has little impact on the patient's decisions to use IoT for eHealth, thus encouraging developers, medical professionals, and advertisers to enhance the design of connected devices, improve patient connectivity, and specifically target potential consumers (Arfi et al., 2021). R. J Rosati employed a methodology that involved over 100 remote monitors strategically placed in the homes of patients with significant cognitive deficiencies (Rosati, 2009). Supplementary information was collected to understand demographics, ongoing medications, social support, and clinical status. This research aimed to compare whether the outcomes of remote monitoring healthcare on patient improvement had any variance with patients who were hospitalized by using a control group that was entirely similar to the active group, but without remote monitoring. The research found a considerable reduction in the hospitalization rate (a testament to remote monitoring efficacy in the place of hospitalization). Regardless of diagnosis, the control group had 45.5% of hospitalization compared to 35.6% of patients on remote healthcare monitoring (Rosati, 2009). The study also found a significant reduction in nursing visits per week for remote monitor patients compared to the control group.

A study by T. Bratan and M. Clarke concluded that remote patient monitoring (RPM) offered the potential to provide high-quality care to the elderly and the severely ill at home. This challenges the notion that severe clinical cases may be challenging to manage through remote healthcare monitoring (Bratan et al., 2006). Recent research has proposed various features indicative of detections and complete monitoring of an employed fully automated AD monitoring reports. The framework also offers a distinction between healthy and non-healthy people (Khan and Zubair, 2020). Remote healthcare monitoring is essential and critical to the architecture of healthcare systems. A recent study concluded that 13 healthcare projects and services in the United Kingdom utilized RPM. The report highlighted eight projects to be monitored: chronic obstructive pulmonary disease (COPD), one chronic heart failure (CHF), one diabetes, one unstable condition, such as heart conditions, blood pressure, and pulse, and one monitored patient on oxygen. Before the project, the systems did not achieve common health services goals, even though the models and operational framework contained a link to primary care. Having perused the system's failures, they designed a clinical and more integrated monitoring system based on primary healthcare.

2.5. IoT healthcare applications

Another additional component in IoT services is the close monitoring of IoT applications (Islam et al., 2015). Novel research has been undertaken to develop a framework for healthcare systems that provides a wide variety of analytical data applications for managing data sources ranging from EHRs to medical photographs (Palanisamy and Thirunavukarasu, 2019). While it is inevitable that sick persons and other users use applications, it is obvious that application development is based on the services required (Lucisano et al., 2016). Thus, it could be said that services are based on what the developer has to offer, while applications are developed to suit the users. Divergent ML methods have recently been used in several related applications in various areas, such as emotion recognition in functional technologies, accident intensity estimation in severe injuries, and efficiently grading the alcoholics (Jayadev and Bellary, 2021).

IoT-driven healthcare systems and technologies have received considerable R&D coverage, as well as how the IoT can assist with pediatric and elderly treatment, chronic illness tracking, personal well-being, and exercise management. Islam et al. (2015) also discussed the various gadgetry, wearables, and medical tools that could be obtained from the market presently. These new healthcare items and devices could be seen as part of IoT innovativeness and creativity to provide different medical interventions. The following segments below address the different IoT-based medical care applications, which include applications that are both single and clustered-condition. In Table 3, a summary is presented for IoT-based sensors used for healthcare applications and other specific usages, cases, and implementations.

2.6. Healthcare implementations using smart device applications

In recent times, there has been an upsurge in developing devices that work electronically with sensors connected to smart devices that control them. This development shows that smart devices have risen to become drivers of IoT technology. Integrating IoT with specific disciplines is crucial for achieving quality service parameters, such as perfection, reliability, and mobility across different devices (Patel and Shah, 2021). Different software applications and hardware products have been designed to ensure their compatibility with smart devices, enabling smart devices to become a useful tool in administering medical care (Islam et al., 2015). A review carried out extensively on the functionality of health applications and their integration into the smart devices features was detailed step by step (Chang Soh et al., 2018; Green et al., 2018; Kang and Kim, 2016). The paper discussed applications that patients can utilize and health apps generally. It also discussed apps that could help educate, train, and inform patients about healthcare, and other related apps are known collectively as auxiliary applications.

The features added to smart devices today could efficiently carry out the medical checks and diagnoses required for the medical conditions mentioned below. Furthermore, advancements are useful in the medical sciences for accurately diagnosing diseases and assisting. It may help differentiate between urgent treatment, such as emergency room visits, and chronic care with complicated disease (Khan and Shamsi, 2021). Patients with severe diabetic problems face multiple symptoms. These symptoms include asthmatic problems, severe diseases obstructing the respiratory tract, allergic rhinitis, nostril-related symptoms affecting the lungs, the cardiac rate, BP, a saturation of oxygen in the blood, skin diseases, and infections (Chong et al., 2018; Shi et al., 2018; Wang et al., 2018). In Table 4, a summery about the details for the current commercial medical items that could be seen as foundational products as part of the IoT-based network health devices.

3. Discussion

On the core question of the research, in terms of the most relevant application domains, three appear to be the most vital. They include a response to emergencies, population surveillance, and active aging monitoring. However, four more application domains were further highlighted. These include promoting a healthy life-

Table 3
IoT Healthcare Applications and Specific Use Cases (Islam et al., 2015).

Applications	Descriptions	Specific Use Cases	Technology Applied	References, Year
Glucose Level Sensing	A noninvasive tool that measures blood sugar level. It includes a sugar level collector, background processors, and a phone call or PC	Monitoring of blood sugar level. Transmit somatic information from the patient to healthcare professional in real-time	IoT, IPv6	(Alamri, 2018)
Electrocardiogram Monitoring	IoT-related ECG checking network comprising a wireless acquisition and transmission device	Monitoring of ECG using an algorithm that detects the electromagnetic signal	Electrocardiogram, IoT frameworks, anomaly detection	(Castillejo and Wireless, 2013; DSouza et al., 2019; Kang and Larkin, 2017; Nazir et al., 2019; Yazdan et al., 2019)
Blood Pressure Monitoring	A KIT meter for blood pressure and an NFC cellphone are interspersed to make an IoT-based BP monitor. The combined tools optimize the blood pressure checking process	Used with an Apple Smart Devices, which is an IoT device to collect BP data. An IoT-based terminal also automated the blood pressure checking process	IoT frameworks, Pressure Sensor	(DSouza et al., 2019; Milacski et al., 2015; Zouka et al., 2019)
Body Temperature Monitor	This involves the combination of a thermometer and an IoT channel. The RFID node of the IoT system takes the measurement of body temperature and also aid in the transmission of data	Used to measure temperature and transmit data in real-time	Thermometer Sensors, IoT System	(Z. L. In, 2014)
Oxygen Saturation Monitoring	The oximeter is connected to an IoT channel such as Bluetooth or the Internet to ensure the real-time transmission of data between the patient (who may be in a different location) and the health practitioner	In wearables that measure the oxygen level in patients requiring great attention and notifies nurses and doctors of body changes in real-time	Oximeter, IoT system	(Kang and Larkin, 2017)
Rehabilitation System	A proposed smart rehabilitation network that is IoT-based that provides real-time data concerning the mental state of patients undergoing rehabilitation	Used in shortening the duration of the rehabilitation process in hemiplegic patients through integrated applications that can serve as self-care	IoT Frameworks, Machine Learning	(Avila et al., 2017; Wojciechowski and Al-Musawi, 2017; Zouka et al., 2019)
Medication Management	A potential medication management method that uses I2Pack and the iMedBox to verify the authenticity of prescribed drugs	Ambient Assistant Living Interventions to control medication prescription systems	RFID, IoT frameworks,	(Laranjo et al., 2013; Pang and Tian, 2014)
Wheelchair Management	Potential wheelchair design with a WBAN integration beaming in sensors pivoted by the IoT network to create a fully automated wheelchairs app	Create a smart wheelchair capable of monitoring a patient's health Processing prompts and relays location data	IoT Frameworks, Machine Learning	(Matsuo et al., 2014; Mendoza, 2014)
Imminent Healthcare	Potential mobilization of IoT-based services, architectures, and applications facilitate medical reception globally and security advancements	Pediatric and elderly care, chronic disease supervision, private health, and fitness management	IoThNet framework, Intelligent Security Model	(Islam et al., 2015)
Smart Devices	Capture data, process, and relay them in real-time	Temperature and BP measurement. Train patients and relay treatment information based on data gathered	IoT framework, Cloud Computing, Big Data	(Chang Soh et al., 2018; Chong et al., 2018; Green et al., 2018; Nazir et al., 2019; Shi et al., 2018)
Essential Healthcare Services	Cardiovascular Diseases, Ambient Assisted Living, Fitness, and Neurological	Cardiovascular diseases pertain to the monitoring of the heart and blood vessels. Supporting physical activities such as walking, running, jogging	Machine learning, cloud computing, big data	(Serhani et al., 2020; Yazdan et al., 2019)

style, care service organization, support to disabled people, and socialization. From these results, it can be deduced that it is possible for smart cities to positively influence public health, particularly in health promotion and disease prevention, which puts it in alignment with resolving some of the existing problems. Overseeing and supervision are crucial portions of the international health fairness plan (Menchie Mendoza, 2014). A scope of periodical review of data exists on issues concerning disease surveillance, health services statistics, healthcare utilization registries, or administrative records. They deliver data needed to observe the state of health and results obtained from the public. However, the data only possess details of people that desire healthcare. Recent research claims that elderly users emphasize more personal and usage-related issues. Enhancing such clinical trust by encouraging collaboration among all concerned parties is the key to improve the status quo (Xing et al., 2021). Hence, smart cities' execution symbolizes a chance to explore creative methods of obtaining vital information from people.

Regarding the reaction to urgent situations, the tools and equipment of smart cities permit allocated supervision and facilities for distant control, which might serve as the footing for productive reactions. One of the most fascinating and influential smart-city services is providing incident control and emergency management intelligence, as it collects, integrates, and processes all likely data (Annear et al., 2014). Active aging is denoted by the process of making the best use of chances for social engagement, sustaining health situations, and for the individuals' protection to improve their disposition of life as they get old (Annear et al., 2014). Since active aging needs to take note of the traits of older grown-ups and the environmental components that can serve as either obstacles or enablers (Annear et al., 2014; Cosco and Prina, 2014), adequately structured technological solutions can serve as enablers. The effects of physical exercise on health situations and common suggestions suggest that individuals should carry it out regularly. There has been considerable study on innovative answers to improve the advantages of physical activity (Serhani et al., 2020; Yazdan et al., 2019). In line with this, the improvement in living healthy should be considered when implementing smart cities. Smart cities are developing rather sophisticated experiments regarding the maturity level of the applications because their performance is difficult to pattern and control. They need the partnership of various stakeholders,

Table 4
Research gap and comparison with related works by other researchers.

Study	Study Purpose	Outcome Measures	Relevant Findings
Patel, M. Vaghela, H. Bajwa, and H. Seddik. "Conformable patch antenna design for Remote Health monitoring." Long Island Systems, Applications, and Technology Conference. 2010	Presents a design of a nanostructure conformable patch antenna array and full system-level radio design that could be integrated with the conformable antenna.	The proposed system designed for biomedical applications can provide real-time Remote Health monitoring, thus improving the patient's life quality.	– CNT has the potential for a less conformable polymer-CNT nanocomposite antenna. – Radio-Frequency transmitters can help to improve a patient's remote health monitoring.
Xiao, Z. Wang, L. Wang, and Y. Ren. "Super-Resolution for "Jilin-1" Satellite Video Imagery via a Convolutional Network," Sensors. 2020	Proposes a five-layer end-to-end network structure without any preprocessing and post-processing.	Experimental results on real-world satellite video data show a boosted performance in objective metrics and visuals.	There is a need to train it through clinical data from clinical activities such as screening, diagnosis, and treatment.
G. Kokkonis and S. Kontogiannis, "Design and Implementation of Wearable e-health Monitoring System with medical and tactile Sensors for Remote Patient Surveillance." 2018	Presents the design and development of an e-health jacket for healthcare monitoring, the architecture of which is based on commercially available and cost-effective hardware components.	The proposed communication protocol considers the battery of the wearable system, the distance between the patient and the access point, and the nature of the medical data.	Signal auditing, personalized assessment of bio-signal, mobility and gesture sensing, and sampling of conditions were some of the data they were able to accumulate.
R. J. Rosati, "Evaluation of Remote Monitoring in Home Health Care," 2009 International Conference on e-Health, Telemedicine, and Social Medicine, Cancun. 2009	To compare if the outcome of remote monitoring healthcare on patient improvement has any variance with patients who are hospitalized by using a control without remote monitoring.	The research found a considerable reduction in hospitalization. Regardless of diagnosis, the control group has 45.5% of hospitalization compared to 35.6% of patients on remote healthcare monitoring.	Significant reduction in the nursing visit per week for remote monitor patients when compared to the control group.
T. Bratan and M. Clarke, "Optimum Design of Remote Patient Monitoring Systems," 2006 International Conference of the IEEE Engineering in Medicine and Biology Society, New York, NY. 2006	Paper surveys and compiles the state-of-the-art smart home technologies and telemedicine systems for Individuals with disabilities who face some obstacles for their out-of-home medical visits.	A distributed diagnosis and home healthcare paradigm is the best approach for affordability, and quality smart home telemedicine systems will be deployed at an increasingly rapid pace in the years to come.	Having perused the system's failures, they designed a clinical and more integrated monitoring system based on primary healthcare.
S. Sankar, P. Srinivasan and R. Saravanakumar, "Internet of Things based Ambient Assisted Living for Elderly People Health Monitoring," Research Journal of Pharmacy and Technology. 2018	The proposed system performs three operations, such as Elderly people monitoring, activity recognition, and health status prediction using a Support Vector Machine (SVM).	In health status prediction, the SVM algorithm provides an accuracy rate of 89% and 84% for 1 week and 1-month data. Similarly, the K - SVM algorithm provides an accuracy rate of 91% for 1-week data and 88% for 1-month data.	It reveals how it is possible to combine a KIT meter for BP and an NFC-enabled KIT cellphone together, which then becomes a part of the process of IoT-based BP checking,

Table 5
Limitations, Implications, and Improvement Processes in IoT Smart Healthcare Implementations.

Limitations	Domain	Implications	Improvement Process	References, Year
Absence of clean and trained data for Artificial Intelligence algorithms. Tendentious dataset	Data	It prevents incorporating all possible models.	Machine Learning is associated with statistical analogy in decision making. It uses existing data to predict future experiences. The ML-based method should offer an efficient examination of training datasets.	(Ahamed et al., 2018)
Noisy data, dirty data, and incomplete data	Data	Reduces the probability of arriving at a conclusive health-related diagnosis and advisory note.	Data Learning must feed predictive analysis and referencing various labeled trained examples. Utilize domain expertise.	K. Boulos et al., 2019; Al-Sharekh, 2019)
Poor QoS, reputation, Confidentiality, packet forwarding ratio, reputation, varying social features, and reviews	Trust	Distortion in Interoperability and reliability.	Trust management must operate at the transaction level Clarify the duties of service providers and system developers Give directions in which components can navigate IoT-based systems with minimal technicality.	(Boulos et al., 2019; Ruan and Durresi, 2017)
Machine learning apps, devices, and Bandwidth are highly powered by energy and vastly rely on electrical resources to transmit information	Power, Energy	Batteries' source limitation and capacity lead to network failure and service disruption.	There are a few IoT devices that use a large amount of power with no rechargeable features. Hence, the use of low bandwidth connections are advised for the implementation. Explore power-aware and power generation methods to enable the transmission of data information over IoT. Software-Defined Networks (SDNs) and virtualization technologies implemented across multiple points to efficient power generation methods.	(Huang et al., 2017; Jabal Al et al., 2018; Xu et al., 2018; Yazdan et al., 2019)
Machine learning tools are exposed to generate, collect, and process a vast amount of information, which includes unstructured and structured data.	Data	The exponential increase in the volume of data coupled with peculiarities makes it challenging to manage. In keeping track of all the data, those truly needed may be omitted.	There is a need for centralization to enable it to run smoothly and simultaneously. An algorithm must be designed to designed not to expend additional time tracking unimportant data.	(Al-Sharekh, 2019)

either from the private or public sectors, citizens, or domain professionals, and complicated allocated applications holding large data quantities. As a result of this complication, it is essential to design new modes of conducting research, layout procedures, and review structures to conquer this new domain's particular obstacles. Thus, Smart Cities consist of complex ecosystems that need new speculative and multidisciplinary strategies. In this regard, the recovered articles did not suggest new development strategies and examination techniques.

Most of the models featured in the literature were evaluated with real implementations. The literature also exposed ideas for additional improvement, the elicitation of necessities, speculative models, definition of structural frameworks, description and confirmation of structures, and models to illustrate the possibility of the ideas. The application documented by Cosco and Prina (2014) and Fouad et al. (2020) intended to create homes where sensors could be activated and fully operational with an aging setup. One exhibition was carried out in an elderly care home in Singapore with the aid of wireless sensor networks incorporated for healthcare services. Lastly, in Trencher and Karvonen (2019), information collection that supported the outcome was conducted with the aid of qualitative data acquired from secondary sources. Secondary data were amassed from 2013 to 2020 by evaluating literature from the Web of Science and IEEE journals, which detailed the promotional and illustrative elements of smart cities, internal reports, and academic publications. The literature showed that individuals were adequately involved and carried out substantial alterations geared toward living more healthily (Zahid et al., 2021).

4. Limitations

Intelligence algorithms. In Table 5, a list of most of the possible limitations, implications, and improvement processes for IoT-based smart healthcare implementations is represented for comprehensive understanding. ML was associated with statistical analogy in decision making. It uses existing data to predict future experiences. While monitoring a patient, the ML-based method examined the training dataset that played a crucial role in successfully predicting a problem's tendency in the future (Ahamed et al., 2018). The main challenges were that the dataset could be tendentious and failed to incorporate all the possible models. Issues such as noisy data, dirty data, and incomplete data can reduce the probability of arriving at a conclusive health-related diagnosis and advisory note. For example, in monitoring and tracking sleep apnea in patients, the patterns and routines differed from person to person, depending on age and health status, leading to data ambiguity. Hence, the possibility of a comprehensive dataset of some case studies might not be obtainable in tracking sleep patterns. This can be a scarcely available resource. ML apps, devices, and bandwidths were powered by energy and heavily relied on electrical resources to transmit information (Yazdan et al., 2019). Some of the challenges were related to electric power quality, primarily due to irregular power sources. There have been enhancements in cloud computing use with the IoT; however, the overall system still struggles with energy efficiency. The rate of power consumption is one of the primary problems addressed by researchers in IoT and the cloud environment. The emergence of IoT and cloud computing came with limitations in energy efficiency and resource-constrained devices. Battery source and capacity are quite limited, causing network failure due to its inadequacy. Energy adequacy is a significant challenge in developing IoT devices and their communication protocols (Jabal Al et al., 2018).

5. Recommendation

Data learning is essential since it may help in predictive analysis by referencing various labeled trained examples (Boulos et al., 2019). Information collected from data will likely help proactively determine exact locations, risk rates, treatment periods, and heal time. To ensure that the implementations are error-free, some domain expertise is required. Having a critical understanding of the relationships between the different systems, devices, and networks should help in successful implementation. It is crucial to carry out properly designed research utilizing the right information prior to implementation (Boulos et al., 2019).

A functional trust framework would help clarify service providers' and system developers' duties and provide directions on which components can navigate IoT-based systems with minimal technicality. Models and features proved efficient, and functional features should be implemented to ensure a high probability of conformity to the weighting elements. Using a human-centric trust framework will provide efficient and functional management of services to confused providers and users. Network security and data privacy and safety will play a significant role in the widespread adoption of IoT and related technologies. IoT is somewhat vulnerable to protection and privacy threats due to its ambiguity and diversity (Ray, 2018). A trust framework that can be scaled as required for IoT-based systems and software programs self-defenses to ensure security management and control distribution is needed. One other component of the IoT framework is that it will assist in dealing with large volumes of data, and the utilization of the IoT model aids software program distributions. Application developers should keep their designs simple and ensure threats are managed within a trust framework that has manual driving effectiveness and easy communications (Ruan and Durresi, 2017).

This trust framework could also integrate innovative components into the system, which could be added securely when a requirement is met, rather than relying on a spontaneous addition of components that exposes the entire system. Additionally, systems could be instructed to institute a relatively easy reference control when interacting with other systems on the network channels for availability purposes (Ruan and Durresi, 2017). Protecting user privacy, vital infrastructure, and websites from large-scale threats involves protecting interconnected IoT computers. Potential attacks use IoT devices as bots to inundate targeted websites or networks with large traffic, which extends their bandwidth capability (Ahmad and Alsmadi, 2021). Developers and providers of the IoT-based system must place innovative features after ensuring that potential privacy protection risks have been duly vetted. The IoT model will likely require upscaling, such that the modeling process is connected adequately to individual components. This could consist of standardized names and references easily recognized and paradigms designed universally permitted components with varying capabilities to comfortably and securely interact with the IoT system. It was essential to make the features easy to navigate for varying caliber individuals to ensure proper security implementation on the IoT-based systems (Ruan and Durresi, 2017). There is a need to explore power-aware and power generation methods to enable data transmission over IoT. Various power generation methods are in place that could aid power generation environmentally. These energy harvesting methods could help prolong the network channels' lifespan and promote green communication (Xu et al., 2018). SDNs offer more improved models that better handle high powered applications and virtualization, which assist in managing hybrid power resources in future communication network channels (Huang et al., 2017).

The implementation of DL within a software-defined network is an area that needs to be looked into comprehensively to assist in extracting meaningful data content. M-IoT drives compression models to function more vigorously and with reduced complexities and ensures a reduced bandwidth output while optimizing the spectrum and network channel resources. The models of compression are researched widely as well as their applicability in the transmission of data over wireless channels (Misra et al., 2008). For attack detection and prevention, numerous ML algorithms have been suggested: Genetic algorithm (GA), firefly algorithm (FF), particle swarm optimization (PSO), rider optimization algorithm (ROA), whale optimization algorithm (WOA), and others are a few instances (Reddy and Shyam, 2020). However, no concrete works are available on compression methods or models for encoding data content transmitted on the M-IoT framework. This area must be thoroughly explored, especially ways of coding related to data services on the M-IoT network, while also considering the constraints faced with interfacing and energy consumption.

6. Conclusion

IoT solutions have evolved in the healthcare sector from a simple design to much more complex and smart systems. Where AI and IoT have played an essential part in healthcare, their implementation was also equally important. The primary purpose of this research analysis was to specify which applications were functional with smart-city frameworks. By discussing models and designs for remote healthcare monitoring, we established that several models, such as mHealth, 6LoWPAN, CoAP, and IEEE 11073, could be used to transmit data accurately and to modify current processes. Moreover, this paper highlighted tools that influenced healthcare availability. A comprehensive survey of related publications was carried out to determine which tools and technology could be implemented. Results demonstrated that the latest technology, such as carbon nanotubes, RF transmitters, kit meters, and NFC, could extrapolate data. The research paper also presented solutions recommended by different authors for use in a smart city. These authors shed some light on implementing IoT for smart-city healthcare models, technologies, designs, and systems.

This paper analyzed smart-city healthcare implementation in terms of applicability. The practical analysis was designed to deliver intriguing and unique ideas. The most relevant applications identified for implementation were active aging, population surveillance, healthy lifestyles, socialization, care service organization, and emergency response. This paper also presented a secure and low-cost method to develop a health monitoring system, which provided real-time monitoring of patients by employing IoT technology and ML practices.

By reviewing and comparing different researchers' work, we also determined that smart healthcare designs and models have evolved to produce some challenges. However, there is space for refinement and improvement amid such challenges, which are also discussed in the paper. One problem highlighted is that medical institutions lack a unified standard among different organizations and regions, and there is a need for improvement to ensure data integrity. As extensive data have to be gathered, it will likely make the system rather complicated, which will lead to difficulties in communication and data management. Another problem identified from the research is data identification and analysis within multiple connected devices and platforms. Another solution is to create an open mHealth model that enables doctors and patients to use it easily. A unified platform will allow patients to access telemedicine services and advice, enabling doctors to easily monitor their patients' health status. Mobile architectures such as mHealth will likely help reduce medical errors, reduce medical treatment difficulty, improve medical services' timeliness, and provide an economical option for health services.

ML will mainly rely on the dataset and algorithms available to organize the information with the aid of regulated or unregulated learning. Humans do make wrong choices, as we rely on our amassed knowledge to make decisions. While emotions occasionally influence the choices we make, computers are not constrained by emotions.

Declaration of Competing Interest

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

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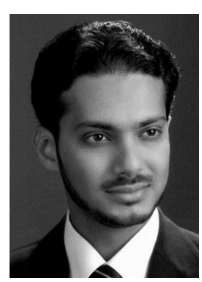

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