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Review

Pervasive Healthcare Internet of Things: A Survey

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Abstract: Thanks to the proliferation of the Internet of Things (IoT), pervasive healthcare is gaining popularity day by day as it offers health support to patients irrespective of their location. In emergency medical situations, medical aid can be sent quickly. Though not yet standardized, this research direction, healthcare Internet of Things (H-IoT), attracts the attention of the research community, both academia and industry. In this article, we conduct a comprehensive survey of pervasive computing H-IoT. We would like to visit the wide range of applications. We provide a broad vision of key components, their roles, and connections in the big picture. We classify the vast amount of publications into different categories such as sensors, communication, artificial intelligence, infrastructure, and security. Intensively covering 118 research works, we survey (1) applications, (2) key components, their roles and connections, and (3) the challenges. Our survey also discusses the potential solutions to overcome the challenges in this research field.

Keywords: Internet of Things; healthcare; pervasive computing

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1. Introduction

Pervasive computing, or ubiquitous computing, is a computing paradigm that leverages the user interaction with microprocessors or gadgets in an "anywhere and anytime" manner. The users do not need to access a PC or laptop; instead, they can use their body-worn devices. Due to the rapid proliferation of handheld and wearable devices, the Internet of Things (IoT) enabled technology is evolving healthcare in the era of pervasive computing. The development of cloud technology empowers pervasive computing even more by providing communication across different objects for data sharing. Thanks to that, IoT offers a stage to associate heterogeneous devices from smart homes, and smart urban communities, to smart healthcare. These interconnected objects and sensors harvest the information for complicated tasks such as recognition, prediction, planning, and recommendation [1]. With the tremendous growth in recent years, smart IoT systems are expected to play a vital role in many pervasive healthcare applications. Indeed, IoT integrated with other advanced technologies could significantly transform the landscape of pervasive healthcare in an uninterrupted and ubiquitous monitoring manner. This new direction is regarded as the Healthcare Internet of Things (H-IoT), which is very important, especially during the pandemic era. For example, to prevent the spread of the virus, social distancing can be implemented by deploying IoT devices, including smart watches and monitoring devices. Here, we would like to highlight the differences between generic IoT and H-IoT. The generic IoT is usually deployed over a large-scale area such as smart cities or urban planning. On the other hand, H-IoT is usually deployed in a small-scale area such as the human body or a smart home or hospital. H-IoT nodes, miniaturized to be unobtrusive, are used to monitor human body vitals. These nodes can collect energy from a human via body heat or motion.

In this paper, our overarching goal is thus to provide a comprehensive survey of pervasive computing in H-IoT. We would like to provide a broad vision of its components and their connections. We classify the vast amount of publications into different categories such as applications, sensors, communication, storage infrastructure, security, and artificial intelligence. Intensively covering more than 100 publications, we survey (1) applications, (2) key components and their roles, and (3) the challenges.

The remainder of this paper is organized as follows. Section 2 compares this work to other existing surveys. Section 3 surveys the applications of pervasive computing in H-IoT. The key components of H-IoT are reviewed in Section 4. Section 5 reviews the existing challenges. Finally, Section 6 concludes this paper.

2. Comparison with Other Surveys

There have been many surveys on H-IoT in the literature. Qi et al. [2] discussed the applications, the data sensing and processing, and their challenges in H-IoT. However, this survey is outdated since it did not address the latest technology in cloud computing or security issues in personalized healthcare systems. In 2018, Alam et al. [3] surveyed the roles of communication technologies in H-IoT applications. They introduced four applications on infectious diseases, cardiovascular diseases, musculoskeletal disorders, and neuromuscular disorders. They also discussed the issues and challenges along with the emerging communication technologies. However, this survey disregards the impact of artificial intelligence, which is a key component in HIoT applications. Meanwhile, Shaikh et al. [4] reviewed smart healthcare systems using the Internet of Things, for example, e-health systems, telehealth and home monitoring systems, and RFID-based monitoring systems. They also discussed issues related to smart healthcare systems such as reliability, low-latency tolerance, and interoperability. However, Shaikh et al. [4] did not discuss the key components within HIoT systems. In another work, Ahmadi et al. [5] reviewed the applications of the Internet of Things in healthcare. In particular, they reviewed the main components and their functions along with the main issues and challenges. Still, they did not consider the security and privacy issues in H-IoT. In addition, artificial intelligence is not addressed in the survey. Similarly, Rajini [6] reviewed different applications and services in smart healthcare systems. However, the survey is lacking discussions regarding the key components of such systems.

Habibzadeh et al. [7] surveyed the H-IoT from a clinical perspective. They reviewed the key components such as sensing, communication, and data analytics. They also discussed the open issues and future trends in this field. This survey, however, did not discuss the importance of artificial intelligence and cloud computing in this research field. In a different survey, Usak et al. [8] reviewed the health care service delivery based on IoT. They also discussed the pros and cons of other surveys. However, the key components within the IoT healthcare system are not visited. This is not helpful for readers to gain an understanding of the existing IoT healthcare system. Dhanvijay and Patil [9] introduced a survey of technologies in H-IoT and their applications. Like other surveys, open issues and the main challenges are discussed. Similarly, artificial intelligence and cloud computing were not addressed in this survey. Recently, Ali Tunc et al. [10] compiled a survey on emerging technologies, applications, challenges, and future trends for IoT-smart healthcare. The key components such as sensors and privacy issues were not addressed in the survey.

Table 1 shows the comparison between our survey with the existing surveys in the literature. Our survey covers all the important content related to pervasive computing in H-IoT.

Table 1. Literature survey comparison. The checkmark (✓) denotes the availability of the mentioned content in the survey.

Surveys	Survey Comparison	Review of Applica-tions	Key Components					Challenges
			Devices/Sensors	Commu-nication	Artificial Intelligence	Cloud Computing	Security and Privacy	
Qi et al. [2]		✓	✓	✓	✓			✓
Alam et al. [3]		✓		✓		✓		✓
Shaikh et al. [4]		✓						✓
Ahmadi et al. [5]	✓			✓		✓		✓
Rajin [6]		✓						
Habibzadeh et al. [7]	✓	✓	✓	✓			✓	✓
Usak [8]	✓	✓						✓
Dhanvijay and Patil [9]	✓	✓		✓			✓	✓
Ali Tunc et al. [10]	✓	✓		✓	✓	✓		✓
Ours	✓	✓	✓	✓	✓	✓	✓	✓

3. Applications of Pervasive Healthcare Internet of Things

Pervasive computing in H-IoT can be found in various application domains as shown in Figure 1. We summarize some notable applications below.

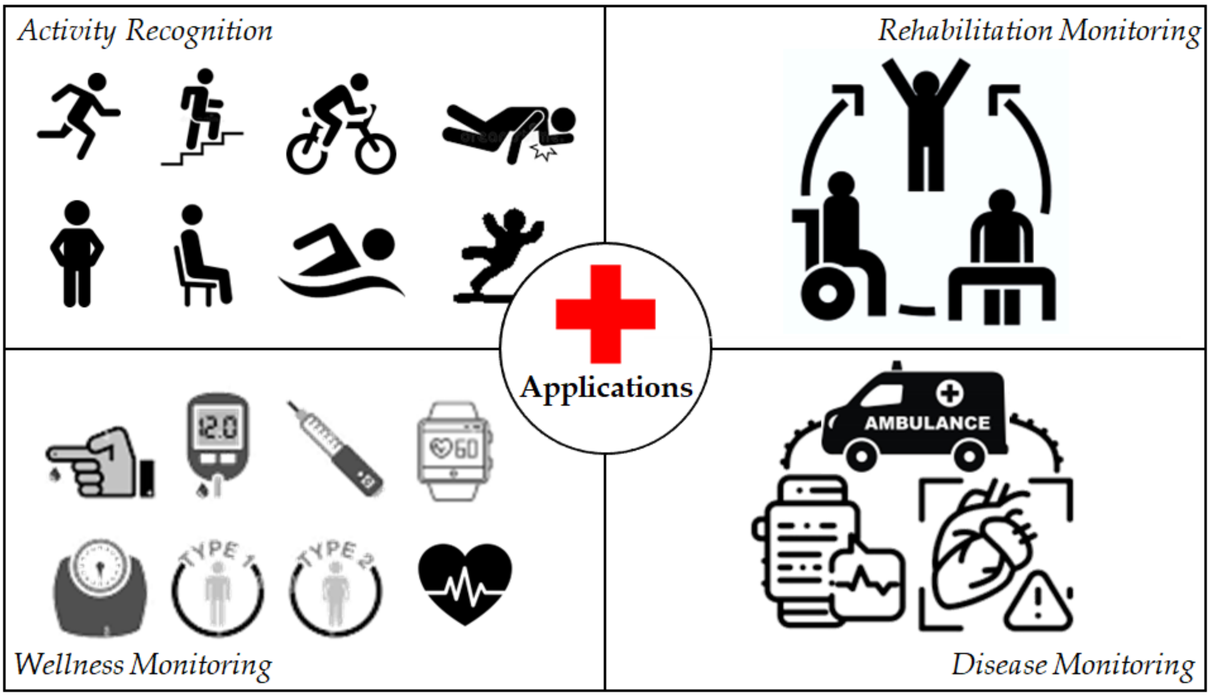

Figure 1. Some applications of pervasive computing in the healthcare Internet of Things. Section 3 reviews these components in detail.

3.1. Activity Recognition

Activity recognition is crucial in the sense that it provides a context of what is happening so that the IoT system can respond appropriately. Note that the activity can be recognized via various sensors. Nguyen et al. [11] used a spatial-temporal attention-aware pooling for action recognition in video. First, the visual saliency is predicted from the input video. Saliency-aware matching kernels are thus derived as the similarity measurement of these channels. The kernels are then fed into support vector machines for activity classification. Falls are one of the major health threats to independent living, especially for elderly people. Note that the elderly often live alone and receive only irregular visits. Thus there is a legitimate need to detect a fall or abnormal activities. Ni et al. [12] used Kinect, an RGB-D camera for fall detection in hospitals. From both color and depth video frames, the motion and shape features are extracted. Then, the extracted features are fused via a multiple kernel learning model to detect the anomalous events. Once the system detects a patient getting up from the bed, nursing staff are informed to provide immediate assistance. Wang et al. [13] detect falls by using a WiFi signal. In particular, they take advantage of the wireless physical information-Channel State Information (CSI) in widely deployed commercial wireless infrastructure. They found that the static human body does not affect CSI in the time domain. Instead, human activities, such as walking, sitting, standing up, and falling will change the variance of CSI. Therefore, the variance change of CSI can be used to detect the anomaly of human activities. Ruan et al. [14] used Radio-frequency identification (RFID) tags to determine the fall in an unobstructed manner. The RFID tags are used to sense regular actions and fall events simultaneously. When a person falls from standing, the Received Signal Strength Indicators (RSSI) show different fluctuation patterns, indicating the potential for detecting a fall. The detected fall event is sent to caregivers along with the contexts of fall orientations. Uddin and Soylu [15] proposed a body sensor-based activity modeling and recognition system using a time-sequential information-based deep learning algorithm. First, data are obtained from multiple wearable sensors while the subjects perform their daily routine activities. The collected time-sequential information then goes through the feature extraction component. The extracted time-sequential features are later fed to the deep learning model, i.e., long short-term memory (LSTM) for activity recognition. Wang et al. [16] recognized multiuser activities by using wireless body sensor networks. An RFID reader is located on each hand to detect the presence of a tagged object within a few centimeters. There is an ultra-high frequency (UHF) RFID reader located in each room to sense the proximity of a person wearing an UHF tag. The sensor data consist of the 3-axis acceleration data for both hands, object use for both hands, temperature, humidity, light, and user location. The sensor data is then used to recognize the activity via a pattern recognition model. Zhu et al. [17] proposed ambient radar for indoor human activity recognition. In particular, they used a 7.8 GHz radar to emit 16 pulse signals per second and sample the reflected signals at 128 kHz to recognize the fine dynamics of human activities.

3.2. Rehabilitation Monitoring

The assessment after stroke is very important for patients, especially for outpatients who need to be evaluated often like inpatients but can still come back to their normal lives as soon as possible [18]. Furthermore, in America, the risk of a second stroke in the first year is 23% in 2022 [19]. Standen et al. [20] introduced a virtual reality system for home-based arm rehabilitation for a post-stroke patient. The proposed system uses Kinect and smart glass to monitor patients after stroke to predict and assess the recovery process. In [21], Hoda et al. designed and developed a prototype to simulate real post-stroke rehabilitation exercises. To find the correlation between the kinematics of the upper limb and the muscle strength, they use least-square regression method. Like [20], a Kinect depth sensor and a force sensing resistors glove are used to track the subject's data such as limb joints and muscle strength. The data are collected while the subjects are performing their exercises. The evaluation on 13 subjects demonstrates the usefulness of the system in recognizing the muscle strength of stroke patients without wearing any devices. Meanwhile, Bobin et al. [22] introduced a system to monitor and guide stroke patients. The system consists of a smart mug that tracks the patient's drinking activities. For example, the information such as drinking frequency, liquid level, drinking orientation, and liquid type, i.e., water, coffee. This solution allows therapists to monitor the patient and assign the suitable exercises for rehabilitation sessions.

3.3. Wellness Monitoring

According to the American Diabetes Association, about 37.3 million people (11.3% US population) suffer from diabetes [23]. Blood sugar monitors play an important role in managing the blood glucose level. Al-Taee et al. [24] suggested a method to assist in improving diabetes in young people by using smart robots. Fioravanti et al. [25] used a texting system for helping patients who have problems with abnormally high blood sugar levels. Kaiya et al. [26] used wireless devices to set up a diabetic meal plan by gathering the figures from IoT tag systems. About 116 million (nearly 47%) adults in the United States have problems with blood pressure, especially hypertension (high blood pressure) [27]. Janjua et al. [28] introduced a Bluetooth chest wearable device to monitor vital signs. Since then, we can detect and prevent the chance of hypertension. This early intervention can significantly reduce the risk of mortality caused by abnormally high blood pressure. Meanwhile, Iakovakis and Hadjileontiadis [29] monitored orthostatic hypotension (low blood pressure caused by postural changes) by using smartwatch sensors.

Cardiovascular disease is one of the most common causes of mortality globally, occurring in both men and women, and it is also the number one killer in the United States [30]. There are 659,000 people in America who die from heart disease every year, comprising 25% of total deaths [31]. Kiranyaz et al. [32] designated an individual monitoring device and advanced alert notification system for patients with an irregular heartbeat (cardiac arrhythmias). Schmier et al. [33] developed a small sensor (the size of a paper clip) placed in the pulmonary artery to check the heart rate with the cardioMEMS HF system like a remote home monitoring unit. Xia et al. [34] presented an automatic wearable electrocardiogram (ECG) to classify and monitor patients with the diagnosis of cardiac arrhythmia. Hijazi et al. [35] proposed the effectiveness of electronic monitoring by using machines for supporting victims of a cardiac-related disease. Arppana et al. [36] analyzed cardiac rate and rhythm from real-time face images to extract the activity of the heart in a cycle by a non-contact-based method.

Respiration Rate Monitoring: respiration is one of five vital signs (heart rate, temperature, blood pressure, oxygen saturation, and blood glucose level) that reflect patient breathing problems. The respiration rate also plays an important role which is useful to be admitted to ICU (Intensive Care Unit). Tan et al. [37] presented a real-time vision-based respiration activity monitoring platform. Ferreira et al. [38] presented a smart system dubbed Baby Night Watch to protect children from SIDS (Sudden Infant Death Syndrome) by wearing a chest belt. In addition, Raji et al. [39] introduced a system for doctors to regularly monitor asthmatic patients by using multiple remote sensors through an Android application.

Sleep is an essential state of rest that recharges the body and refreshes the mind. Appropriate sleep can help one stay healthy and fight off diseases [40]. Therefore, pervasive H-IoT systems can be used to monitor patients during sleep. Phan et al. [41] proposed SeqSleepNet to automatically recognize the sleep stages. Nguyen et al. [42] developed a system called LIBS (Light-weight and Inexpensive In-ear Bioelectrical Sensing System) to monitor patients' whole-night sleep and then classify four stages in sleep cycles through the activity of the brain, eye, and muscle. Meanwhile, Yang et al. [43] used millimeter waves to monitor vital signs, particularly with regard to detecting posture and irregular breathing rhythms during sleep.

With the fast rhythms of developing society, work-related stress becomes more and more common. People living with high stress suffer the risk of cardiovascular diseases, mental health problems, eating disorders, and menstrual problems. Many pervasive H-IoT systems have been designed to detect stress using wearable sensors. Clarke et al. [44] presented a recommendation mobile application for just-in-time adaptive interventions to recognize and reduce stress by detecting heart rate and suggesting the adapted treatment model. McWhorter et al. [45] innovated a remote wearable sensor for PTSD (Post Traumatic Stress Disorder) patients. Vidal et al. [46] developed a smartwatch-based platform to support autistic people's self-control of their emotions. Oti et al. [47] presented a real-time stress level estimation approach for pregnant women. They adopted an unlabeled response method to estimate the stress level from the heart rate during pregnancy.

3.4. Disease Monitoring

In 2020, it is estimated that 5.8 million Americans are diagnosed with Alzheimer's Disease [48]. One new dementia case occurs every three seconds. Alzheimer's patients generally require daily assistance during their lives given their existing condition. IoT-based systems can provide day-to-day support in many areas. Ishii et al. [49] introduced a system for early dementia recognition using the machine-to-machine/IoT platform. Tamamizu et al. [50] proposed a device to detect anomalous activities for home dementia care. The users can define the anomaly and the corresponding cares. Once the anomaly is detected, the corresponding care will be provided. In another work, Szeles and Kubota [51] used smartphones for location monitoring for elderly people. The mobile application gives them reminders based on their current location.

Parkinson's and Huntington's diseases are neurodegenerative and are characterized by movement disorders. Huntington's disease is an inherited condition caused by a mutated gene from a parent. However, Parkinson's disease may happen as a result of many genetic or non-genetic factors. About one million people live with Parkinson's disease (PD) in the US [52]. This number is projected to rise to 1.2 million in the next eight years. Nearly 60,000 Americans are living with PD every year and more than 10 million people are diagnosed with PD worldwide [52]. Meanwhile, about 30,000 Americans suffer from Huntington's disease (HD) and another 200,000 have a chance of developing the condition [53]. The IoT systems provide a significant platform for screening the movement disorders associated with PD/HD and managing disease status, advancement, and treatment effectiveness. Dinesh et al. [54] and Adams et al. [55] proposed methods to affix multiple wearable sensors detecting unusual movement symptoms in people with PD and HD. These sensors can distinguish between individuals with motor symptoms and those that do not have them. The combination of medication and the sensor-based system is needed to apply in treatments effectively. Flagg et al. [56] introduced real-time virtual monitoring of posture and gait valuation for PD.

From the summarized applications, we found that sensors, communication, artificial intelligence, storage and computing infrastructure, security, and privacy are the key components. Figure 2 shows the key components inside an H-IoT system. The following section will review the key components in detail.

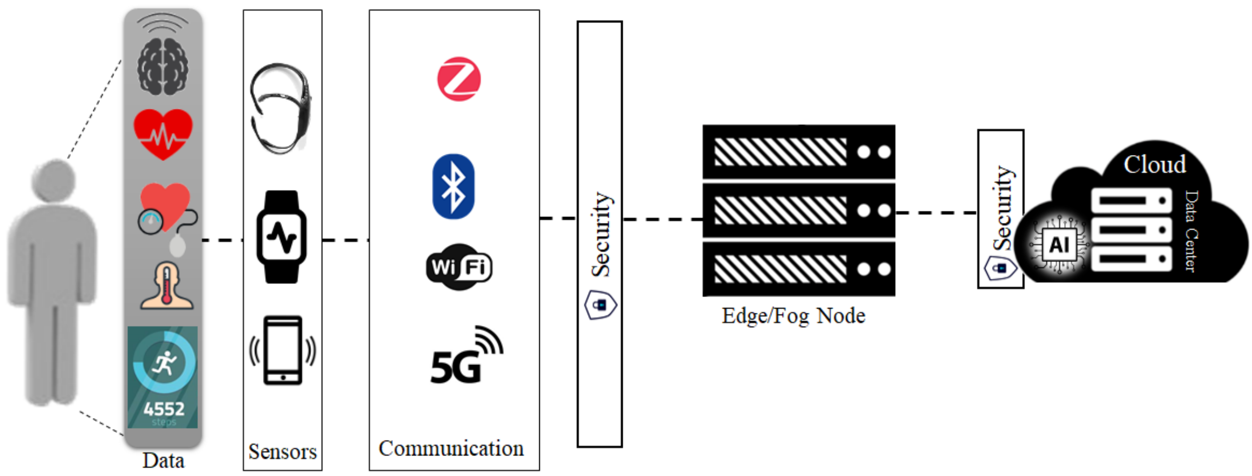

Figure 2. The key components in an H-IoT system, namely sensors, communication, AI, fog/edge/cloud computing, and security. Section 4 reviews these components in detail.

4. Key Components in the Pervasive Healthcare Internet of Things

4.1. Sensors

Sensors are essential in pervasive H-IoT systems. They are used to collect user data such as heart rate and body temperature. In addition, sensors are used for sensing environmental information such as humidity, temperature, light, noise, and air quality. In this subsection, we consider two types of sensors, namely, wearable sensors and environmental sensors [57–82].

Regarding wearable sensors, the most common inertial sensors yield valuable information such as accelerometers [70] (position change) and gyroscopes [71] (rotational change) are suitable for assessing human physical movement. They are worn on different body parts to detect human motions such as bending the knees and walking up stairs. Moncada-Torres et al. [57] categorized activity based on inertial and barometric pressure sensors at separate positions of body parts. In addition, identifying the location of humans is very important. There are many location sensors such as the Global Positioning System (GPS) [72], the Death Reckoning Module (DRM) [73], and RFID [74,83]. Next, the sensors reading vital signs are very crucial in any pervasive H-IoT. These sensors read the heart rate, blood oxygen, and pressure [75]. The advancement of hardware integrates these sensors into wearable devices for convenience, and the data can be transmitted via the Internet. Bulling et al. [61] fused different data modalities from body-worn sensors to recognize human activity. Recently, ego-centric cameras have become more popular. Therefore, the images/videos captured from the head-mounted camera can be used in H-IoT for activity analysis [76]. Journal et al. [63] used a wearable sensor for limbic encephalitis patients to improve their biographical memory by using a camera as an image diary. After viewing a visual diary, the user is able to recall approximately 80% of recent, personally experienced events. Meanwhile, 49% of an event can be remembered by reading a written diary.

Regarding environmental sensors, modern thermostats [77] can be connected to WiFi and provide information such as temperature and humidity. In addition, there are position trackers such as Beacon [78], AirTags [79], and RFID tags [80] which are used to localize certain physical objects. For example, Yang et al. [68] efficiently found objects by using sparsely distributed passive RFID tags. Lastly, other sensors such as the doorbell, bulb, and motion sensors [80–82] are important within an H-IoT system. Table 2 shows the categories of sensors in pervasive H-IoT.

Table 2. Categories of sensors and devices used in pervasive healthcare Internet of Things, namely wearable sensors and environmental sensors.

Sensors						
Wearable Sensors				**Environmental Sensors**		
Inertial	**Location**	**Vital Signs**	**Imaging**	**Thermostat**	**Position Tracker**	**Others**
Accelerometer, gyroscopes, altitude	GPS, Death Reckoning Module, RFID	Blood oxygen, pressure, heart rate	Live photos, videos	Temperature, humidity	Beacon AirTag RFID	Smart Doorbell, bulb, motion sensors

4.2. Communication

The data retrieved from the aforementioned sensors will be transmitted for further processes such as activity recognition, anomaly detection, or recommendation. In this subsection, we review the popular communication standards used in pervasive H-IoT.

4.2.1. Wireless Sensor Networks and Smart Body Area Networks

Wireless sensor networks (WSNs) consist of spatially dispersed sensors that collect environmental data such as temperature, sound, pollution levels, humidity, and wind. The collected data will then be forwarded to a central station [84]. With the ubiquitous setting, WSN suits pervasive IoT systems with many devices or sensors [65–67]. The sensors can communicate with each other via WiFi, Bluetooth, or Zigbee connections. However, there exist several well-known limitations in WSNs such as power consumption, communication range, and body-to-body communications. Therefore, Smart Body Area Network (SmartBAN) technology [83,85–87] was proposed to support a range of medical, health improvement, personal safety, and wellbeing via a network of small, low-power devices. In particular, SmartBAN is designed for supporting body-to-body communications. SmartBAN is based on a multi-radio approach to connect devices via radio standards.

Furthermore, SmartBAN has separate control channels, namely, a data channel and a control channel for data transmission and control message transmission. Takabayashi et al. [87] evaluated SmartBAN in H-IoT applications. Javaid et al. [83] studied the feasibility of using SmartBAN in monitoring COVID-19 [88] cases.

4.2.2. Cellular Technologies

The aforementioned WSNs and SmartBAN can be deployed for a small area such as a home or hospital. To increase the deployment scale, cellular communication technology needs to be involved [89]. Cellular technology has evolved from 1G to 5G. At the moment, 5G supports faster and more secure connectivity that is advancing everything from self-driving vehicles to AI-enabled robots. This benefits a massive-scale IoT ecosystem of billions of connected devices. There have been many studies on 5G and IoT architecture [90,91].

4.3. Artificial Intelligence

Artificial intelligence (AI) and machine learning (ML) is the brain of any health IoT system. Figure 3 illustrates the application of AI/ML in H-IoT. We categorized the AI/ML applications into the following groups.

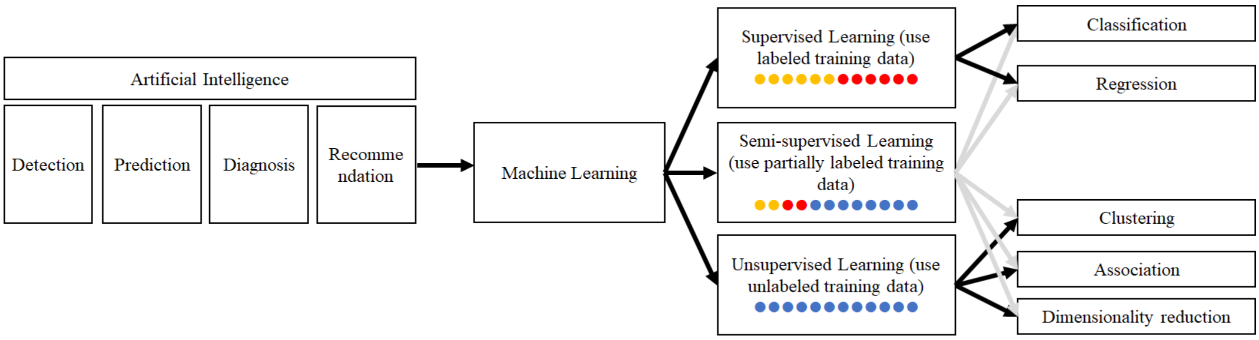

Figure 3. The application of artificial intelligence in a pervasive healthcare Internet of Things system. **Orange** and **red** dots denote the annotated training data, whereas the **blue** dots represent the unlabeled training data.

4.3.1. Activity Detection

Machine learning techniques such as modern deep learning can be used to understand and analyze the users' heterogeneous data. In [92], Zhou et al. introduced deep learning to improve activity recognition in IoT. They proposed a semi-supervised deep learning framework to recognize motion from sensor data. Note that semi-supervised learning only uses partially labeled data, so it saves labor costs for data annotation. Nguyen et al. [11] used a supervised method, namely, kernel Support Vector Machine (SVM) to classify the input features such as visual and motion cues into different action labels. Meanwhile, Ni et al. [12] extracted 3D block features from RGB-D videos to efficiently classify the fall activity in hospitals.

4.3.2. Disease Diagnosis

Machine learning is used in diagnosing some of the most popular eye problem disorders such as angle-closure glaucoma and age-related macular degeneration [93]. Some of the ML techniques used in various disease diagnosis applications include support vector machines, deep learning systems, convolutional neural calculates, and backpropagation calculates [94]. The input information varies based on the diagnoses being established. Machine learning is normally used in media image processing to give the diagnosis. In parallel, chronic diseases are diagnosed based on time progress data, including other factors such as patient history, demographics, genes, and symptoms [48].

The most-reported information includes vital signs, age, X-ray features, and blood cell count [60]. Machine learning algorithms are significantly effective, as they can access many pulmonary images of patients during the COVID-19 pandemic and can distinguish between those infected by COVID-19 or not. Therefore, images, tabular, text, and time series are the input data types for these prediction models. For example, X-rays can be supported with ML classifiers to recognize COVID-19 [90]. Wynants et al. [95] developed prediction models to diagnose the COVID-19 cases. Another study demonstrated significant accuracy in the diagnosis of COVID-19 by using eight binary features: sexagenarian, gender, exposure to COVID-19 virus, and five other vital signs [96].

4.3.3. Disease Prediction

AI can help physicians by suggesting more options for diagnosis or prediction. Yan et al. [97] studied the application of AI and ML in predicting heart disease. The physicians can give the diagnosis through an AI model for another round of screening. This may lower the risk of misdiagnosis. In [98], Almustafa predicted cardiovascular disease by assessing different ML methods such as KNN, SVM, Adaboost, and Decision Tree. The user enters the features such as age, gender, cholesterol level, blood pressure, and fasting glucose. The experiments show that the KNN classification is the best since it is a data-driven method. Another patient with similar health conditions tends to have the same diagnosis.

4.3.4. Medical Decision Recommendation

Artificial intelligence can analyze the activity of users and recommend changes; for example, doing exercise, changing one's diet, or visiting the doctor. Michie et al. [99] analyzed the behavior of individuals to determine the necessary changes. In particular, they modeled the features and the series of activities in the form of ontologies and they executed ontology reasoning for the final recommendation outcome. Asthana et al. [100] proposed a recommendation system for personalized advised wearables. Given the user's medical history, the system identifies the diseases that this person is at risk for. The system then provides recommendations via a computational model. Almeida et al. [101] proposed a recommendation system to automatically discover cohorts of interest. The cohort here is a group of users sharing common information. The system uses context-aware retrieval and collaborative filtering to localize relevant cohorts regarding Alzheimer's disease. Erdeniz et al. [102] introduced virtual nurses to help chronic patients (i.e., diabetes, asthma) reach their goals. The system reads the patient's data via IoT sensors such as a wristband or smartwatch. It then calculates the distance from the current health condition to the predefined target and provides suitable recommendations.

4.4. Cloud Computing Infrastructure

Cloud computing (cloud storage) [103] is an available system model to deliver different services for enabling ubiquitous, convenient, on-demand internet access to a shared pool of customizable computing resources: networks (horizontal, physical, or virtual), servers, storage, software, databases, analytics, and intelligence. This method can minimize the management and interaction from the provider rapidly and effectively [104]. Large clouds usually have functions diffused over various regions/locations, each region being a data center (traditional cloud). According to the National Institute of Standards and Technology (NIST), fog computing is also known as an architecture located between traditional cloud and smart end-devices. This paradigm delivers vertically isolated, latency-sensitive services for ubiquitous, scalable, federated, and distributed computing. The cloud now becomes a hierarchical structure since the edge is usually confined to some peripheral layers. In practical terms, edge computing can be described as the system layer including the peripheral devices and their users. This network encourages the edge to support local computing proficiencies for mIoT devices. These edge and fog infrastructures show a tendency to bypass the gap between the data and the end user. Recently, Laroui et al. [105] conducted research on current activities and future directions of cloud and edge computing for many different fields. Figure 4 shows the relationship between edge, fog, and cloud computing in the context of IoT-based smart healthcare.

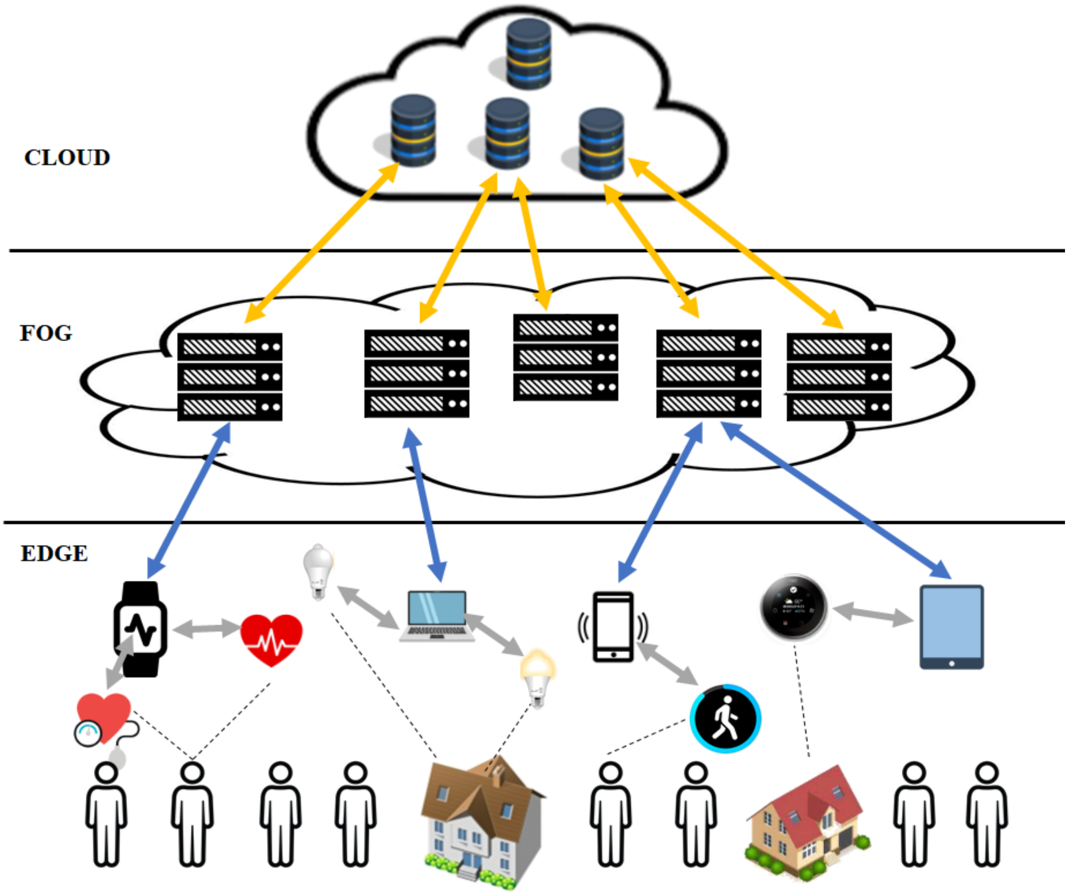

Figure 4. The relationship between edge (sensors), fog (nodes), and cloud (data centers/cloud services) computing in the context of pervasive healthcare Internet of Things.

4.5. Security

Security issues include security, authentication, privacy, identity management, and ethical challenges.

Security is always considered in H-IoT communication, whenever the communications happen: in body, on body, or around body. Synchronizing those of any other type of communication device protecting vulnerable data is not simple. Security problems such as accuracy and data privacy must be addressed to ameliorate confidentiality. Diminution of a variety of threats and attacks (some types of attack are active, authentication, access control, and availability) becomes more and more essential in cybersecurity [106]. Moreover, evil twin access points, eavesdropping, and man-in-the-middle attacks are common strategies that can threaten the security of a system, while replay attacks, denial-of-service (DoS), or frame injection attacks confront the system's integrity. Beacon flood, radio frequency jamming, and association/authentication flood can damage the availability and constitute a menace to the individuality of patients. In some cases, vindictive hackers may abuse other ways of extreme and occasionally undignifying types to obtain private data. As discussed by Yu et al. [107], audio signal processing and machine learning are secretly used to eavesdrop on handwriting and can be executed using nearby smart devices. The authors emphasize that they can obtain up to 50–60% of word recognition with certain support conditions. This approach has been customized to other areas, such as a hand motion tracking technique to upgrade the work of the eavesdropping, thus enhancing the performance to 70–80% [108]. The variety of attacks prove that cybersecurity and individuality for H-IoT are seriously important for the viability of smart healthcare.

Authentication is the act of proving an assertion, such as the identity of a system user. Recently, biometric information such as face photos and fingerprints has been used for authentication. However, deepfakes, synthesized images, and videos generated by generative adversarial networks (GAN) [109] pose a cybersecurity threat. A deepfake superimposes one person's face and voice onto another to create fake videos that appear authentic. Thus deepfakes may fool electronic devices/sensors for authentication.

Privacy in the context of IoT-based healthcare may be considered as the right of each individual to decide how much of their private information is shared. Therefore, patient privacy may be in danger when security is violated. Privacy issues have become the biggest challenge for analysts and also for patients using the smart healthcare service [110], where they share their s-Health records (SHRs) [111] and trust that only authorized professional healthcare staff can access them. As discussed in [111], in the situation where traditional access conduct techniques are applied, either data security is violated or only coarse-grained access policies are approved. To attenuate this matter, Zhang et al. [111] suggested a privacy-aware s-health access control system (PASH). In PASH, privacy information related to access permissions is invisible, and generic attribute names are available. A competitive decoding test is attached before full decoding to boost efficiency. Hackers may access any wearable or in-body, off-body sensor devices that can penetrate the privacy data of patients (e.g., loss or change of data) or loss of device managing rights. This can lead to the unexpected operation of the medical device system [112]. It is therefore compulsory to improve the protection of data security and privacy.

Identity management is very important since patients expect their personal data, such as social security numbers, their medical records, and even credit card numbers, to remain confidential. However, such valuable information can be illegally retrieved through ransomware and phishing attempts, unrestricted access to computers, and even patients' lack of adequate knowledge. Abdullah et al. [113] proposed using digital signatures for identity verification. The signing operation utilizes a hash function and a private key to encrypt the data. Meanwhile, the verification operation utilizes the hash function and the public key to decrypt the data. If the output of the hash function and the data decryption match, the signature is valid.

Ethics challenges and legal issues are worthy of being addressed in H-IoT. Most of the ethical challenges are about accessibility rights and the private use of information. In the IoT attacks, the losses will reach the point that they will affect people's lives. For example, if an attacker can log in to a medical application and make a small change in a patient's file. The unauthorized change may result in the wrong medication, which could affect the patient's life. Meanwhile, there are many legal issues related to questions raised in H-IoT. For example, who will be responsible when the Internet is down in medical applications? What will happen if a medical service provider goes out of business? How does this affect patients? And how will the patient's data be used? AboBakr and Azer [114] introduced new policies to address the ethical challenges and legal issues. New laws and standards should be introduced to maintain complete security and privacy and cover all legal issues.

5. Existing Challenges

From the extensive review of previous surveys, applications, and key components, we observe the following challenges. The first challenge is computational intensity. We have a loss of information; for example, the interruption of data collection from wearable devices. The second challenge comes from the restricted storage in mobile devices. For example, thanks to wearable cameras, people can easily do lifelogging. However, how to design an architecture to store and update huge volumes of image data is a big challenge. Such time-series data requires a huge volume of storage space. One potential solution is to apply machine learning to retrieve the intrinsic information of the data by reducing the number of feature dimensions.

The training process of artificial intelligence models also requires large amounts of data and high computational costs. Furthermore, we have difficulty in filtering an authentic and reliable correlation among various health information. Due to heterogeneous data, the network overhead may continuously change patient data. In the future, we expect a real-time and interactive decision-making IoMT system that provides accurate monitoring and diagnosis in medical fields. Such systems can support data from various sources and multimodal deep learning frameworks for decision making.

Regarding the recommendation of healthcare systems, the suggestions should be characterized and related to the guideline of every user's specific data. The suggester could play an important role in gathering data from patients and characterizing a plan that accommodates available objectives. In addition, a physician (semi-supervised recommendation) should be the key in the filtering stage and in collecting the information that is more related to the health issues of the patient.

Security and privacy become more severe when there are more and more users in pervasive H-IoT. There may be an abuse of a patient's personal information, false medical data, and unauthorized access to data. Lately, 5G massive machine-type communications was introduced to link millions of different medical kinds of sensors together to the service network. Patient lives might be in danger if such sensor security is vulnerable. 5G networks are estimated to be attacked more and more in comparison to the previous 4G networks. In the future, with the powerful processing capabilities of quantum computing, public-key cryptography will be vulnerable. Therefore, this challenge must be addressed with more advanced cryptography [115] in the near future. For other communication standards for both short-range and long-range distance communication technologies, please refer to the extensive reviews [116,117].

Lastly, power may pose a big issue. On the one hand, for smart devices to execute multiple tasks, a significant amount of power must be used. In particular, devices and nodes must be charged with sufficient energy. On the other hand, the high-power consumption of smart devices and device shutdown may result in vital consequences. Therefore, the research on batteries for prolonged periods will attract more attention in the near future. In addition, the introduction of compact models [118] is appreciated since they can greatly reduce storage space and computational cost resulting in less power consumption.

6. Conclusions

In this paper, we conducted an extensive review of 118 papers on pervasive computing in H-IoT. In particular, we compared our survey with others with a strong emphasis on applications, key components, and existing challenges in this field. We observed the wide range of applications of H-IoT. We summarized the key components with cutting-edge technologies. We discussed many applications such as fall detection, rehab monitoring, and early medical disease detection which will greatly benefit future healthcare systems. Such systems will minimize the need for dedicated medical personnel for patient monitoring and provide the patients with high-quality medical services.

We believe this survey will significantly contribute to the existing body of research. There are a few research challenges in H-IoT systems, including privacy, security, and trust issues. In addition, there exist energy optimization issues and challenges of dealing with big data. We can see a lot of stakeholders affected by this research direction such as AI researchers, policy makers, governments, municipalities, and healthcare organizations. We foresee the future of medical IoT systems with more innovative and modern kinds of sensors such as nanotechnology. We also expect the future utilization of advanced communication technologies as well as advanced artificial intelligence in terms of accuracy, speed, and human-centric personalization.

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