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Research article

Factors influencing the Supply Chain Management in e-Health using UTAUT model

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Abstract: Logistics in the healthcare industry involves coordinating the distribution of medical supplies and equipment across various departments and organizations. Supply Chain Management can help healthcare facilities identify weaknesses and devise strategies to address them. Using the Unified Theory of Acceptance and Use of Technology (UTAUT), the study investigates the motivations behind the individuals' desire to use Internet of Things (IoT) solutions in healthcare. In order to better understand the factors that influence the use of IoT for e-HMS, a survey was administered to 210 healthcare IoT users. The study focuses on the potential medicinal applications of IoT technologies and incorporates the concepts of performance expectations, healthcare hazard, and trust (PHT) and perceived enabling circumstances (PFC) to complement past findings in the field. Overall, the study appears to be focused on contributing to the existing knowledge about the factors that influence the adoption of IoT technologies in healthcare, and it emphasizes the importance of considering theoretical constructs such as PHT and PFC in this context. The findings of the study can be used by IoT creators, medical experts, and vendors to optimize e-HMS and provide insight into the potential and limitations of UTAUT simulation to improve the logistic of Supply Chain Management in healthcare 4.0. The results have been analyzed by applying machine learning classifiers and have been visualized using different metrics.

Keywords: Web of Things; Cloud of Things; healthcare; Using the Unified Theory of Acceptance and Use of Technology; structural equation modeling; artificial neural network

1. Introduction

E-health is the electronic transmission of healthcare services and information, which can be accomplished using various technologies such as the internet, mobile devices, and telecommunication systems. Examples of activities that fall under this category include remote consultations, telemedicine, electronic health records, and health information systems [1]. The IoT has the potential to have substantial social and financial repercussions in the field of electronic health care [2]. According to [3,4], the IoT has made it possible to access healthcare systems from any location at any time, which is reflective of the mobility that is common in modern life. In recent years, significant technological advancements have been made in software and electronic equipment in order to create a dependent, efficient, flexible, and patient-centered environment [5]. These technological advancements have been made possible by recent technological advances in software and electronic equipment. Based on the information provided, it appears that the study aims to explore the factors that influence the adoption of IoT technologies in the healthcare industry. The study incorporates theoretical constructs such as performance expectations, perceived healthcare hazard, considered enabling circumstances, perceived trust, and behavioral intention to gain a better understanding of how these factors contribute to the adoption of IoT technologies. The study focuses on the potential medicinal applications of IoT technologies and incorporates the concepts of PHT and PFC to complement past findings in the field. Overall, the study appears to be focused on contributing to the existing knowledge about the factors that influence the adoption of IoT technologies in healthcare, and it emphasizes the importance of considering theoretical constructs such as PHT and PFC in this context.

According to Bala et al., there is a significant amount of space for innovation in the field of healthcare [6]. This is because of the broad adoption of novel hardware, software, data processing techniques, and other advancements, the IoT is now in a position to be able to enable the provision of critically essential new public services. IoT devices, such as those connected to the internet that are used in medicine, are getting easier to use and are becoming more generally available. In 2005, the phrase IoT was invented to describe a system in which hardware, such as an Arduino board, communicates across a network with software and other devices. This type of system is referred to as the IoT. A sensor, networking components, and a web-based service are the individual components that make up the system [7], and they all collaborate with one another. This global trend toward healthcare that is proactive, predictive, individualized, and patient-centered is gaining popularity, and the increased use of digital health tools can be traced back to the origin of this trend [10]. Proactive, predictive, individualized, and patient-centered healthcare is gaining popularity around the world.

The IoT is defined as a network of networked medical devices that are capable of creating, collecting, and storing data, according to the academic literature [8,9]. The system analyzes the quality of the medical imaging, the validity of the vital body signs, and the genetic function. The IoT is a paradigmatic example of a revolutionary technological development that will characterize the epoch of the future [11]. It is envisioned as a dynamic global network of interconnected items and equipment. It is built on a number of different standards, and it enables technology to execute a broad variety of operations such as detecting, identifying, networking, communicating, storing, and calculating [12]. The term IoT has become synonymous with "Machine to Machine" (M2M), which describes a machine that is talking with another device across a network. M2M stands for "machine to machine." [13,14] Previous research has demonstrated that M2M is identical with IoT. The Web of Things (WoT) is the second trend, and it requires developers to adhere to certain software standards in order to build services and applications that are able to interface with a variety of web-connected objects. The Internet of Everything (IoE) is the next phase in the evolution of computer networking, linking not just digital processes and data but also physical items, people, and communities. The Cloud of Things (CoT) is the fourth technology that gives individuals the ability to analyze, remotely control, and rheostat objects and instruments that are connected to the IoT [15].

The term "e-health" refers to the practice of providing medical services and information to patients via the use of various forms of electronic communication and technology, such as the internet, mobile devices, and telecommunications systems. Examples include health information systems, electronic health records, and online medical consultations [1]. [Note: When applied to the field of electronic health care, the IoT has the potential to have repercussions that will have a significant impact not just on society but also on the economy [2]. The mobility of modern life is reflected in the fact that healthcare systems have become more accessible from any location at any time as a result of the IoT (see references [3,4]). In recent years, considerable technological developments have been made in software and electrical equipment in order to create an environment that is trustworthy, efficient, adaptable, and centered on the patient [5].

The term "supply chain" refers to a network of businesses and individuals who collaborate in order to provide a product or service to a customer. This network is responsible for the sourcing, management, and transportation of medical products and services to patients and clinicians in the field of healthcare. The manufacturers, insurance firms, hospitals, providers, group purchasing groups, and regulatory authorities are all part of the supply chain for the healthcare industry.

The management of healthcare logistics is difficult for a multitude of reasons, one of which being the recent interruptions in the supply chain that have been generated by the COVID-19 pandemic. As a result of the pandemic, it has become abundantly clear that the healthcare industry needs robust and flexible supply chain management, as well as various and redundant supply chain routes, in order to reduce risks and guarantee the continued availability of vital medical supplies. The inability of healthcare providers to get the supplies they require is leading to increased expenses and a reduction in the number of patients who have access to medical treatment.

Supply chain management done well may be beneficial to businesses of any kind, including those that provide healthcare delivery services. Insurance firms, hospitals, and regulatory agencies are just a few examples of the multiple stakeholders involved in the healthcare supply chain. Each of these entities has its own distinct economic structure and set of goals, which aren't necessarily compatible with one another. Because the acts of a single person might have unforeseen implications on the preferences and financial commitments of other people, it can be difficult to accurately estimate the demand for services.

It is also important to note that, in contrast to the manufacturing sector, the healthcare business is a service industry. This distinction is significant because it indicates that supply and demand are both unknown, which makes it difficult to foresee and fulfill the requirements of customers. In spite of these complexities, there are some similarities between industrial supply chains and healthcare delivery systems. Furthermore, some insights and modeling methods from industrial supply chains can be applied to healthcare delivery sys-terms; however, this should only be done after taking into consideration the one-of-a-kind characteristics of the healthcare industry.

Centralized decision models can be helpful for coordinating the actions of different elements of a larger system that are controlled by a single decision-making body, but they are unable to govern the entire system on their own. The development of decentralized operational models that are capable of improving the overall performance of the system is the key obstacle to overcome.

According to [6], there is a significant amount of space for innovation within the healthcare business. The IoT is now in a position to facilitate the delivery of critically essential new public services as a result of the broad adoption of novel hardware, software, data processing techniques, and other advancements. For instance, internet-connected medical instruments are becoming more user-friendly and more readily available. A system in which hardware, such as an Arduino board, connects with software and other devices over a network was referred to as the "IoT" in 2005. This phrase was invented to characterize the system that was being described. The components of the system, which include a sensor, networking components, and a web-based service, communicate with one another through the system [7]. The rising utilization of digital health technologies may be credited with contributing to the rise in popularity of healthcare models that are proactive, predictive, customized, and patient-centered [10]. This trend can be seen all over the world.

The IoT is defined as a network of networked medical devices that are able to generate, gather, and store data in the scientific literature [8,9]. The technique assesses genetic function, the precision of crucial physiological signals, and the calibre of medical imaging. A revolutionary technological paradigm for the future, the IoT, sometimes referred to as the "IoT," is envisioned as a dynamic global network of linked devices and equipment [11]. It is founded on a set of standards, which makes it possible for equipment to be developed that is capable of detecting, identifying, networking, communicating, storing, and processing [12]. Previous study [13,14] established that the phrase "Machine to Machine," also known as "M2M," refers to a machine talking with another device over a network and that this word is identical with the term "IoT." The process of developing services and applications that make use of certain software standards in order to communicate with various web-connected things is referred to as the "WoT". The IoE, often known as IoE, is the next evolution of computer networking that will connect not just people and digital processes but also physical things and data. Fourth, with the help of the CoT, consumers are able to remotely monitor, operate, and personalize the IoT devices and items that they own [15].

1.1. IoT Architecture in healthcare and its application

The author [16] advocates storing data from IoT devices in the cloud in order to boost processing capacity, scalability, and flexibility. IoT devices are responsible for collecting data from a wide variety of sensors, and this information is then saved in the cloud, which is also referred to as a cloud storage repository. The delivery of healthcare can be made more effective by utilizing cloud technology to incorporate the work of several medical researchers into the cloud [17]. The system is capable of managing enormous volumes of data by keeping it in the cloud; however, the level of complexity skyrockets when it is integrated with the IoT. We may utilize the cloud to assess and preserve in a number of forms any patent physiology-related features [18]. As soon as the user activates the system, the data that it has obtained is immediately sent to a cloud server where it will be analyzed. This endeavor is directed on addressing the problem of network latency, which is a significant obstacle in the use of remote healthcare monitoring methods. Ube-Health is a technology that improves the overall performance of healthcare in smart cities by analyzing network latency and Quality of Service (QoS) measurements [19]. Disease identification and prevention are now both within reach, thanks to the assistance of the fuzzy neural detector. This approach to managing cloud data examines a number of different processes, including separation, retrieval, and consolidation [20].

In spite of the advancements made in academia, there has not been a lot of study done on the IoT. The IoT is a real-time entity-combining technology that, according to the aforementioned body of research [21], is only in its first phases of development within the framework of the internet. Because it takes a basic object and turns it into a complicated entity, it is a strategy that is employed frequently in many different areas of medicine. In the future, this will have significant repercussions for the surveillance of patient clinical information, administration of patient services, and provision of patient care. Keeping tabs on ever-increasing data loads while preserving security is made easier by using cloud storage, which has become an increasingly widespread practice. Since the transmission of data across cloud data centers might compromise both the data's integrity and its privacy, ensuring its safety is of the utmost importance in the IoT [22]. The cloud, being decentralized, is an excellent choice for keeping large quantities of sensitive medical data. This is especially true for patient records. Because of this improvement, medical personnel now have greater leeway in terms of how and when they treat patients remotely. Real-time synergistic processing is only achievable with the IoT and cloud computing, which reduces the infrastructure needed for data transmission and storage. IoT and cloud computing are both made easier by the presentation of a new framework that manages IoT real-time data as well as data based on unrelated scientific research [23].

1.2. Problem statement

Due to the wide range of parties involved, healthcare supply chain management provides its own set of issues. Misalignment and inefficiencies in the supply chain can occur when different parts of the supply chain have different priorities and goals. A product may be well-known and preferred by providers, but it may be difficult to persuade hospital managers to purchase it, either because of cost or quality concerns. The bottom line may take precedence above patient results for some medical device manufacturers. Since a result, supply chain management in healthcare companies can become disconnected and inefficient as various divisions have different needs and goals. For instance, although upper management may be keen on cutting healthcare costs by eliminating unnecessary equipment, frontline doctors may have their sights set on the brands they know and trust. In addition, stock-outs and inefficiencies in the supply chain might result from providers hoarding or secretly storing supplies. Healthcare firms may overcome these obstacles by using a comprehensive approach to supply chain management, which includes including stakeholders from throughout the company to achieve goal alignment and efficient decision-making at all levels.

1.3. Major contributions

Successful applications of the IoT include monitoring patients with diabetes and installing smart home systems [24]. What follows are some of the most critical issues now confronting the healthcare sector.

1) Major benefit of IoT is that it allows patients who require constant care to stay in their own homes rather than clinics while still being closely monitored. Some implanted sensors and gadgets might be a nuisance to the patient (e.g., the sensor machine or a chip).

2) Noise in the environment might have an effect on the data collected by the photodetector, then processed by the control system, and lastly sent to the intensive care unit. It is a hallmark of a better-designed system to be able to transfer information without jeopardizing its privacy or confidentiality. An improved data signal can be achieved by noise cancellation. Systematic analysis of data is now standard procedure in most ECG monitoring protocols. Consequently, the cost increases and there is a possibility that an incorrect diagnosis may be made. To boost output while cutting costs, we may use machine learning to decode the signal.

3) Privacy is another key worry when using this technology since IoT devices are easy to hack. It is challenging to implement encryption methods on such devices because of their low resources [25].

5) It is important to note that the use of t-statistics and confidence intervals based on 95% of the data provides a measure of the degree of certainty that can be attributed to the results of a statistical analysis.

6) Regarding the interpretation of the confidence interval, if the lower and upper limits of the confidence interval do not include the value of 0, then it can be inferred that there is a statistically significant correlation between the variables being analyzed. This is because, based on the sample data, the confidence interval gives a range of values that the real population parameter is likely to lie within.

7) If the confidence interval does not include 0, this means that there is a low probability that the true population parameter is equal to 0 (i.e., no correlation), and a higher probability that it falls within the range provided by the confidence interval. However, if the confidence interval does include 0, then it cannot be concluded that there is a significant correlation between the variables, as the true population parameter may be 0 or any value within the range provided by the confidence interval.

8) Therefore, in the context of the analysis being described, if the lower and upper limits of the 95% confidence interval do not both include 0, this would suggest that there is a statistically significant correlation between the variables being analyzed.

1.4. *Paper organization*

Section 2 describe the State of art and the material and method is described in Section 3, and the data analysis, including the ANN model's results, are described in Section 4. Future research directions, constraints, and consequences are mentioned at the end of the work.

2. Literature review

In [26], the author proposed a multi-tiered IoT architecture that was built exclusively for healthcare usage. Several parties make use of this information, including hospitals, clinics, insurance agencies, pharmaceutical businesses, and retail pharmacy stores. The main goal is to improve performance and make the system more scalable. In another investigation [27], researchers created a cloud-based data storage system for information transmitted from patients connected medical equipment. Researchers showed that 5G equipped devices could exchange patient data securely at rapid rates and with extremely low latency when the technology was integrated with other components. The authors of [28] proposed using a machine learning approach incorporated in an IoT infrastructure to detect cardiovascular diseases at an early stage. The technology takes data from wearable sensors, stores it in the cloud, and then applies a regression model to generate cardiac disease predictions. Developed a technique for monitoring and early diagnosis of arthritis [29]. In another study [30], researchers discuss the Covid-19 sensor devices that have been planned and mapped to the houses of persons with chronic conditions. The experiment is costly and cannot process data in real-time.

There is promise for IoT devices to help in the monitoring of the elderly, but the issue has gotten less attention thus far. The mixing platform includes age-related monitoring services that may be tracked efficiently using IoT gadgets (Akhter and Sofi, 2021). Akhter and Sofi (2021). The elderly is especially at risk for serious injury from repeated falls. The fall detection algorithm [31] looked for patients who had fallen in a particular part of the hospital. More research has been done on the topic of containing RFID data and other forms of location identification data to their allotted area [32]. With this data in hand, a suitable dwelling for the elderly can be located. Due to the findings of these probes, elderly people may stay in their homes, where they are most at ease, while still being closely monitored and, if necessary, having immediate access to medical care and the support of loved ones.

2.1. Needs assessment of supply chain model

Research on e-healthcare services and healthcare wearable devices has been led in part by aspects of the Unified Theory of Acceptance and Use of Technology [33]. A modification of the UTAUT paradigm that was developed in [34] is used to explain the rise in popularity of technologies such as telemedicine and wearable medical devices. The concept of "intent to use" continues to be essential in the dissemination of new technologies since it clarifies the decision-making processes of users, despite the fact that it appears to be rather straightforward. Researchers are continually looking at new facets of how individuals in the modern world make use of technology. In addition, IoT healthcare 4.0 acknowledges the relevance of trust, privacy, safety concerns, regulatory hurdles, and acknowledgement [35]. The level of trust that patients have in the medical personnel who care for them has a significant bearing on whether or not they will use e-health services [36]. [37], who underlined the significance of both inter-IoT connections and users' faith in the capabilities of their devices, underscored the relevance of confidence, which was also reinforced by the importance of confidence in the IoT. Creating a culture in which people have faith in the capabilities of e-health services can make it easier to successfully adopt new technologies. Despite the author of [37]'s assertions to the contrary, there are still a great deal of problems, both theoretical and empirical, that have not been resolved.

The paper focuses [46] on summarizing the applications of IoT in the healthcare industry and identifying the intelligent trend and future research directions in this field. The author draws attention to the significant study that has been done to examine how IT and other technologies might be used to augment and supplement current healthcare services. The study focuses on the widespread use of IoT to link accessible medical resources and provide dependable, efficient, and smart healthcare services to the elderly and those with chronic conditions. A thorough review of the literature is presented by the author [47], who also discusses the progress made by researchers in advancing IoT in healthcare systems from a variety of angles, including enabling technologies and methodologies, IoT-based smart devices and systems, and various IoT applications in the healthcare sector. The study also discusses the difficulties and potential benefits of creating IoT-based healthcare systems. This includes considerations related to data security and privacy, the need for standardization, and the importance of addressing the ethical and social implications of IoT in healthcare. Overall, the article gives a comprehensive review of IoT's use in the healthcare sector and emphasises the potential for further study and advancement in this area. The information supplied may help researchers, healthcare professionals, and politicians better understand the condition of the sector now and prepare for developments in the future.

The focus of this text is on the potential of the blockchain and artificial intelligence (AI) in transforming the transportation industry [48]. The author highlights the increased attention and innovation in these two technologies over recent years, and the potential they have to completely alter transportation methods. A distributed ledger of trustworthy digital records shared by connected networks is how blockchain technology is characterised. The problems in a number of sectors, including transportation, have been solved using this technology. Similar to this, AI and its applications have been utilised to create future robots with intellect comparable to that of humans. The author suggests that the transportation industry has seen tremendous growth due to the use of both technologies. Integration of blockchain and AI has helped many forms of transportation, including new transit systems, metro rails, high-speed railways, linked and automated cars, autonomous trains, hyperloop, e-scooters, and hoverboards [49]. However, the author notes that there are still challenges that need to be addressed, concerns with dependability, security, and ethics, as well as issues with economics, energy efficiency, societal acceptance, and data privacy. The author also highlights the need for standardization and collaboration between different stakeholders in the transportation industry to ensure the safe and efficient integration of these technologies. Ultimately, the essay highlights the significance of tackling the difficulties and ethical issues in their integration while highlighting the promise of blockchain and AI in the transportation business.

The paper [50] proposes a learning-based algorithm for optimizing many-objective problems. The algorithm has a learning automaton that, depending on feedback data gathered throughout the optimization phase, modifies the evolutionary strategies of the algorithm to adapt to the issue features. A reference vector adjustment approach is created to improve the capacity to solve issues with a degenerate or discontinuous Pareto front. An external archive is used to hold the Pareto non-dominant solutions. A comparative experiment using a brand-new authority test suite is used to verify the proposed algorithm's performance, and the results show that it performs well in terms of finding convergence and approximating the Pareto front.

According to the study [51], a novel Adaptive Polyploid Memetic Algorithm (APMA) is suggested as a solution to the issue of truck scheduling at a cross-docking terminal (CDT). The polyploidy theory, which states that copies of parent chromosomes are stored before crossover operations are carried out and offspring chromosomes are produced, is directly included into the APMA algorithm. The adaptive polyploid mechanism regulates the number of chromosomal copies depending on advances in objective function and variations in computation time. The algorithm uses problem-specific hybridization methods to speed up the search process. The APMA algorithm significantly beats several of the well-known state-of-the-art metaheuristics, according to computational studies, and produces truck schedules with reduced overall truck service costs. The findings imply that in order to increase solution quality at convergence, hybridization strategies that specifically take into account problem-specific features are necessary. The suggested APMA algorithm may help with effective CDT operation planning and truck scheduling for servicing at the CDT doors.

The proposed work [51] universal island-based metaheuristic algorithm (UIMA) aims to solve the berth scheduling problem in marine container terminals (MCTs) by minimizing the total cost of serving arriving vessels. The algorithm is designed to address the spatial constraints of the problem by dividing the population into four sub-populations or islands. UIMA uses four alternative population-based metaheuristics on the islands, as opposed to standard island-based algorithms, which use the same metaheuristic on each island. They use various operators to speed up the search process and include the evolutionary algorithm (EA), particle swarm optimization (PSO), estimate of distribution algorithm (EDA), and differential evolution (DE). The use of multiple metaheuristics in UIMA improves its ability to find high-quality solutions, and the island-based approach allows for parallel processing, which can lead to faster convergence times. The suggested approach may generally assist increase the efficiency and throughput of MCT operations. which is essential for meeting the growing demand for containerized cargo.

The research [52] focuses on choosing vehicles for factory-in-a-box production and choosing the best supply chain routes. The research also compares factory-in-a-box manufacturing possibilities with traditional manufacturing processes that include production on-site at the manufacturer. The expenses involved with travelling along the network's edges and stopping at its nodes are reduced using an unique multi-objective optimization approach that is described. As a method for finding a solution, a multi-objective hybrid metaheuristic algorithm is utilised. A case study is conducted for a vaccine project that involves both conventional and factory-in-a-box production, and the suggested solution approach outperforms both numerous well-known metaheuristics and traditional precise optimization methods for multi-objective optimization problems.

The paper [53] addresses the important issue of ambulance fleet management during disaster situations where there is a shortage of relief vehicle capacity. In order to determine the optimal order of routes for each ambulance, the study suggests a mixed-integer linear programming (MILP) model that takes into account the requirements and traits of various patient groups as well as changes in their health state. The goal is to reduce the latest service completion time (SCT) and the quantity of patients whose conditions deteriorate as a result of obtaining delayed medical care. To solve the model, the paper uses two metaheuristic algorithms, Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO), They are renowned for their capacity to find excellent answers quickly. The suggested model [54] is evaluated in a case study of the Iranian province of Lorestan in order to assess its effectiveness and determine how sensitive the answers are to key factors. The results of the study provide valuable insights and managerial suggestions for ambulance fleet management during disaster situations. Overall, the paper offers a valuable contribution to the field of disaster management and highlights the importance of effective ambulance fleet management in saving as many injured individuals as possible.

The input of data for factors influencing the Supply Chain Management in e-Health using the UTAUT model include:

Performance Expectancy: Data on the perceived usefulness of e-Health Supply Chain Management (SCM) by healthcare professionals and patients, including their level of satisfaction with the technology.

Effort Expectancy: Data on the perceived ease of use of e-Health SCM, including information on the usability of the technology and the level of training required to use it.

Social Influence: Data on the influence of social factors on the adoption of e-Health SCM, including the opinions of peers, colleagues, and family members on the technology.

Facilitating Conditions: Data on the availability of resources and support for the adoption of e-Health SCM, including information on the infrastructure, hardware, software, and personnel required to implement the technology.

Behavioral Intention: Data on the willingness of healthcare professionals and patients to adopt e-Health SCM, including their level of interest and commitment to the technology.

Perceived Trust: Data on the level of trust in e-Health SCM, including information on the security and privacy of patient data and the reliability of the technology.

Perceived Healthcare Hazard: Data on the perceived risk of harm associated with e-Health SCM, including information on the potential negative consequences of using the technology.

In light of this disparity, the purpose of this study is to investigate the influence that perceived enabling components, trust challenges, and security concerns have on healthcare that is enabled by the IoT.

The following question is raised as a result of this objective:

RQ: When it comes to the administration of electronic health records, which criteria are the most significant in determining whether or not a patient would adopt the IoT? (e-HMS) In order to accomplish these objectives, the UTAUT model strengthens the relationship that already exists between trust, risk, security, and behavior. PLS-SEM was used to the information gathered from a sample of 210 persons who were selected at non-random for convenience. This method has garnered a lot of support since it (a) enables the analysis of data gathered from a diverse range of sample sizes, (b) enables the study of subgroups, and (c) enables the analysis of complex structural models that comprise a number of components. The rest of this article will perform a study of the literature with the goal of focusing on IoT applications in healthcare, in particular the e-health industry. Following that, we will discuss the concepts that underpin the suggested research paradigm that is presented in Table 1.

Table 1. Summarization of ideas and materials.

Performance Expectations	PE_1: I have improved my performance thanks to the use of healthcare IoT devices. PE_2: The IoT has helped me save time at work in the medical field. PE_3: Yes, Health care IoT absolutely. PE_4: Using the IoT to improve healthcare is enriching to my life.	[39,40]
Perceived Healthcare Threat	PHT_1: Regarding my health, IoT gadgets pose a significant risk. PHT_2: Prepare for the device's unintended repercussions. PHT_3: concerned about the security of employing IoT devices in a clinical context. PHT_4: While utilizing IoT services in the medical field, I would make a critical error. PHT_5: Putting in place an IoT health system is a challenging endeavor.	[41,42]
Perceived Facilitating Constructs	PFC_1: Using IoT items is natural for me because of where I live. PFC_2: Organizations that advocate for patients to adopt IoT services for healthcare. PFC_3: My way of living is well-suited to the IoT of the fourth generation. PFC_4: When I experience health issues, I can get help from the healthcare system.	[43,44]
Perceived Trust	PRT_1: A loss of confidentiality and confidence in healthcare delivery. PRT_2: Connected medical devices provide a secure channel for transmitting sensitive patient information. PRT_3: As a form of prophylactic treatment, IoT gadgets are invaluable. PRT_4: Disabling IoT devices means avoid potentially dangerous medications.	[45,46]
Behavioral Intention	BI_1: IoT diagnostics are cheaper. BI_2: Simple connection and interaction with IoT devices. BI_3: Management of operations and signals is now possible through the use of IoT devices. BI_4: Controlling processes and transmitting signals is now possible thanks to the IoT.	[47,48]

2.2. Formulation of hypothesis

One of the most competent IoT applications is e-health, commonly referred to as intelligent healthcare 4.0. It is exceedingly dangerous to get unauthorized access to patient data produced by IoT devices. Because of the sensitive nature of this information, it should be kept private. The healthcare industry, which is increasingly embracing IoT, is becoming increasingly vulnerable to security breaches, necessitating close monitoring. A patient's medical history comprises details about their present and previous health, as well as details about their lifestyle, prior medical history, and any potential genetic evidence. Based on the aforementioned literature review and conceptual framework shown in Figure 1, the following hypotheses have been developed:

H1: Healthcare technology users' intentions and expectations for their performance are linked. 4.0.

H2: It is the degree to which people feel unsafe in their healthcare settings is correlated with how many of them use BI.

H3: Several pieces of research support perceived enabling constructs indeed affect BI.

H4: There is a robust correlation between users' faith in IoT healthcare and their intent to utilize it.

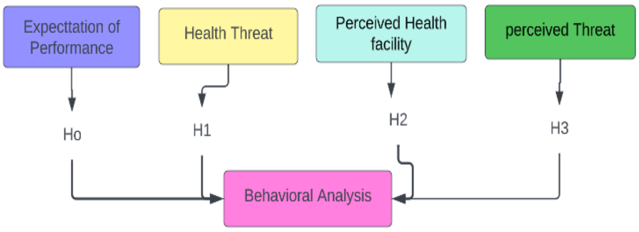

Figure 1. Analytical structure for UTAUT-Related concepts.

2.3. *Strategy and methods for research*

One way that the IoT could significantly improve medical treatment is through continuous monitoring of patients. Wearable Internet-connected instruments are critical for monitoring a patient's health. Table 1 summarizes current research on healthcare 4.0 that employs IoT-enabled health monitoring. SEM testing of the UTAUT model was performed on a subset of manifestations. PLS-SEM is well suited to exploratory research with small sample sizes and little theoretical underpinning for the ideas and hypotheses under test. The heterogeneous nature of the information contained within the constructs is likely to cause multi-collinearity between independent or predictive variables. Furthermore, PLS-SEM finds no correlation between measurement error factors. To account for changes in individual variables, the SEM method gradually adjusts the model's parameters. The model's measurement section is then used to examine the model fit indicators shown in Figure 2. The following studies were used to assess the models' elucidative power as UTAUT reference plane.

250 participants were used due to the exploratory nature of the study and the early stage of IoT deployment in Saudi Arabia. The demographic breakdown of the sample is shown in the Table 2: Males constituted 85% of the sample, while females constituted only 15%. There were 42% of young adults (aged 20–30), 40% of middle-aged people (aged 31–45), and 16% of seniors (those aged 46 and over).

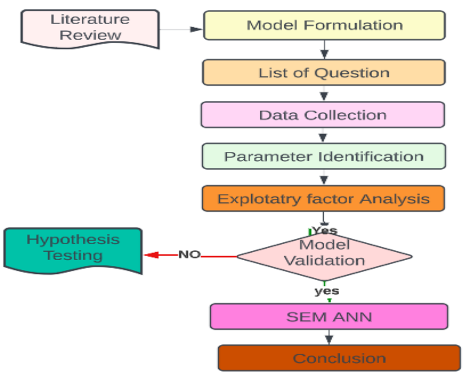

Figure. 2. Framework of research.

3. Result and validations

Table 2 displays the findings of the statistical analysis. To determine the degree of symmetry and the central tendency, the skewness and kurtosis measures were applied to the data. Skews are frequently measured as plus or minus one, and numbers are frequently skewed [49,50]. Respondents' top reasons for using healthcare IoT include meeting performance goals (20.20), lowering healthcare risks (17.35), facilitating (15.10), instilling trust (16.55), and changing behavior (13.74). The results of using biometrics are inconsistent and their co-relation analysis is done in Table 3.

Table 2. Variation in the number of constructs.

Constructs	N	X	σ	Vari.	Skew.	Kurt.
PE (Cum. Mean = 20.2013)						
PE_1	250	4.2263	1.01280	1.012	−0.730	−0.120
PE_2	250	4.1418	0.96124	0.856	−0.710	0.016
PE_3	250	4.1658	1.17835	1.214	−1.100	0.199
PE_4	250	4.0964	1.21573	1.213	−1.033	0.159
PHT (Cum. Mean = 17.3562)						
PHT_1	250	4.9151	0.81761	0.764	−1.242	1.151
PHT_2	250	4.1747	1.10112	1.045	−1.575	2.185
PHT_3	250	4.8789	1.10413	1.295	−0.275	−0.557
PHT_4	250	3.9855	1.03141	1.056	−0.685	−0.035
PHT_5	250	3.6855	1.04150	1.065	−0.695	−0.035
PFC (Cum. Mean = 15.1012)						
PFC_1	250	3.5214	1.45213	1.546	−0.152	−1.241
PFC_2	250	3.6452	1.36241	2.854	−0.362	−0.875
PFC_3	250	3.7541	1.65412	2.250	0.352	−1.245
PFC_4	250	3.2451	1.54126	1.754	−0.251	−1.351
PT (Cum. Mean = 16.5514)						
PRT_1	250	3.5874	1.36412	1.342	−0.325	−0.754
PRT_2	250	3.9541	1.08899	1.234	−1.120	−0.100
PRT_3	250	4.2541	1.10241	1.485	−1.142	0.121
PRT_4	250	4.3621	1.19854	1.512	−1.147	−0.310
BI (Cum. Mean = 13.7451)						
BI_1	250	3.2141	1.32145	1.457	−0.341	−0.621
BI_2	250	3.9412	1.35412	1.678	0.231	−0.912
BI_3	250	3.2145	1.30124	1.215	0.201	−1.210
BI_4	250	2.6214	1.24871	1.364	0.321	−0.124

Table 3. Co-Relation analysis in variation of number constructs.

		VAR00001	VAR00002	VAR00003	VAR00004	VAR00005
		1.000	−0.429**	−0.324*	−0.562**	0.425**
	VAR00002	0.000	0.003	0.020	0.000	0.004
		21	21	21	21	21
		−0.429**	1.000	0.705**	0.467**	−0.616**
	VAR00003	0.003	0.000	0.000	0.002	0.000
		21	21	21	21	21
		−0.324*	0.705**	1.000	0.343*	−0.568**
Kendall's tau_b	VAR00004	0.020	0.000	0.000	0.015	0.000
		21	21	21	21	21
		−0.562**	0.467**	0.343*	1.000	−0.625**
	VAR00005	0.000	0.002	0.015	0.000	0.000
		21	21	21	21	21
		0.425**	−0.616**	−0.568**	−0.625**	1.000
	VAR00006	0.004	0.000	0.000	0.000	0.000
		21	21	21	21	21
		1.000	−0.649**	−0.449*	−0.712**	0.625**
	VAR00002	0.000	0.001	0.020	0.000	.001
		21	21	21	21	21
		−0.649**	1.000	0.856**	0.687**	−0.804**
	VAR00003	0.001	0.000	0.000	0.000	0.000
		21	21	21	21	21
		−0.449*	0.856**	1.000	0.547**	−0.762**
Spearman's rho	VAR00004	0.020	0.000	0.000	0.005	0.000
		21	21	21	21	21
		−0.0712**	0.687**	0.547**	1.000	−0.815**
	VAR00005	0.000	0.000	0.005	0.000	0.000
		21	21	21	21	21
		0.625**	−0.804**	−0.762**	−0.815**	1.000
	VAR00006	0.001	0.000	0.000	0.000	0.000
		21	21	21	21	21

Table 4. Validity and trustworthiness of the measures.

Scale	Ch. α	rho_A	CR	AVE	MSV
PE	0.698	0.822	0.748	0.622	0.485
PHT	0.825	0.816	0.812	0.564	0.396
PFC	0.830	0.853	0.731	0.714	0.592
PT	0.789	0.713	0.795	0.594	0.726
BI	0.775	0.665	0.658	0.724	0.495

Even the Fornell-Larcker standard meets the suggested values' criteria shown in Table 4. As a result, the model evaluation meets the criteria for validity, dependability, and discrimination. Following that, the PLS model was put to the test. As a result, the PLS model testing was successful shown in Table 5.

Table 5. Criterion analysis using Fornell-Larcker.

Constructs	PE	PHT	PFC	PRT	BI
PE	0.662				
PHT	0.362	0.784			
PFC	0.639	0.483	0.876		
PT	0.434	0.249	0.469	0.655	
BI	0.487	0.377	0.577	0.452	0.751

3.1. Structural model

The model's multi-collinearity was also investigated in the study (MC). Because all of the VIF were children, there is no MC issue. An increase in F2 indicates a larger effect size, implying that more research into the impact of predictor factors on the dependent variable is needed [43,44]. Furthermore, as shown in [45], a lower value of F2 is required to include the dependent variables in a variety of ways. This parameter's current value is greater than 0.02, which is within a reasonable range [46]. The chosen constructions have a significant and positive impact on healthcare IoT business intelligence shown in Figure 3.

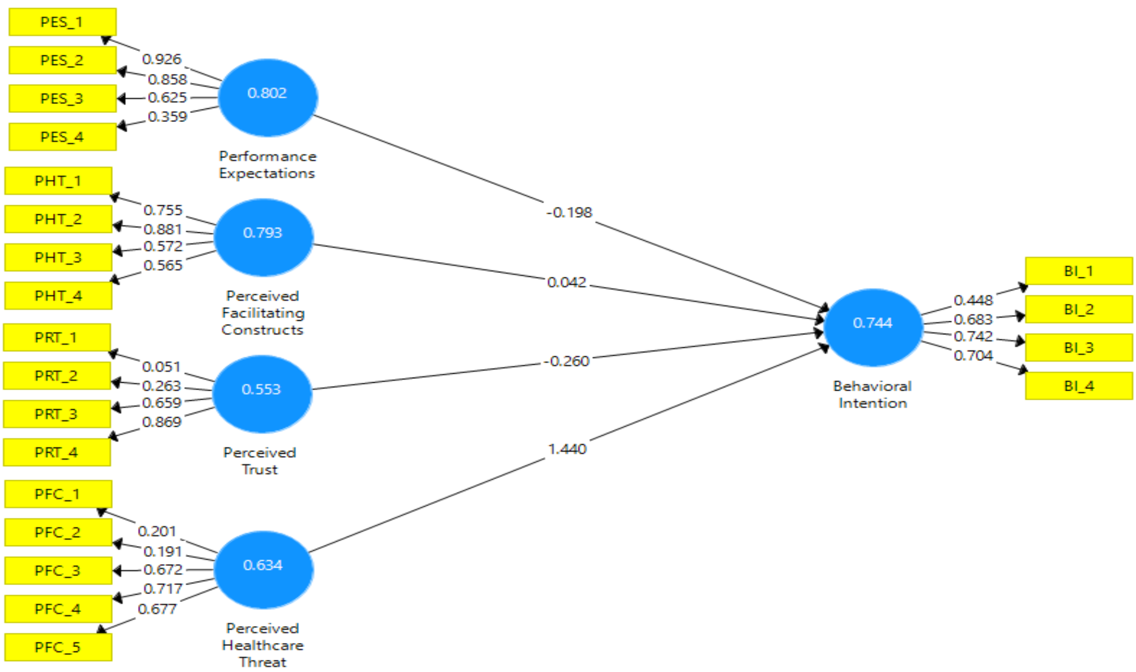

Figure 3. e-HMS-PLS structural model.

The results of cross-loadings and HTMT are displayed in Table 6, and both show that the items load more heavily on the hypothesized factors, which demonstrates that the items can discriminate between the two sets of factors [47]. Both the route analysis and the model bootstrapping demonstrate that each of the four BI routes is necessary in order to adequately describe the IoT in healthcare. T-statistics and confidence intervals based on 95% of the data were used by the researcher for this analysis. In light of this, we can deduce that there is a correlation if the lower limit and the upper limit of the confidence interval for 95% are not both equal to 0.

Table 6. Cross loading of manifests.

Manifests	PE	PHT	PFC	PRT	BI
PE_1	0.846	0.146	0.342	0.221	0.148
PE_2	0.68	0.184	0.173	0.199	0.319
PE_3	0.727	0.29	0.181	0.443	0.247
PE_4	0.601	0.328	0.179	0.262	0.295
PHT_1	0.251	0.717	0.276	0.286	0.369
PHT_2	0.261	0.748	0.266	−0.066	0.206
PHT_3	0.058	0.824	0.125	−0.017	0.283
PHT_4	0.253	0.836	0.173	0.18	0.134
PHT_5	0.264	0.696	0.128	−0.03	0.11
PFC_1	0.537	0.152	0.889	0.182	0.16
PFC_2	0.333	0.135	0.715	0.359	0.212
PFC_3	0.458	0.175	0.963	0.144	0.268
PFC_4	0.555	0.052	0.918	0.162	0.202
PRT_1	0.211	−0.103	0.237	0.919	0.17
PRT_2	0.221	−0.02	0.204	0.977	0.145
PRT_3	0.18	−0.056	0.139	0.75	0.135
PRT_4	0.235	−0.082	0.085	0.822	0.261
BI_1	0.459	0.117	0.158	0.218	0.867
BI_2	0.465	0.163	0.201	0.257	0.483
BI_3	0.381	0.141	0.172	0.344	0.803
BI_4	0.38	0.109	0.415	0.422	0.698

3.2. Testing of hypotheses and discussion

As can be seen in the table to the right, the t-statistic, the F2, and the confidence interval for 95% are all within the "good" range. It is also important to take into account the signs of the path coefficients and the p-values, which are presented in Tables 7 and 8. When carrying out hypothesis's tests, a common statistic that is utilized is known as the p-value of a route coefficient [48]. For the sake of argument, let's assume that the p-value is lower than the cutoff value (i.e., the p-value threshold). In this particular instance, the data that have been gathered might lend support to the hypothesis that is being taken into consideration, enabling us to disprove the null hypothesis. To validate the proposed model and quantify the efficacy of enabler clusters in relation to IoT healthcare 4.0 Behavioral Intention, acceptable performance criteria such as Performance Expectations (0.031), Perceived Healthcare Threat (0.040), Perceived Facilitating Constructs (0.005), and Perceived Trust were used (0.020). The vast majority of the strategies adhered closely to the information that had been acquired in the past [49,50]. As a result of this, we are able to reach the conclusion that the model that was proposed is accurate.

Table 7. Heterotrait-Monotrait ratio (HTMT).

Particular	PE	PHT	PFC	PRT	BI
PE	0.732				
PHT	0.432	0.644			
PFC	0.639	0.333	0.755		
PT	0.324	−0.133	0.223	0.777	
BI	0.557	0.244	0.234	0.333	0.776

Table 8. Testing of hypotheses and path coefficient.

SN	Structural Path	Original Sample	Sample Mean	95% Conf. Interval (LB, UB)	T Stat.	p.val	F2
H1	Performance Expectations → BI	00.168	0.152	(0.139, 0.245)	5.366	0.041*	0.080
H2	Perceived Healthcare Threat → BI	0.058	0.061	(0.034, 0.163)	1.127	0.060*	0.154
H3	Perceived Facilitating Constructs → BI	0.149	0.281	(0.148, 0.214)	4.331	0.025*	0.281
H4	Perceived Trust → BI	0.237	0.241	(0.172, 0.362)	5.642	0.050*	0.191

Note: *$p<0.05$, LB-lower boundary, UB-upper boundary

After identifying the main factors influencing supply chain management in e-health, a promising projection would be to implement strategies to address these factors and improve the efficiency and effectiveness of supply chain management in the e-health sector. if the main factors identified were related to inventory management, such as the lack of real-time visibility into inventory levels or inefficient distribution processes, then implementing automated inventory tracking systems and optimizing distribution routes could be effective solutions. Additionally, if the main factors were related to data management and integration between different systems, then implementing interoperability standards and developing integrated data systems could be effective solutions. Overall, addressing the main factors influencing supply chain management in e-health can lead to improved patient outcomes, reduced costs, and increased efficiency and effectiveness of the supply chain. This can result in increased adoption and uptake of e-health technologies, as well as increased collaboration and communication between different stakeholders in the e-health supply chain.

3.3. Results of neural network modeling

For the purpose of evaluating the effectiveness of neural networks, Python and SPSS were utilized. Statistically significant SEM features have been incorporated into the model after it was updated to include them. The findings of the structural equations point to a total of four hypotheses that need to be researched further. In order to fix the issue of the model being over-fit, we used something called cross-validation. The sigmoid function is responsible for the activation of neurons in both the output and the hidden layers [50]. It was decided that all of the inputs and outputs, which are shown in Table 9, will be standardized so that the effectiveness of the training can be increased to its full potential.

Table 9. Training and testing data of root mean square error.

Sample size (Tr.)	SSE	RMSE	Sample size (Ttg.)	SSE	RMSE	RMSE(Tr)-(Ttg.)
186	42.556	0.381	22	4.826	0.576	0.024
185	45.615	0.484	24	3.566	0.381	0.146
184	36.323	0.436	24	3.635	0.371	0.104
191	31.702	0.410	27	3.566	0.458	0.042
193	31.757	0.421	20	4.256	0.429	0.065
194	33.331	0.4323	22	5.556	0.479	0.044
184	32.521	0.414	26	4.569	0.778	0.046
187	39.433	0.460	23	2.965	0.299	0.194
195	40.939	0.409	18	1.286	0.491	0.061
197	41.254	0.474	19	2.981	0.463	0.091
Mean	37.62682	0.437755	22.5	3.7810	0.511	0.0796
σ	5.172	0.101	σ	2.062	0.075	0.042

To avoid overfitting, only 10% of the data was used to assess predictability after training a network, whereas 90% was used to train the network. A prediction's accuracy can be measured using training data, test data, the mean, and the standard deviation shown in Table 10.

Table 10. Performance analysis of factor after one sample t-test.

t	df	Sig. (2-tailed)	Mean difference	95% Confidence interval of the difference	
				Lower	Upper
8.260	21	0.000	0.37982	0.2842	0.4754
3.885	21	0.001	0.25236	0.1173	0.3874
5.207	21	0.000	0.31541	0.1894	0.4414
5.012	21	0.000	0.31973	0.1871	0.4524
6.161	21	0.000	0.29614	0.1962	0.3961

The artificial neural network (ANN) model takes in four variables as input from the neurons and produces just one output, BI. Standardized Mean Squared Error (RMSE) values are 0.031 and 0.72 for the training and testing models, respectively, whereas SSE values are 5.17 and 1.06 shown in Table 11.

Table 11. Multivariate test performance analysis of factor affecting.

Multivariate Test						
Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	0.942	55.289b	5.000	17.000	0.000
	Wilks' Lambda	0.058	55.289b	5.000	17.000	0.000
	Hotelling's Trace	16.262	55.289b	5.000	17.000	0.000
	Roy's Largest Root	16.262	55.289b	5.000	17.000	0.000

a. Design: Intercept, b. Exact statistic

The importance of a variable in a network model is determined by how far its projected value deviates from the observed values of the independent variable shown in Figures 4 and 5. It shows the normalized and sensitive evaluations of each predictor. The goal is to quantify and standardize the relative importance of each predictor. We can learn how important each input variable was in determining the final value predicted by the neural network's many valves by analyzing the results. The most popular PEs in healthcare IoT are PE 1 (99%), PE 2 (96%), PE 3 (63%), and PE 4 (77%). The influence of healthcare security concerns on IoT device deployment actions is accounted for across all five Personality and Health Technology dimensions (PHT 1), 56, 71 and 75%. PFCs include PFC 1 (reported by 100% of respondents) and PFC 3 (68% of respondents). Both of these factors are significant enough to encourage the use of Healthcare IT version 4.0. PRT 1 (49%) and PRT 2 (63%), are the top two Perceived Trust issues that indicate whether or not people would embrace IoT in healthcare.

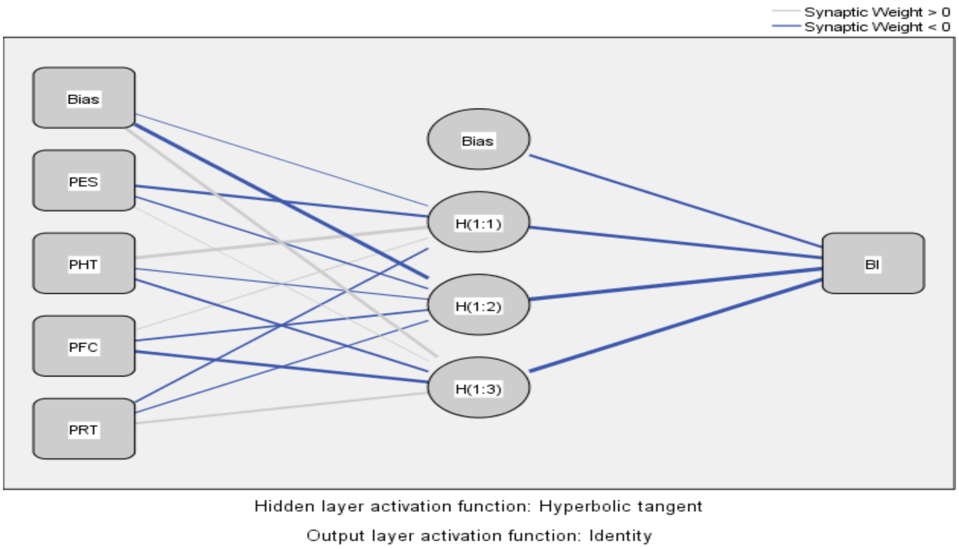

Figure 4. ANN model for e-HMS.

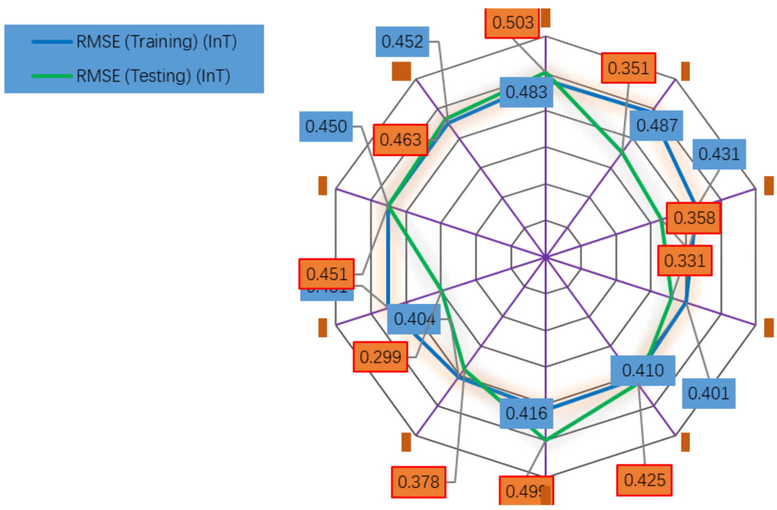

Figure 5. RMSE statistics of training and testing.

3.4. *Theoretical implications*

The IoT is a pervasive technology that, due to the numerous benefits it offers, has spread across a variety of different industries. In the healthcare industry, more research is being carried out in order to provide patients with the most accurate and helpful information possible. The IoT presents tremendous opportunities for growth in the area of electronic medical care, as evidenced by the [54]. As a consequence of this, the results of the current research are significant both in terms of theory and application. The goal of this study is to gain a better understanding of the role that theoretical constructs such as performance expectations, perceived healthcare hazard, considered enabling circumstances, perceived trust, and behavioral intention play in the adoption of IoT technologies in the healthcare industry. The current findings, which incorporate PHT and PFC concepts and emphasize their potential medicinal applications, complement the findings of the past because of this incorporation. This analysis is one of a kind due to the fact that its model for the adoption of technology does not include such components. This study has the potential to pave the way for future research on the characteristics and concerns of IoT users, particularly in the medical field. The level of product knowledge may vary from person to person in healthcare 4.0 due to the wide variety of devices that are used. As a direct consequence of this, individuals afflicted with this disease may have redirected their BI toward e-health tools.

4. Conclusions

Healthcare 4.0 has been a driving force behind the widespread use of cutting-edge technology in healthcare settings and procedures since its inception. Because of the IoT, remote locations and emergency services can better monitor critically ill patients. We intend to do just that in this study by analyzing the numerous studies that have been conducted on IoT healthcare 4.0. To achieve a high level of efficiency, it is critical to find a system that uses less electricity, and several studies have shown that power consumption can be reduced using optimization techniques. The current IoT system is capable of providing excellent patient monitoring in terms of scalability and dependability. Using cameras, speakers, and sensors, this technology aids in the observation of the elderly. By considering its manifestations and model, it is possible to improve the work's security, privacy, trust, and adaptability. To conclude, IoT device developers must improve precision and resource efficiency while lowering device costs. In addition, the instrument was experimentally tested and validated using data from just one nation. This is a significant limitation of the research. The assertions made in the case study might be investigated in further research in the future. Another reason why the findings can't be generalized because of this restriction. Testing the instrument in a variety of countries would help improve its accuracy and widen its scope of application. To determine the validity of these findings and their ability to be generalized, additional research is required. The methodology that was utilized in this study may be utilized in future research to investigate how the IoT influences the adoption of healthcare and how it compares to other diagnostic methods.

4.1. Limitation and future scope

This study has a few limitations, but those limitations actually open up a new avenue of research. Initial limitations of the study include the limited scope of the investigation and the small size of the sample population. The sample size of 210 people was sufficient for the purposes of the study; however, it was not large enough to permit extrapolation of the results.

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Conflict of interest

The authors declare there is no conflict of interest.

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