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Effective factors for the adoption of IoT applications in nursing care: A theoretical framework for smart healthcare

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ABSTRACT

The utilization of the Internet of Things (IoT) presents a promising opportunity for the healthcare industry which is continuously expanding and persistently aspiring to enhance the quality of medical services and reduce its operational costs through the implementation of new technologies. Despite the proven benefits of utilizing IoT-based technologies, its integration in the healthcare sector is minimal, particularly in nursing care. The purpose of this study is to establish a conceptual model to guide program designers and implementation leaders in evaluating the adoption of IoT products and services in nursing care, from the perspective of nurses. The study employed an empirical quantitative research design utilizing a structured online questionnaire to collect data from a convenience sample of nursing staff gathered data were subjected to statistical analysis using Statistical Package for the Social Sciences (SPSS) and Structural Equation Modeling Partial Least Square (SEM-PLS). Data analysis led to the establishment of a framework to identify factors influencing the integration of IoT and barriers that may impede its adoption in nursing care. The study makes a valuable contribution to academia by addressing a gap in the existing literature relating to the adoption of IoT in medical services, particularly in nursing care, and providing a novel theoretical framework that encompasses effective factors for the integration of IoT in medical care. This model provides deep insight and guidance to healthcare industry leaders, system developers, and nursing professionals to improve program design and implementation of IoT applications in healthcare. In addition, the model guides building engineering in the planning and design of medical facilities aligned with the IoT technologies and its physical environment. Finally, the study paved the way for further research exploring the implementation of IoT-based technologies and expanding the model to other stakeholders and functions within medical departments as well as other industries.

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1. Introduction

At the core of healthcare delivery, the provision of care remains a fundamental principle of nursing practice. The ability of nurses to foster patient recovery and promote overall wellbeing serves as a key determinant of care quality and patient outcomes. The increasing demand for healthcare services has been a pressing concern in recent years, which imposed significant work pressure on nurses [1]. The growing challenge is evident in the rise of errors, declining effectiveness in communication between healthcare professionals and patients, and compromised abilities for ongoing health monitoring, both in clinical environments and at home.

Together, these factors significantly contribute to the escalating rate of errors in patient care [2]. Unquestionably, the global healthcare sector aspires to realize high-quality service deliverywhile minimizing operational costs. The IoT technology presents a promising avenue to this end. IoT's robust sensor systems amplify patient monitoring capabilities, thereby reducing the need for extraneous tests and appointments, and ultimately driving down healthcare costs [3]. Furthermore, IoT offers efficacious solutions in nursing practices, leveraging IoT-enabled methodologies and technologies to deliver superior care. In response to the multifarious pressures pervading the healthcare sector, IoT successfully integrates within established healthcare environments. In addition, it elevates the efficiency and effectiveness of healthcare personnel, concurrently attenuating expenses associated with healthcare institution performance [4].

The implementation of the IoT in healthcare, particularly in the domain of nursing care, presents certain challenges. Despite the demonstrated efficacy of the IoT in healthcare and its associated technologies in addressing nursing care challenges, the integration of IoT systems into healthcare organizations remains incomplete [2]. In light of the low adoption of IoT (AIoT) in the healthcare sector, it is difficult to implement it if users are not ready. Moreover, the decision to adopt IoT applications requires a structured approach that is capable of identifying the technological and operational structures. Indeed, technology adoption is one of the more mature areas of research in information systems, especially IoT adoption [5]. A review of relevant literature shows that research in this field is still in its infancy, and there is a need for more investigation. A case in point is Jordan, where IoT adoption is still at a low level, according to Mustafa y Alzubi [6] and AlZghoul et al. [7]. So, IoT applications must be designed as a nurse-centric healthcare system as healthcare providers, and create relationships between patients, and their families to align decisions with patients' needs, and preferences. For designing such a system, an understanding of such relationships must be made among nurses and their duties So, the design of the system needs to take into account the social and psychological behavior of the nursing staff, because they are the primary providers of healthcare services.

The purpose of this research is to identify the effective factors of IoT adoption from the perspective of nurses. Therefore, such factors are evaluated and taken into account prior to the design of technology-based systems to support the nursing function. Therefore, a conceptual model needs to be created to facilitate the adoption of IoT in healthcare. This study aims to identify effective factors for adopting IoT applications among nurses in Amman City, Jordan. The selected medical departments for data collection in this study are the Al-Bashir hospitals located in Amman City. The Al-Bashir hospital group comprises several hospitals that provide healthcare services to a significant population. Three hospitals from this group were specifically selected as the primary sources for obtaining the study sample. In this study, convenient sampling was used because it was easy for people to volunteer or choose units based on their availability or how easy to reach. A survey was conducted in the form of an online questionnaire distributed to nurses. A theoretical framework was developed, and hypotheses were formulated for this research. Structural Equation Modeling (SEM) using Partial Least Squares (PLS) and the Statistical Package for Social Sciences (SPSS) is employed to analyze the proposed measurement model. Lastly, the literature review is addressed in the following section, followed by the theoretical framework, formulation of hypotheses, and development of the conceptual model. Furthermore, the research methodology, data analysis, and empirical results are presented in the following section.

1.1. Problem statement

Healthcare society has recognized the emerging technology's potential to move healthcare systems beyond the conventional use of information technology and provide a more advanced type of service [8]. Despite the clear merits of IoT technologies within healthcare, broad-scale adoption isn't automatic and is tense with complexities. Overcoming these challenges requires particular system examination, focused education for professionals, notably within nursing care, and patient acceptance, fostered through comprehensive awareness initiatives [9,10]. Indeed, discovered that even though IoT-based solutions can provide an improved and better approach to healthcare management, end-user adoption is very low, according to, the studies of Masmali et al. [11], Al-Turjman et al. [12], and Hossain et al. [13] who emphasized that the adoption of IoT technology and its applications in the healthcare sector have not been as fast as the uptake in other industries, and they have explored the effective factors for adopting IoT in healthcare. Moreover, researchers Hossain et al. [5], Mieronkoski et al. [14] and Kang et al. [15] concluded that IoT technology is providing innovations for the use of primary nursing care, and they found that the IoT has a low level of adoption in nursing care, and also the benefits of IoT are still not being used as much as they should in nursing care. This study has figured out effective factors, particularly among nurses in Amman city, relating to IoT applications in health care. In addition, it has investigated the barriers that prevent the adoption of IoT technology and developed a framework to extract the main factors that would help in improving the design and implementation of IoT applications in healthcare. The factors extracted will help in improving the functioning of applications for nurses as professional users, at the same time they will also help to find out methods for the nursing domain to adopt IoT in their work.

1.2. Objectives

The main objective of this study is to identify effective factors which play a significant role in increasing the adoption of IoT technologies for nurses and significantly influence the utilization of a system, as well as the level of user satisfaction, ultimately contributing to the overall success of the system. The process will require a thorough examination of nurses's awareness and perception regarding the adoption of IoT in healthcare. The specific objective of this research can be outlined as follows.

1. To formulate a predictive theoretical framework that elucidates the factors influencing the adoption of IoT technology among nursing professionals in Amman City, Jordan.
2. To figure out the mediating influence of behavioral intention to use IoT on its adoption among nursing professionals in Amman City, Jordan.
3. To figure out the moderating effect of Top Management on the relationship between behavioral intention to use IoT and the adoption of IoT among nurses in Amman City, Jordan.

1.3. Novelty

Today's medical technology is more advanced and more effective. Rapid advancements in medical technology and availability led to high-technology diagnostics, with changing practice patterns of professional staff. This revolution in technology healthcare is being delivered today [16]. The novelty of this study lies in its potential to serve as a valuable resource for various stakeholders, including healthcare administrators, patients, their relatives, and developers of healthcare systems. The study's findings aim to provide guidance on guide how to effectively implement and utilize IoT technology and applications within the healthcare sector, with a particular focus on nursing care. Besides, it aims to investigate the factors influencing the incremental adoption of IoT technology, specifically from the viewpoint of nurses. Nurses play a crucial role in facilitating the integration of IoT technologies, such as wearable IoT devices, into their practices. Therefore, it is critical to enlist their commitment and ensure their readiness.

This study will additionally provide support to healthcare administrators in the development of policies aimed at bridging the divide between academic research and practical application. The disparity between research and practical application has a detrimental effect on the integration of innovative technologies within the healthcare sector. The proposed study aims to make a valuable contribution to academia by addressing a gap in the existing literature. This will be achieved through the development of a novel framework that incorporates new constructs and the identification of factors that influence the adoption of IoT applications in nursing care and patients' lives. Moreover, The study will provide valuable insights for the healthcare industry, encouraging nursing care professionals to critically assess and reassess their existing practices to adopt IoT technologies such as wearable IoT devices into their activities, it might be useful for healthcare system developers, who must be aware of obstacles and goals before the design, testing, and implementation phases, and user needs must be determined.

2. Literature review

Before the launch of this study, our team of researchers conducted an extensive review of the available literature relating to integrating IoT in healthcare services to get acquainted with similar studies and identify potential gaps that this research may attempt to bridge. This review revealed that existing literature relating to the topic of IoT adoption in medical services, particularly in nursing care in our region, is quite limited and does not offer a viable theoretical framework to guide initiatives geared toward further integration of IoT in nursing care. This review covered relevant research and publications relating to: 1) the adoption of IoT in nursing. 2) IoT adoption in nursing care in Jordan. 3) theories, and methods used for the adoption of IoT in healthcare and nursing. 4) the adoption of electrocardiogram monitoring systems in healthcare. 5) effective factors for IoT adoption.

2.1. Adoption of the Internet of Things in nursing care

As mentioned before, IoT and its supporting technology reduce issues and mitigate challenges relating to the field of healthcare, such as medical errors, fraud, failure, illicit products, and ineffective workflows. Nevertheless, despite the growing phenomenon and its advantages. Nevertheless, despite the growing phenomenon and its advantages, IoT systems are not fully integrated into healthcare organizations. One of the most important reasons for the lack of integration is users' low level of acceptance of these innovations [17]. IoT technology and its corresponding developments in the nursing sector were not as fast as the implementation and adoption in other industries. In the nursing sector, the decision-makers are healthcare managers, who are also responsible for adopting IoT in delivering healthcare services [11]. According to Bodur et al. [2], there is a lack of studies conducted on IoT in healthcare and nursing procedures. Most studies conducted focus on the adoption factors of healthcare technology. However, there are currently limited studies that highlight and explore the adoption and possibilities of IoT in nursing care.

2.2. Internet of Things adoption in nursing care in Jordan

Researchers Osmonbekov y Johnston [18] suggest that IoT is the third wave of information technology-driven innovation and provides a basis for rethinking and reworking business processes for maximum efficiency and quality. IoT adoption is difficult to implement if users are not ready. Adopting of IoT requires a structured approach capable of identifying the technological and operational structures within which IoT will increase process efficiency and minimize the risk of failure. IoT adoption differs from other information technologies for several reasons.

Privacy issues represent one of the significant reasons that make adoption slower and harder, which is why few studies have been conducted in this field [19]. A review of the past literature shows that research in this field is still in its infancy, and there is a need for more investigation. A case in point is Jordan, where IoT adoption is still at a low level, according to AlZghoul et al. [7]. There is a dearth of literature on IoT adoption, specifically in healthcare in Jordan.

2.3. Theories, method used for adoption of IoT in healthcare and nursing

Research on the topic of how and why people use new technologies is one of the most well-established in the field of information systems. Technology adoption, as described by Carr (1999) is the action of deciding to employ technology. The problems associated with the widespread adoption of new technologies have come to the fore as a direct result of the exponential growth of technological advancements in every industry. Companies and governments alike are spending heavily on inventions that could cause a major change in the way people live [20]. The review of IoT literature demonstrated that adoption and dissemination can be used interchangeably.

According to Ref. [20] study, diffusion is defined as "the phase during which the technology expands to general use and application". Therefore, while adoption refers to a change at the level of an individual, diffusion can be seen as a change at the level of a population. Important though each idea may be, adoption and diffusion go hand in hand. The correlation between adoption and diffusion is shown in Fig. 1.

It is important to note that user acceptance and trust are key to improving the success chances adopting of any new technologies. Improvement is a result of consumer participation in the development of applications. It is a common question for both practitioners and academics to assess if people are accepting new technology. Rather than being simply tied to technological factors, technology adoption has been demonstrated to be a far more complex process including many factors, including user attitude, personality, social effect on trust, and a variety of nabling conditions [21].

More than one theoretical approach is needed for a full understanding and clarification of the wide range of issues related to integrating IoT in healthcare [22,23]. Fig. 2 shows a quick view of the most popular theories and models of technology integration used in healthcare and nursing care. Several studies have shown that technological acceptance is not linked exclusively to the characteristics of technology but has developed as a much more complicated process involving the dimensions of individual attitude and the nature of the social influence of confidence and a variety of enabling factors. Several theories and models can better explain the processes of technology adoption arising from the conceptualization of new influences [24].

The Technology Acceptance Model, Motivational Model, Theory of Planned Behavior, Diffusion of Innovation Theory, Theory of Reasoned Action, Unified Theory of Acceptance and Use of Technology, Model of Personal Computer Use, and Social Cognitive Theory are just some of the theories, models, and frameworks that have been developed to explain user adoption of new technologies. Many researchers have used these typical frameworks to conduct their evaluation, while others have combined or extended them [25]. Most studies require more than one theoretical approach to gain a full understanding and clarification of the issues involved [23], adoption theory attempts to identify, predict, and explain the variables that affect the conduct of adoption at three levels: individual, group/team, and organization [26]. Innovation Diffusion Theory (IDT), the Theory of Reasoned Action (TRA), and the Social Cognitive Theory (SCT) are only a few of the adoption models developed in social psychology. All three theories have been validated for their ability to anticipate and explain a wide range of human behaviors.

However, TRA and TPB are distinct from DOI because the former two theories are concerned with explaining the actions of individuals, whereas the latter two are concerned with making evaluations of adoption in which organizational factors play a central role. In contrast, the Model of PC Utilization (MPCU) is based on the work of psychologists and other behavioral scientists [23]. In (Fig. 2) illustrates the majority of theories and models used in studies on the adoption of IoT in healthcare, according to Ref. [25].

2.4. Adoption electrocardiogram monitoring systems in HealthCare

Nowadays, IoT application is considered one of the most important, latest and fastest-expanding technology. IoT consists of devices with sensors linked to the Internet through wireless sensor networks, leading to the invention of new ways of interacting with the devices, which was not possible before. In the IoT world, many wearable devices for various health monitoring/measuring symptoms exist.

Moreover, the proactive monitoring of an individual's health can help avoid many dangerous health-related events. IoT in health helps to better maintain an individual's well-being [1]. WearableElectrocardiogram (ECG) monitoring has been widely used in hospitals and medical research centres as a monitoring system as seen in Fig. 3. In addition, it is used in the diagnosis of heart-related diseases [27]. According to a study by Yang et al. [28], the data collected by the ECG is based on the IoT cloud which supports high data

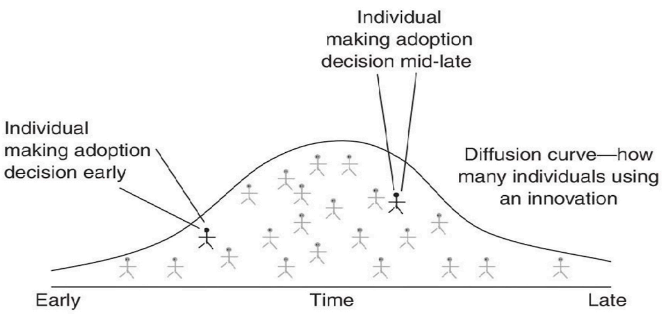

Fig. 1. Individual adoptions compose diffusion [20].

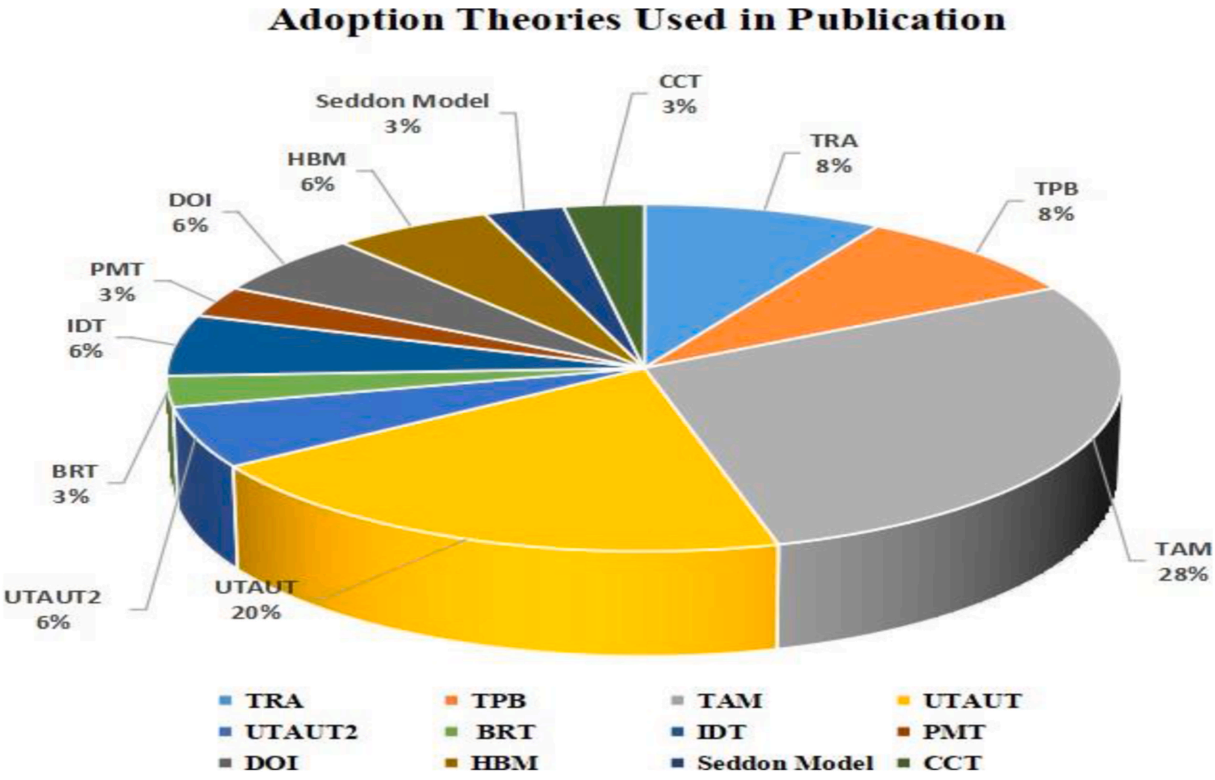

Fig. 2. Adoption theories used in adoption of IoT studies in healthcare [25].

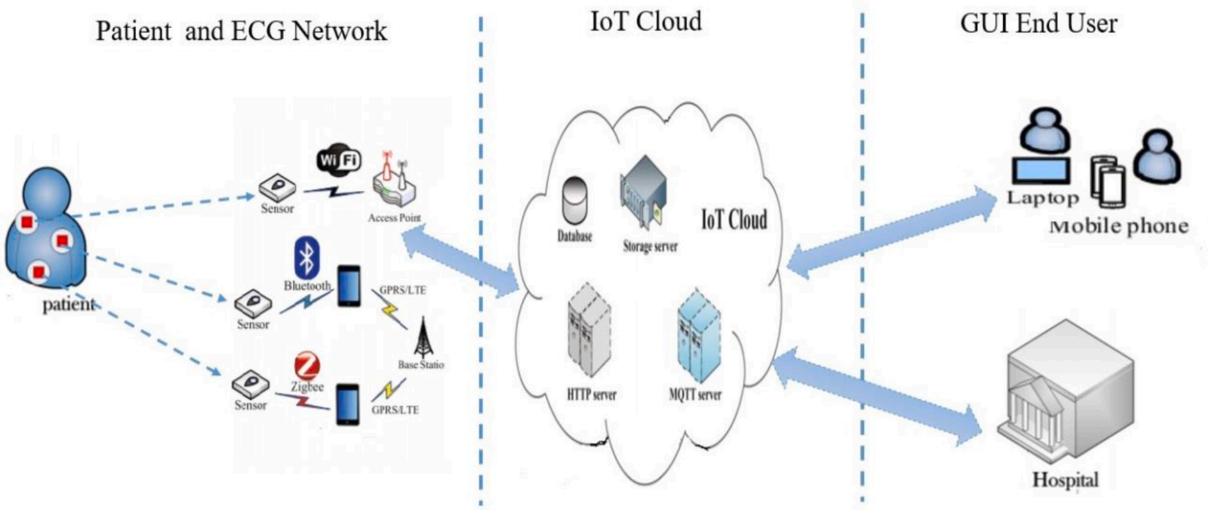

Fig. 3. Architecture of the ECG monitoring systems the IoT-based.

rates and wide coverage areas in comparison to conventional ECG procedures. Fig. 4 shows the devices that can be used for reading vital signs and their functions in the system, which fulfil the requirements of this system.

The literature has extensive research on ECG monitoring systems. Nonetheless, the multifaceted nature of these systems makes it difficult for medical personnel to choose monitoring needs, match the context of their use, and support monitoring conditions [29]. Many studies discussed the rapid rise of IoT in ECG monitoring systems for preventative healthcare and assisting in the detection of patients' unexpected medical concerns or changes in behavioral patterns according to Ren et al. [30] study. As a first step, the researchers proposed a generic health monitoring system. The Raspberry Pi serves as both a sensor node and a controller. Yang et al. [28]; Khan [31]; Abawajy y Hassan [32]; Mostafa et al. [33]; Shaji et al. [34]; Kulkarni et al. [35], have all proposed IoT-enabled ECG monitoring systems. Despite all of the research done to develop ECG monitoring based on IoT, there is still a dearth of information on effective aspects and behavioral intention to use, according to studies by Abawajy y Hassan [32]; Ren et al. [30]; Yang et al. [28].

Fig. 4. Architecture of the ECG monitoring systems the IoT-based.

2.5. *Effective factors of IoT adoption*

Based on DeLone and McLean's (1975) IS success model, effective factors are those factors that affect system usage as well as user satisfaction with system success. Hence, effective factors are required for healthcare systems as they have a crucial role to play in saving users from death. The evaluation before the final stage of the development of the medical system can be conducted to identify the efficient factors for the success of the system. The system life cycle is composed of complementary and interrelated phases of system use, system design, and implementation.

Thus, before system design and implementation, the usability of the system must be confirmed. Healthcare professionals and users or patients are considered the main users of healthcare systems. Therefore, their behavioral intention to use healthcare systems is very crucial, the healthcare system will in most cases rely on their continued use by them (Keikhosrokiani y et al., 2019). As can be seen, the healthcare success system depends on effective factors from the perspective of the professional staff. These factors lead to an increased intention to use, thus leading to an increased adoption level. According to Al-Rawashdeh et al. [25] study, the effective factors of the adoption of IoT must be well identified, because these factors may facilitate or impede healthcare professionals' use of IoT technologies, and their results show that IoT adoption is affected by several effective factors at the individual, technology, security, health, and environmental levels.

3. Theoretical framework and hypotheses formulation

This section is dedicated to discussing the research framework employed in this study, encompassing the development of conceptual models, research hypotheses, and the methodology employed. Previous research has explored the utilization of IoT technologies within healthcare, with numerous studies investigating the benefits of this technology in general healthcare contexts or focusing on patient acceptance of these emerging technologies. Numerous theories explicating the process of technology adoption have been proposed over the years. As formerly stated, this research primarily seeks to investigate the effective factors influencing the integration of the IoT within nursing care practices in Amman City.

The research's theoretical framework has been wisely developed by mixing a multitude of esteemed theories and models that are considered pivotal in clarifying the procedure of technological adoption. Different theories often emphasize different aspects of a problem or process. By integrating multiple theories, researchers can ensure that their framework adequately covers the full range of relevant factors. This increases the explanatory and predictive power of the framework, improving its usefulness for both theoretical exploration and practical application. In the specific case of studying IoT adoption in nursing care, the integration of multiple theories is justified by the multi-faceted nature of the adoption process. Factors such as personal attitudes, perceived usefulness, social influence, organizational support, and technical knowledge all play roles in the decision to adopt new technology. Each of these factors is best captured by different theories, so a comprehensive understanding requires the integration of multiple theoretical perspectives.

A novel framework for enhancing awareness and adoption of the IoT in nursing care is constructed by integrating constructs from four established theoretical models, namely, the Unified Theory of Acceptance and Use of Technology (UTAUT), the Health Belief Model (HBM), the Technology Acceptance Model (TAM), and the Theory of Planned Behavior (TPB), as illustrated in Table 1 below. Moreover, The innovative aspect of the framework lies in its classification of constructs drawn from various theories into three distinct categories: technological context, health context, and individual awareness context as shown in Fig. 5. This classification pro-

Table 1
Theories and constructs used in study.

Theory of Adoption	The Importance of Theories	Constructs (Effective Factors)
UTAUT Model	It is used to define the user's desire to utilize Information System (IS)	1-Effort Expectancy (EE) 2-Performance Expectancy (PE) 3- Anxiety (AX) 4-Trust (T) 5-TopManagement (TM) 6-IT Knowledge (IT) 7x-Technologywarenes
The Health Belief Model HBM	It is used to predict and explain human behaviour in particular environment	8-Perceived Severity (PS)
Technology Acceptances Model (TAM)	It is used to explain computer-base behavior	9-Social Influence (SI) 10- Behavioral intention Attitude (BI)
Theory of Planned Behavior (TPB)	It is used to predict and explain how human's related health behavior in a particular environment	11-Adoption IoT among Nurses (IoT)

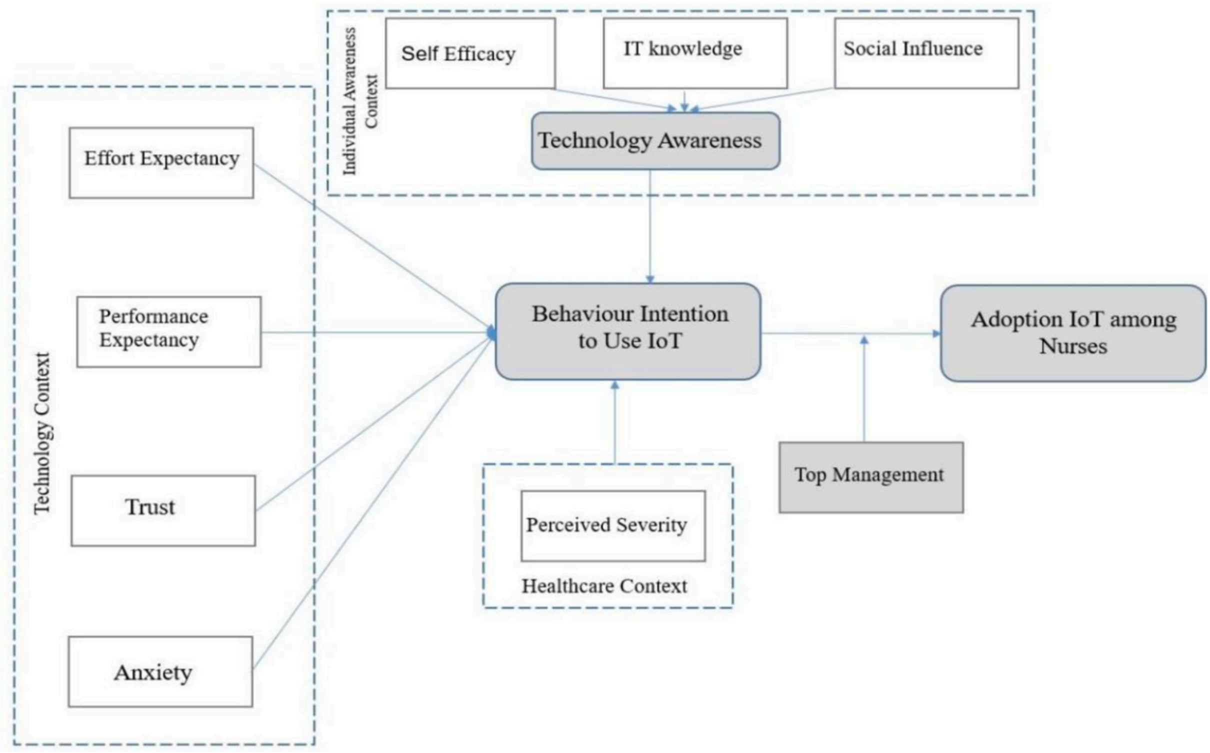

Fig. 5. Theoretical Model for Study Adoption I oT among Nurses.

vides a structured approach to understanding the different factors influencing adoption and establishes a foundation for an interdisciplinary understanding of IoT adoption in healthcare.

3.1. The conceptual model and definition of constructs

In the context of IoT adoption in nursing care, constructs are the basic elements that make up a phenomenon or idea. Some common constructs in this study are efficiency, data privacy, and security, how people use technology, and how to train healthcare staff, these elements interact with each other and help make IoT adoption in nursing care more effective overall.

Several models have been proposed to explain the adoption of IoT in nursing care, including Technology Acceptance Model (TAM), the Diffusion of Innovations (DOI), and the Unified.

Theory of Acceptance and Use of Technology model (UTAUT), models and theories consider variables such as performance expectation, effort expectation, social influence, and facilitating conditions, in addition to individual characteristics such as age, gender, and experience, as predictors of technology acceptance and use [36,37].

In this section, the researcher examined adoption theories and models, and different studies in which the success of the proposed model is measured using the UTAUT, TPB, TAM theories, and The Health Belief Model (HBM). This study integrates TPB, TAM, HBM and UTAUT adoption theories with twelve additional variables (constructs), including Performance Expectancy (PE), Effort Expectancy (EE), Trust (T), Anxiety (AX), IT.

Knowledge (IT), Self Efficacy (SE), Social Influence (SI), Technology Awareness (AT), Perceived Severity (PS), Top Management Support (TM), Behavioral Intention to Use (BI), and Adoption IoT among Nurses (A IoT). In Table 2 summarizes the definition of each construct, and the conceptual research model is illustrated in Fig. 5. The conceptual model depicts three independent variables (Social Influence, IT knowledge, and Self-Efficacy), which affect the dependent variable (Technology Awareness).

3.2. Hypotheses formulation

This research aims to draw upon widely recognized theoretical frameworks including the TPB, TAM, UTAUT, and HBM. These established models and theories will provide the foundation for examining and understanding user behavior toward technology adoption, specifically in the realm of IoT. The research model will comprise three primary categories of constructs: technological context, health context, and individual context. These categories were deliberately chosen to represent a comprehensive spectrum of factors influencing the adoption and use of IoT in healthcare settings. The technological context focuses on the technical aspects of IoT devices. The health context encompasses factors related to the specific health-related applications and implications of IoT technology. This could involve aspects such as perceived health benefits, relevance to specific health tasks, and the impact on patient care and health outcomes.

The individual context pertains to individual attributes of the users, including their attitudes, perceptions, beliefs, and individual readiness towards adopting and using IoT in their professional healthcare practices. By integrating these diverse determinants into a unified framework, this research aims to provide a more holistic and nuanced understanding

of user behavior toward IoT adoption in healthcare.

Delving deeper into the technological context, the Unified Theory of Acceptance and Use.

of Technology (UTAUT) will serve as a pivotal framework for this research. UTAUT, which encapsulates factors driving both the intention to adopt and the actual use of information technology, presents a comprehensive perspective on technology acceptance [9]. As concluded from an exhaustive exploration of relevant literature, there are four key variables integral to determining Behavioral Intention (BI) to adopt of IoT technologies. These influential factors include EE, PE, T, AX. Therefore, four hypotheses were proposed, and they are as follows:

Effort Expectancy: EE fundamentally encapsulates the perceived ease of use of technology. This construct represents the degree of ease associated with the use of the system in question [9]. The significance of EE arises from its influence on an individual's behavioral intention to use a system. As asserted by Venkatesh et al. [37], a positive correlation exists between Effort Expectancy and an individual's intention to adopt a technology.

Notably, this relationship hinges upon certain elements such as complexity and ease of use. Complexity refers to the degree of difficulty inherent in understanding and using the new system, whereas ease of use relates to the user's belief that using the system would be free of effort [38]. Taking into consideration the aforementioned aspects of Effort Expectancy and its proven relationship to the use of technology, the following hypothesis is put forward for empirical validation in this study. This hypothesis would explore the potential impact of Effort Expectancy on the intention of nursing professionals to use IoT technology in their practice. This exploration can offer valuable insights into designing and imple-menting IoT systems that are user-friendly and thereby more likely to be adopted by the end-users.

H1. Effort Expectancy has a positive impact on nurses's behavioral intention to use IoT applications.

Performance Expectancy: PE as conceptualized by Venkatesh et al. [37], encompasses an individual's belief that utilizing a particular system would aid them in achieving their objectives and enhancing their job performance. The construct of PE is multi-

Table 2
Definition of constructs (effective factors) for study.

Construct	Definitions
Performance Expectancy (PE)	The degree to which a nurse believes that the use of IoT applications would enhance his or her performance.
Effort Expectancy (EE)	The degree to which a nurse believes that the use of IoT applications would be effortless (free of physical and mental effort)
Trust (T)	A set of beliefs that IoT applications would fulfil the expected commitments under conditions of vulnerability and interdependence.
Anxiety (AX)	The degree to which a nurse's fear, concern, hesitation and, being embarrassed to use the IoT devices.
Perceived Severity (PS)	The degree of the negative outcome that is expected to occur in the process of the nurse's use of the IoT service, and the psychological expectation of the seriousness of the perceived health risk when using IoT applications.
Behavioral Intention to Use IoT among nurses (BI)	The degree to which a nurse's motivation intends to use IoT applications.
Technology Awareness (TA)	The degree of a nurse's knowledge about the existence and benefits of IoT technology in their activities.
IT knowledge (IT)	The ability of customers to handle the internet and its applications, including IoT applications.
Self-Efficacy (SE)	The nurse's perceptions of his or her ability to use IoT applications in the accomplishment of the nursing task.
Social Influence (SI)	The extent that nurses feel other people think they ought to be using IoT technology.
Top Management Support (TM)	Facilitating conditions are defined as the degree to which nurses believe that hospital and technical infrastructure exists to support the use of the IoT applications.
Adoption IoT among Nurses (AIoTN)	Stage of selecting an IoT technology for use by nurses in hospitals.

dimensional, encapsulating perceived usefulness, job fit, extrinsic motivation, and relative advantage. PE has been identified as a salient factor influencing an individual's behavioral intention to adopt and use a system Therefore, a higher PE is likely to stimulate an individual's intention to use a system. Given the above theoretical underpinnings, we propose the following hypothesis for this study. This hypothesis aims to investigate the possible influence of Performance Expectancy on the behavioral intention of nursing professionals to use IoT technology. Understanding this relationship is crucial for devising strategies to improve the acceptance and adoption of IoT systems in nursing practice.

H2. Performance Expectancy has a positive impact on nurse as behavioral intention to use IoT applications.

Trust: T, as delineated by Gedam y Paul [39], pertains to the degree to which an individual believes that others will act in a socially acceptable, reliable, and trustworthy manner. The construct of trust plays a pivotal role in shaping a user's relationship with technology, including IoT devices. Trust can encourage acceptance, reduce uncertainty, and influence behavioral intention to adopt new technology. A positive correlation between trust and the behavioral intention to use IoT has been demonstrated in prior research [40]. A user's trust in an IoT system's reliability, security, and effectiveness can strongly influence their decision to use the technology. In light of the aforementioned theoretical discussions, it is proposed the following hypothesis for this study. This hypothesis aims to investigate the potential influence of Trust on the behavioral intention of nursing professionals to use IoT technology.

Understanding this relationship is paramount in devising strategies to facilitate the acceptance and adoption of IoT systems in nursing care.

H3. Trust has a positive impact on nurses's behavioral intention to use IoT applications.

Anxiety: Ax the construct of anxiety is particularly relevant in the context of user interactions with technology. The novelty or complexity of technology, such as IoT devices in healthcare, can induce a sense of anxiety among users. The fear of misuse, data security, and other unknown implications may become potential barriers to technology adoption [41]. Hence, understanding and addressing user anxiety is critical for fostering the successful implementation and use of IoT technology within nursing. The following hypothesis for this study.

H4. Anxiety has a positive impact on nurse's behavioral intention to use IoT applications.

In the healthcare context, HBM proposes that an individual's decision on whether or not to take a health-related action is based on his, or her perception of the perceived threat [42,43]. The adoption of health information technology varies from acceptance of technology in certain fields because many health-related considerations affect people as they want to follow health-related habits [44]. Thus, the hypothesis is set as follows: Perceived Severity: PS is seen as an individual's appraisal of the possible aftermath associated with a potential threat (Milne et al., 2006). Scholarly agreement suggests that perceived severity could indirectly sway the intention to adopt technologies or systems. A number of studies have identified a significant correlation between perceived severity and attitude [42]. Thus, the hypothesis is set as follows.

H5. Perceived Severity has a positive impact on nurse's behavioral intention to use IoT applications. Within the individual context, upon comprehensive examination of preceding discussions and literature reviews, this study integrates four variables: Self-Efficacy, IT Knowledge, Social Influence, and Technology Awareness. These factors, proposed in the model, collectively portray the individual context [45]. Consequently, the ensuing hypotheses are structured as follows:

Technology-Awareness: TA can be considered a construct that measures an individual's knowledge of, and familiarity with, a particular technology. It involves an understanding of the technology's features, capabilities, potential benefits, and possible limitations or risks [46]. An individual's level of Technology Awareness could influence their likelihood of adopting an IoT device, with higher awareness potentially associated with a greater likelihood of adoption. Hence, the forth coming hypotheses are designed as follows.

H6. TechnologyAwareness has a positive impact on nurses' behavioral intention to use IoT applications.

IT knowledge: IT knowledge as per the definition provided by Acquity Group (2014), pertains to the competency of individuals to effectively navigate and utilize the Internet, its various applications, and other associated services. The context of the IoT refers to the proficiency and understanding of individuals in leveraging IoT services and devices. This involves a comprehensive understanding of how to navigate, operate, and optimize the use of IoT technologies and the myriad applications these devices enable Koohang et al. Consequently, the ensuing hypotheses are structured as follows.

H7. IT knowledge has a positive impact on nurses' technology awareness to use IoT applications. Self-Efficacy: Self-efficacy refers to an individual's belief in their capacity to execute the behaviors necessary to produce specific performance outcomes. This concept was introduced by psychologist Albert Bandura in his Social Cognitive Theory. In the context of technology use, self-efficacy could be considered as technology self-efficacy or computer self-efficacy, reflecting an individual's confidence in their ability to use technology or computer systems effectively [13]. Higher levels of self-efficacy are often associated with a greater likelihood of adopting and effectively using new technologies.

H8. Self-Efficacy has a positive impact on nurse's technology awareness to use IoT applications.

Social Influence: Venkatesh et al. [47] proposes that Social Influence (SI), the extent to which an individual perceives the relevance of others' beliefs in their decision-making, plays a crucial role in the adoption of novel systems. This suggests that the Behavioral Intention (BI) to employ a system is, to a degree, influenced by the perspectives and endorsements of influential individuals within one's social or occupational networks. Venkatesh et al. [37]. further postulate that the effect of Social Influence on Behavioral Intention is most observable during the early stages of system experience, often taking the form of adherence to societal expectations. Concurrently, the research literature has indicated a significant correlation between SI and attitude [48,49].

The following hypothesis for this research.

H9. Social Influence has a positive impact on nurse's technology awareness to use IoT applications. Behavioral Intention to Use: The relationship between Behavioral Intention (BI) and Usage Behavior (UB) has been a topic of significant exploration, with a consensus emerging around the direct correlation between these two aspects. This relationship is evident in models such as the (UTAUT), where [47] posited a direct connection between BI and UB. Concurrently [36], in the (TAM) emphasized the clear linkage between BI and UB. Within these parameters, BI is interpreted as the individual's preparedness to interact with a given technology, while UB is indicative of the actual employment and adoption of the technology. This line of reasoning is predicated on the assumption that a user's intent to utilize a certain technology typically leads to the actual usage of the same. This proposition has been corroborated by recent studies by Arfi et al. [9], and Rajmohan y Johar [50]. Thus, the forthcoming hypothesis is established within the context of this research:

H10. Behavioral Intention to Use IoT applications has a positive impact on the Adoption of IoT among nurses.

Top Management Support: In the context of (UTAUT), Top Management Support (TMS) refers to the strategic actions and backing provided by high-level administrators to encourage and facilitate the adoption and implementation of technology within an organization Venkatesh et al. [47]. The TM in facilitating the integration of technology into an organization is widely recognized within the academic research community. Actions demonstrating managerial support are crucial to success-ful implementation, as they legitimize the significance of System Innovations (SI), reflect management's commitment to ensuring successful adoption, and serve as a strategic instrument to galvanize the necessary effort for adopting these innovations [51]. Such an assertion has been validated by subsequent studies in the field [40]. Therefore, within the framework of the present study, the ensuing hypothesis is formulated, taking into consideration this significant correlation between top management support and successful technology integration.

H11. Top Management Support has a positive impact on Behavioral Intention to Use IoT applications.

H12. Top Management Support has a positive impact on the Adoption of IoT among Nurses.

In statistical analysis, mediation is characterized by the influence of an independent variable on a dependent variable through one or more intermediary variables, known as mediators. A mediating variable essentially serves as a bridge between the dependent and independent variables, elucidating the pathway through which the variables are interrelated [52].

For instance, in the context of our study, Technology-Awareness could mediate the relationship between demographic variables such as IT knowledge, Social Influence, and self-efficacy, ultimately affecting Behaovioral Intention to Use IoT. Therefore, each of these constructs will be examined individually as potential mediators [45]. Consequently, the mediating hypotheses can be constructed as follows.

H13. Technology Awareness of IoT applications will be a mediator in the association between IT knowledge and behavioral intention to use IoT applications.

H14. Technology Awareness of IoT applications will be a mediator in the association between self-efficacy and behavioral intention to use IoT applications.

H15. Technology Awareness of IoT applications will be a mediator in the association between Social influence and behavioral intention to use IoT applications.

Also, Behavioral Intention (BI) often plays a mediating role in the acceptance and utilization of technology. The mediating function of BI is predicated on the notion that the individual's intention to use technology is an intermediary step that facilitates the transition from the perception of a technology's usefulness to its actual use. In the context of technology acceptance models, recognizing the mediating role of Behavioral Intention provides a more nuanced understanding of technology acceptance and use. It emphasizes the importance of user intention in determining the successful adoption and implementation of technology within various contexts, including but not limited to IoT in nursing, thereby providing valuable insights for technology developers, and policymakers [53]. Thus, considering the pivotal mediating role of Behavioral Intention within the context of technology integration and adoption, the following hypothesis is articulated within the structure of this research study.

H16. Behavioral Intention to Use IoT applications will be a mediator in the association between Effort Expectancy andadoption of IoT among nurses.

H17. Behavioral Intention to Use IoT applications will be a mediator in the association between performance Expectancy and adoption of IoT among nurses.

H18. Behavioral Intention to Use IoT applications will be a mediator in the association between Trust and adoption of IoT among nurses.

H19. Behavioral Intention to Use IoT applications will be a mediator in the association between Anxiety and the adoption of IoT among nurses.

H20. Behavioral Intention to Use IoT applications will be a mediator in the association between Perceived Severity and the adoption of IoT among nurses.

H21. Behavioral Intention to Use IoT applications will be a mediator in the association Technology-Awareness between and the adoption of IoT among nurses.

H22. Behavioral Intention to Use IoT applications will be a mediator in the association of Top Management Support between and Adoption of IoT among Nurses.

H23. Technology-Awareness of IoT applications and Behavioral Intention to Use IoT applications will be a mediator in the association between IT knowledge and the Adoption of IoT among Nurses.

H24. Technology-Awareness of IoT applications and Behavioral Intention to Use IoT applications will be a mediator in the association between Social Influence Adoption of IoT among Nurses.

H25. Technology-Awareness of IoT applications and Behavioral Intention to Use IoT applications will be a mediator in the association between Self-Efficacy and Adoption of IoT among Nurses.

In the context of the (UTAUT), Top Management Support (TMS) plays a critical moderating role too. TMS is pivotal in facilitating and encouraging the acceptance and use of technology within an organization. Therefore, within the framework of UTAUT, TMS is a crucial element that influences the acceptance and use of technology by moderating the relationships between the core determinants of technology acceptance and the actual technology usage behavior. As such, the role of TMS should be considered when studying technology acceptance and usage within an organizational context according to many studies such as Hsu y Lin [54]; Chen et al. [55]. The following hypothesis is articulated within the structure of this research study.

H26. Top Management Support will moderate the relationship between Behavioral Intention to Use IoT applications and the adoption of IoT among nurses.

H27. Top Management Support will moderate the relationship between the adoption of IoT among nurses. and Behavioral Intention to Use IoT Applications.

In summary, the research hypotheses for this study are outlined in Table 3. This research includes a total of twenty-seven carefully prepared hypotheses, designed to fulfill the research objectives.

Table 3
The Hypotheses for Adoption study.

NO	Hypotheses for Study
H1	Effort Expectancy has a positive impact on nursesâ Behavioral Intention to Use IoT applications.
H2	Performance Expectancy has a positive impact on nurseâs Behavioral Intention to Use IoT applications.
H3	Trust has a positive impact on nursesâ Behavioral Intention to Use IoT applications.
H4	Anxiety has a positive impact on nurseâs Behavioral Intention to Use IoT applications.
H5	Perceived Severity has a positive impact on nursesâ Behavioral Intention to Use IoT applications.
H6	Technology-Awareness has a positive impact on nursesâ Behavioral Intention to Use IoT applications.
H7	IT knowledge has a positive impact on nursesâ Technology-Awareness to use IoT applications.
H8	Self-Efficacy has a positive impact on nursesâ Technology-Awareness to use IoT applications.
H9	Social Influence has a positive impact on nurseâs Technology-Awareness to use IoT applications.
H10	Behavioral Intention to Use IoT applications has a positive impact on the Adoption of IoT among nurses.
H11	Top Management Support has a positive impact on Behavioral Intention to Use IoT applications.
H12	Top Management Support has a positive impact on the Adoption of IoT among Nurses.
H13	Technology-Awareness of IoT applications will be a mediator in the association between IT knowledge and Behavioral Intention to Use IoT applications.
H14	Technology-Awareness of IoT applications will be a mediator in the association between Self-Efficacy and Behavioral Intention to Use IoT applications.
H15	Technology-Awareness of IoT applications will be a mediator in the association between Social Influence and Behavioral Intention to Use IoT applications.
H16	Behavioral Intention to Use IoT applications will be a mediator in the association between Effort Expectancy and adoption IoT among nurses.
H17	Behavioral Intention to Use IoT applications will be a mediator in the association between performance Expectancy and adoption IoT among nurses.
H18	Behavioral Intention to Use IoT applications will be a mediator in the association between Trust and adoption IoT among nurses.
H19	Behavioral Intention to Use IoT applications will be a mediator in the association between Anxiety and adoption IoT among nurses.
H20	Behavioral Intention to Use IoT applications will be a mediator in the association between Perceived Severity and adoption IoT among nurses.
H21	Behavioral Intention to Use IoT applications will be a mediator in the association Technology-Awareness between and adoption IoT among nurses.
H22	Behavioral Intention to Use IoT applications will be a mediator in the association Top Management Support between and Adoption of IoT among Nurses.
H23	Technology-Awareness of IoT applications and Behavioral Intention to Use IoT applications will be a mediator in the association between IT knowledge Adoption IoT among Nurses.
H24	Technology-Awareness of IoT applications and Behavioral Intention to Use IoT applications will be a mediator in the association between Social Influence Adoption IoT among Nurses.
H25	Technology-Awareness of IoT applications and Behavioral Intention to Use IoT applications will be a mediator in the association between Self-Efficacy Adoption IoT among Nurses.
H26	Top Management Support will moderate the relationship between Behavioral Intention to Use IoT applications and the adoption of IoT among nurses.
H27	Top Management Support will moderate the relationship between the adoption of IoT among nurses. and Behavioral Intention to Use IoT Applications.

4. Research methodology

4.1. Research design

This research is based on empirical methods of research following a deductive and exploratory approach. The study aims to identify the key factors that facilitate the integration and utilization of IoT technology among nurses in Amman City. This research investigates practical elements that contribute positively to the success of the healthcare system, including factors that impact user interaction and satisfaction [56]. In this case, utilizing IoT technology for ECG monitoring within the scope of this research enables a comprehensive examination of the factors influencing the adoption of healthcare technology. This is particularly significant within the nursing profession. IoT-based ECG monitoring devices provide a facility for the real-time observation of patients' cardiac health, contributing to a continuous data stream. This ceaseless flow of data can generate valuable insights into the factors influencing healthcare professionals' preparedness to adopt such advanced tools, as well as the practical challenges that may arise during the process.

The relevance of adopting IoT-based ECG monitors spans diverse healthcare settings, ranging from hospital environments to home care situations. Therefore, a detailed study of this technology is capable of identifying factors that have wide-ranging implications for the incorporation of IoT in healthcare. Gaining a thorough understanding of these devices' adoption could furnish invaluable information on promoting the acceptance of technologies capable of augmenting patient care and improving operational efficiency in healthcare [27]. Moreover, some effective factors play a vital role in adopting IoT technology, the users must have enough knowledge about this technology, so this study tries to explore the effect awareness (independent variable) has on the adoption of IoT technology in nursing (dependent variable) through an intervention. The research steps started with an intervention study through the workshop. The workshop was conducted virtually on the Zoom web application due to the COVID-19 pandemic.

The workshop focused on wearable ECG monitoring systems that utilize IoT technology, providing detailed discussions, materials, and videos showcasing the main functions, data streaming, and benefits of the system for nursing care. Following the workshop, participants were asked to complete a questionnaire that aimed to collect data on their perceptions of barriers to adopting IoT in nursing care. According to Creswell et al. [57] study An experimental design in quantitative research tests the impact of a treatment (or an intervention) on an outcome, controlling for all other factors that might influence that outcome".

The study's steps are designed to answer each research question. These questions are.

(Q1. How to figure out the effective factors for the adoption of IoT technology among nurses in hospitals in Amman City, Jordan?)
(Q2: How can behavioral intention to use IoT affect the adoption of IoT among nurses in Amman City, Jordan?).
(Q3: How top management can affect the adoption of IoT among nurses in Amman City, Jordan?).

The findings of this study help before the design, testing, and implementation stages of healthcare systems. It also helps developers be aware of barriers, objectives, and user requirements**.**

4.2. Sampling

This study used convenience sampling (also known as haphazard sampling or accidental sampling). Researchers worldwide have incorporated the said technique in their research. For example, Keikhosrokiani et al. [56] study employed convenience sampling in studying nurses' perceptions of spirituality and spiritual care in Jordan. Al-Adwan y Berger [58] followed the said technique while attempting to explore physicians' willingness toward the adoption of electronic health care records in Jordan. In particular, the use of convenience sampling in this research is primarily justified by the ongoing COVID-19 pandemic, which has presented unique challenges to conducting studies with time-consuming sampling techniques. Firstly, accessibility to the research participants is considerably limited due to safety measures such as social distancing, lockdowns, and the resulting limitations on human movement and in-person contact.

Convenience sampling allows the researcher to recruit readily available participants, mitigating these challenges. Secondly, nurses, who form a crucial participant group for this research, are currently under unprecedented strain due to the demands of the pandemic response. Hence, it may be challenging to engage them in research activities that require substantial time commitment. The population chosen for this research are registered nurses with at least one year of experience and who have worked in a clinical unit. The study's sample was taken from the Al-Bashir Hospital a public hospital in Amman City, consisting of several hospitals as in Table 4. Indeed, several key considerations inform the decision to concentrate this research study on public hospitals in the city of Amman. Primarily, public hospitals serve a wider and more diverse demographic in comparison to private institutions.

This broad representation enables an expansive perspective, facilitating a comprehensive comprehension of the influence and uptake of IoT-based ECG monitors. Secondarily, public hospitals adhere to standardized protocols and directives established by governmental entities, lending uniformity to their operations. This consistency facilitates the extrapolation of generalizable conclusions from the research outcomes. Additionally, discoveries derived from public hospitals can directly influence public health policy decisions associated with technology adoption. Hence, they are more likely to incite policy-level transformations, potentially benefiting a larger societal segment.

Table 4
Number nurses in hospitals hospital name healthcare sector number Nurese.

Cardiac Surgery Hospital	Public	100
Batinah Hospital	public	120
Emergency and Ambulance Hospital	public	80

Lastly, the focus on Amman, the capital and the most populous city in Jordan, is driven by its high concentration of public hospitals. This makes the city an apt and representative selection for the investigation. Moreover, the insights gained from the research conducted in Amman could be extended to understand technology adoption in comparable urban contexts. Significantly, for this research, the researcher chose three hospitals as in Table 4, to provide a solid foundation for the decision model. The number of nurses in each of these hospitals is recorded in Table 4. The population for this study, totaling 300, was obtained from the Ministry of Health in Jordan, as recorded on June 6, 2021.

The general sample size guidelines by Krejcie and Morgan (1970) served as the cornerstone in determining an appropriate sample size for this study. According to their table, for a population size of 300, the minimum recommended sample size for generalization is 169 cases. However, the final sample size chosen for this research was 200 nurses exceeding the minimum recommendation [59]. This decision was taken to ensure a more robust set of findings and to account for potential attrition or variations in the response rate that could threaten the validity of the results. A larger sample size also enhances the statistical power of the study, resulting in more accurate and generalizable outcomes. Therefore, the decision to utilize a sample size of 200 nurses is both justified and strategically sound, considering the scope and requirements of this study.

4.3. Design of questionnaire and data collection

This study employed electronic questionnaires as the primary data collection instrument. A survey of existing literature reveals a large number of information systems studies that have effectively utilized questionnaires for data gathering. For instance, Bodur et al. [2] study was conducted that measured awareness of IoT using a questionnaire, similarly, Silva et al. [60] study applied a questionnaire to indicate the influential factors of IoT technology.

The study used electronic questionnaires, which is a common and reliable research practice. This approach aligns with established methods, adding credibility and reliability to the investigation. To create the questionnaire, the researchers followed established guidelines outlined by Wu et al. [61]. The process was initiated with the determination of question types, including close-ended, multiple-choice, or Likert scale questions [62]. Following this, the questions were formulated, ensuring clarity, conciseness, and relevance to the research objectives while eschewing leading or loaded queries that might skew responses. Subsequently, the questions were arranged in a logical sequence, progressing from straightforward and non-intrusive to more complex or sensitive topics.

The format for respondents to record their answers was also decided, with options ranging from checkboxes and drop-down menus to text boxes, depending on the question type. The preliminary version of the questionnaire was then reviewed by experts in the English languageand computer science to ensure the accuracy of the content. After incorporating their inputs, a pilot test was conducted, and the findings were employed to revise and improve the questionnaire, further enhancing its reliability and validity. Thus, the questionnaire emerged as a robust tool tailored to fulfil the objectives of this study. In the context of this study, the measurement scale refers to the method used to quantify the variables from the research.

Specifically, the study utilized a Likert scale, which is a type of ordinal scale used within questionnaires [57]. A Likert scale allows for the measurement of attitudes or opinions along a continuous scale, typically ranging from one extreme to another. In this case, a five-point Likert scale was used, which ranged from 1 (strongly disagree) to 5 (strongly agree).

5. Data analysis

In this research for descriptive analysis of the entire sample, SPSS (Statistical Package for the Social Sciences) software was used. To test the hypothesis of this study, Structural Equation Modeling (SEM) was used. SEM is a statistical technique for determining the relationship between observable variables. There are two types of SEM: Variance-Based SEM (PLS-SEM) and Covariance-Based SEM (CB-SEM). Hence, this method is more suitable for the proposed model. PLS-SEM, which consists of two basic components: (1) the structural model and (2) the measurement model, offers the most effective approach for estimating simultaneous multiple regression analysis. There were two categories of measurement models: formative measurement and reflective measurement. The measuring model is reflective if the indicators are representational of the constructs, constructs in the constructs.

In contrast, formative measurement is when there is no correlation among the constructs and the differences in one indicator do not necessarily cause modification in others. Every one of the research's constructs is considered to reflect indicators. In the first stage which is the measurement model, the analyses are conducted on variables and theoretical constructs. This is the initial stage of measurement model evaluation using Confirmatory Factor Analysis (CFA). In this step, the constructs' dependability and validity can be analyzed. In evaluating Reliability, Cronbach's alpha and CFA were utilized to evaluate the internal consistency of measures. For the validity of the constructs, both convergent and external validity are assessed. The main purpose of the second step is to test the hypotheses that indicate the relationship between the constructs. Model fit is verified using the goodness of fit indices and the significance of the paths using coefficient parameter estimates. Two-stage approach SEM is recommended as a representation of the measurement model and structural model separately is the best and the conflicts between these two models will be reduced.

6. Empirical results

6.1. Demographics and descriptive analysis

In this fundamental descriptive analysis, a frequency table was used to provide a demographic profile of respondents. The information in Table 5 reveals that over half of the sample (78.4 %) are female, and (21.6 %) are male. Whereas the age below 25 was (18.1 %), 26–35 (56.8 %), 36–45(19.1 %), and 46–55 (6.0 %). More so, this study has no respondents above 55 years old. Table 5 illustrates that the majority of respondents had a bachelor's degree (65.3 %). This indicates that the majority of nurses who took part in

Table 5
Demographic data for study Item response Percent.

Gender	Male	21.6%
	Female	8.4%
Age	Below 25	18.1%
	26–35	56.8%
	36–45	19.1%
	46–55	6.0%
	Above 55	0.00%
Education	Diploma	25.6%
	Bachelor's Degree	65.3%
	Master's Degree	6.0%
	Doctoral Degree	2.5%
	Professional's Degree	0.5%
Experiencing	1Year	21.1%
	2 Years	6.0%
	3 Years	4.0%
	4 Years	1.0%
	More than 4Years	67.8%

the study had a high degree of education, then a diploma (25.6 %), a master's degree, a professional degree (8 %), a doctoral degree (2.5 %), and a professional degree (0.5 %). Finally, Table 5 illustrates that the majority of respondents had an experience of more than four years (67.8 %). This finding shows that most nurses who participated in this study had a sufficient understanding of nursing care tasks, for 4 years (7.5 %). (4.0 %), (6.0 %), and (21.1 %) were the responses to their experience of 3 years, 2 years, and 1 year, respectively. The descriptive analysis results can be reported using minimum, maximum, mean, and standard deviation. The mean is used to identify the central tendency, whereas, the standard deviation represents distribution dispersion and assesses variance from the mean. The descriptive analysis result of the study is shown in Table 6, the mean ranges from 13.07 to 15.57 for anxiety and IT knowledge, respectively. Thus, it shows positive results. According to these findings, participants believe that IT knowledge, and anxiety have an influence on IoT adoption and that they will be successful and effective if they include effective factors. All standard deviation values for all variables are between 2.52 SE, and 3.09 IT, indicating the data are normally distributed and concentrated around the mean and less spread.

6.2. *Validity and reliability of survey instrument*

It is essential to realize that before analyzing the data using statistical software, the survey instruments must be assessed before being used in this study. Reliability and validity are two critical criteria to consider when evaluating measuring tools. A reliable and valid questionnaire is required to improve the study's accuracy. However, if an instrument is reliable, it does not mean it is also valid. An instrument is valid if it measures what it seeks to measure, whereas reliability is the ability of an instrument to measure consistency. Therefore, the reliability and validity of the instrument were analyzed separately.

6.3. *Reliability*

The most comprehensive index for assessing reliability is Cronbach's Alpha. It was developed by Lee Cronbach in 1951 [63]. Thus, when using the Likert-scales questionnaire, it is recommended to use and report Cronbach's Alpha for internal consistency reliability. The value of alpha is between 0.7 and 0.95. However, there are various viewpoints on this value. Alpha values were classified as excellent (0.93–0.94), strong (0.91–0.93), dependable (0.84–0.90), robust (0.81), fairly high (0.76–0.95), high (0.73–0.95), good (0.71–0.91), relatively high (0.70–0.77), slightly low (0.68), reasonable (0.67–0.87), adequate (0.64–0.85), moderate (0.61–0.65), satisfactory (0.58–0.97), acceptable (0.0.4–0.55). The questionnaire for the study adoption study consists of 8 Items and 12 questions. In addition, the reliability of the questionnaires for this study was determined using Cronbach's Alpha, which is between 0.58 and 0.93 for all constructs, as shown in Table 7 so, there are no concerns about the questionnaires' reliability in this research.

6.4. *Validity*

As mentioned before, reliability alone is insufficient to measure an instrument; it must also be valid, meaning an instrument must measure what is expected. Although checking the validity of an instrument is pointless if it is unreliable because the instrument must be reliable to be valid [63]. There are three types of validity comprising (1) content validity, (2) criterion validity and (3) construct validity (Convergent Validity and Discriminant Validity).

Table 6
Descriptive analyses for adoption study.

	EE	PE	AN	T	PS	BI	TM	TA	SI	IT	SE	AIoT
Mean	14.11	15.37	13.07	15.07	13.47	14.98	14.87	15.19	15.27	15.57	15.10	15.02
N	200	200	200	200	200	200	&	200	200	200	200	200
Std. Deviation	2.75	2.97	3.09	2.52	3.09	2.55	2.75	2.57	2.79	3.03	2.58	2.63
Minimum	4	4	4	4	4	4	4	4	4	4	4	4
Maximum	20	20	20	20	20	20	20	20	20	20	20	20

Table 7
Reliability analysis of survey instrument.

Construct	Iitem's Number	Cronbach's Alpha
Technology Awareness (TA)	4	0.866
Social Influence (SI)	4	0.920
IT knowlege (IT)	4	0.934
Self Efficacy (SE)	4	0.862
Effort Expectancy (EE)	4	0.622
Performance Expectany (PE)	4	0.908
Anxiety (AN)	4	0.587
Trust (T)	4	0.830
Perceived Severity (PS)	4	0.761
Behavioral Intention to use (IoT)	4	0.889
AIoT	4	0.906
Top Management (TM)	4	0.895

A measurement's content validity is theoretically grounded, and if all components of the idea are assessed, we can say it has high content validity. A criterion variable compares the actual measurement and the criterion variable. Criterion validity does not use a lot of theoretical ideas. Construct validity is theoretical and empirical and closely related to the instrumentsØ· intended use. Concept validity is determined by calculating the correlation coefficient between two or more constructs that aim to assess the same theoretical construct [63]. According to Campbell and Fiske (1959), convergent suggests a multitrait-multimethod strategy for measuring validity. This technique implies convergent validity and discriminant validity. To determine whether the measures of the same construct are correlated highly or not, convergent validity is analyzed. In addition, to check the correlation between the measures of a construct with other constructs, discriminant validity is utilized. So, convergent validity and discriminant validity are implied in this study to verify the measurement of the concepts and to confirm the reliability and validity of the constructs.

6.4.1. Convergent validity

Convergent validity refers to how well a measure correlates with other measures of the same construct. The domain sampling model treats indicators of a reflective construct as distinct approaches to measuring the same construct. Convergent validity is determined by a few criteria. In the first one, all of the item loadings in a construct must be greater than 0.5. In contrast, Cranach's Alpha values must be greater than 0.6 for construct reliability. In the second one, a construct's Composite Reliability (CR) should be greater than 0.6. It can be interpreted correspondingly to Cranach's Alpha. In the third one, the importance than 0.6, and AVE for all of the constructs is more than 0.5. than 0.5 (Keikhosrokiani y et al., 2019). The majority of the constructs in this research appear to be reliable, as each computed statistic is greater than 0.60. Similarly, CR for all of the constructs is more than 0.6, and AVE for all of the constructs is more than 0.5. Cranach's Alpha was used to assess reliability as shown in Table 8 for the study revealing that the majority of the constructs exhibit satisfactory levels of reliability, as evidenced by computed statistics surpassing the threshold of 0.60. Additionally, the Composite Reliability (CR) for all constructs exceeds 0.6, while the Average Variance Extracted (AVE) for all constructs exceeds 0.5, except for the EE construct. The observed low-reliability value of the EE construct can be attributed to errors in the measurement model. Consequently, a prudent course of action was taken to enhance the construct's reliability by removing the items that have less item loading (EE2 and EE3) that contributed to the low value.

6.4.2. Discriminant validity

Discriminant validity is the extent to which a construct is truly distinct from other constructs according to empirical standards. As a result, establishing discriminant validity implies that a construct is distinct and captures phenomena that are not represented by other constructs in the model. The discriminant validity of the construct using the square root of the AVE for each construct implies that the value must be more than the correlations between it and all other constructs. As presented Table 9. The results show a high degree of discriminant validity.

6.5. Goodness-of-Fit

Goodness-Of-Fit (GOF) according to Maydeu-Olivares y Garcia-Forero [64] is used to find how well a model fits into the set of observations. Acceptance or rejection of the model depends on the adequacy of GOF. The closer the GOF score is to one, the better the model's GOF will be [65]. The model can be assessed in a casual path diagram to

show the relationship between variables. The casual paths that do not fit the model can be modified or removed from the model. It is recommended that GFI, NFI, or NFI, CFI, and SRMR, be used as essential components in determining the optimum model fit. In addition, it is recommended that at least three fit indices be used to assess model fit.

Fit indices are classified into three categories: (1) absolute, (2) incremental, and (3) parsimonious. Absolute values include chi-square (x2), GFI, and RMSEA in the first category, while AGFI, NFI, CFI, and TLI are essential considerations in the second category, which is followed by x2/df in the third (parsimonious) (Keikhosrokiani y et al., 2019). The fit indices consist of the root of mean square error of approximation, the standardized root mean square residual, the goodness-of-fit index, the (X2/df) ratio, the adjusted goodness-of-fit index, and the root mean square residual which are absolute indices [66].

In Table 10 depicts the GOF indices for the study's hypothesized model, which assumes that the observed variables have a normally distributed distribution. In this study before proceeding to test the model, the researcher tested model fit by using Smart PLS

Table 8
Assessment of Convergent Validity for Adoption Study with awareness.

Construct	Items	Item Loading	Composite Reliability	AVE	Cronbach's Alpha
AIoT	Q1AIoT	0.805	0.906	0.707	0.861
	Q2AIoT	0.853			
	Q3AIoT	0.861			
	Q4AIoT	0.842			
BI	Q1BI	0.88	889	0.667	0.833
	Q2BI	0.813			
	Q3BI	0.81			
	Q4BI	0.76			
TM	Q1TM	0.816	0.895	0.682	0.844
	Q2TM	0.81			
	Q3TM	0.826			
	Q4TM	0.849			
PE	Q1PE	0.917	0.908	0.712	0.864
	Q2PE	0.892			
	Q3PE	0.831			
	Q4PE	0.723			
EE	Q1EE	0.702	0.622	0.332	0.401
	Q2EE	0.23			
	Q3EE	0.348			
	Q4EE	0.814			
T	Q1T	0.833	0.83	0.553	0.726
	Q2T	0.684			
	Q3T	0.79			
	Q4T	0.652			
AN	Q1AN	0.902	0.687	0.521	0.650
	Q2AN	0.787			
	Q3AN	0.36			
	Q4AN	0.204			
PS	Q1PS	0.713	0.761	0.559	0.605
	Q2PS	0.693			
	Q3PS	0.835			
	Q4PS	0.384			
TA	Q1TA	0.757	0.866	0.618	0.794
	Q2TA	0.815			
	Q3TA	0.769			
	Q4TA	0.802			
IT	Q1IT	0.892	0.932	0.775	0.903
	Q2IT	0.857			
	Q3IT	0.879			
	Q4IT	0.894			
SI	Q1SI	0.85	0.909	0.713	0.867
	Q2SI	0.825			
	Q3SI	0.834			
	Q4SI	0.869			
SE	Q1SE	0.244	0.601	0.51	0.823
	Q2SE	0.296			
	Q3SE	0.725			
	Q4SE	0.36			

software, and three model fitting parameters: SRMR, NFI, Normed Chi, the SRMR value less than 0.10 or of 0.08, NFI value above 0.5 or 0.90, and Normod Chi-Square between 1.0 X2/df 5. As indicated in Table 10, the majority of the GOF parameters are within the specified acceptable ranges, which is adequate, indicating that the suggested measurement model fits the observed data well.

6.6. *Full structural model findings*

In order to examine the causal relationships among the constructs, a structural model was built for the study of the adoption of IoT in nursing care, as illustrated in Fig. 6. Firstly, hypotheses are examined for the entire model. After checking the direct effects, mediation followed by moderation effects is checked for the proposed structural model for the Study. PLS software does not include a statistical significance test or confidence interval estimation. Consequently, a Bootstrapping analysis was used to estimate path coefficients, statistical significance, and relevant parameters such as means, standard deviations, items loaded, and weighted, amongst other things.

The second step is the calculation of the coefficient of determination R square for endogenous variables to assess the structural model's predictive power. The results of hypotheses testing for the study are illustrated in Table 11 for the study. The R^2 values behavior intention and adoption of IoT are depicted in Fig. 7 respectively (0.854), (0.770). This current model indicates high explanatory

Table 9
assessment of discriminant validity for adoption study.

	AIoT	AN	BI	EE	IT	PE	PS	SE	SI	T	TA	TM
AIoT	**0.841**											
AN	−0.221	**0.633**										
BI	0.724	−0.213	**0.817**									
EE	0.333	−0.000	0.360	**0.577**								
IT	0.725	−0.221	0.710	0.344	**0.880**							
PE	0.560	−0.087	0.627	0.339	0.630	**0.844**						
PS	0.383	−0.037	0.335	0.317	0.294	0.224	**0.677**					
SE	0.208	−0.118	0.234	0.234	0.249	0.141	0.080	**0.448**				
SI	0.666	−0.249	0.638	0.362	0.735	0.530	0.334	0.220	**0.845**			
T	0.651	−0.171	0.662	0.440	0.624	0.608	0.381	0.178	0.613	**0.743**		
TA	0.753	−0.165	0.745	0.379	0.768	0.642	0.371	0.236	0.760	0.647	**0.786**	
TM	0.671	−0.286	0.680	0.247	0.576	0.542	0.310	0.163	0.626	0.645	0.677	**0.826**

Table 10
Summary of goodness-of-fit indices shammout (2007).

Name of Index	Level of Acceptance	Comments
Absolute Fit Indices		
Chi-Square (X_2)	P > 0,05	This measure is sensitive to large sample sizes.
Goodness- of -Fit (GOF)	0.90 or greater	Value close to 0 indicates a poor fit, while value close to 1 indicates a perfect fit.
Root Mean Square Error of Approximation (RMSEA)	Between 0.05 and 0.080	Value up to 1.0 and less than 0.05 is considered acceptable.
Incremental fit Indices		
Adjusted Goodness-of-fit (AGFI)	0.90 or greater	Value close to 0 indicate a poor fit, while close to 1 indicate a perfect fit
Tuker-lewis Index (TLI)		
Normed Fit Index (NFI)		
Comparative Fit Index (CFI)		
Parsimonious fit indices		
Normed Chi-Square ($X^2 df$)	$1,0 \leq X^2/df \leq 5$	Lower limit is 1.0, upper limit is 3.0 or as high as 5.

power for the behavioral intention for the adoption of IoT, while a similar study by Ref. [67] R^2 value was put at (0.442). In addition, the model showed the explanatory power of R^2 for the adoption of IoT devices among nursing in a similar study by Ref. [68] R-square value (0.680).

This high is due to effort expectancy, trust, top management, social influence, IT knowledge, and self-efficacy which are significant in their influence. The researcher found that behavior intention (BI) could mediate the effect on the adoption of IoT (AIoT) as illustrated in Fig. 7.

Besides, H1, H4, H5, and H6 are not supported, as shown in Table 11. This means that independent variables of this study, i.e., effort expectancy, perceived severity, awareness of technology, and anxiety do not have a direct effect on the behavioral intention to use IoT.

The results support the prediction that behavior intention ($\beta = 5.372$), ($p < 0,01$), has statistically significant relationships with the adoption of IoT. Thus, hypothesis H21 is supported.

6.7. Mediating effect

According to Wolfle [69], Sewall Wright started studying an indirect effect in his work on path analysis, in other words, the assessment of a mediation effect.

A mediator is considered a variable that acts as a link between the independent and dependent variables and transmits the effect between them [70]. Path analysis is a method that only measures how two or more variables are linked and does not try to figure out why they are linked [71]. According to Sobel [72] the mediator is a variable in the causal chain that connects the independent variable to the dependent variable. In this study, Smart PLS software is used to analyze data, so that the researcher can leverage the Bootstrapping method.

According to Linder y Babu [73] Bootstrapping is considered a procedure to handle multivariate non-normal data initiated. In the bootstrapping method, the first sample generates several more samples, and the initial sample represents the population. In other words, it is an empirical representation of the sample distribution of indirect effect used to represent the population. Re-sampling is done to simulate the original sample during bootstrap analysis [74]. The researcher evaluated the mediating variable's effect on the behavior intention and awareness technology between independent and dependent variables in the structural model in this study.

The first mediator variable is technology awareness (TA). It has a mediating effect between three independent variables (IT knowledge, Self-Efficacy, and Social Influence) and the dependent variable (behavioral intention). The second mediator variable is the behavioral intention between six independent variables (Effort Expectancy, Performance Expectancy, Trust, Anxiety, Perceived Severity, and Technology Awareness) and the dependent variable (adoption of IoT in nursing). As shown in Table 12 and depending on

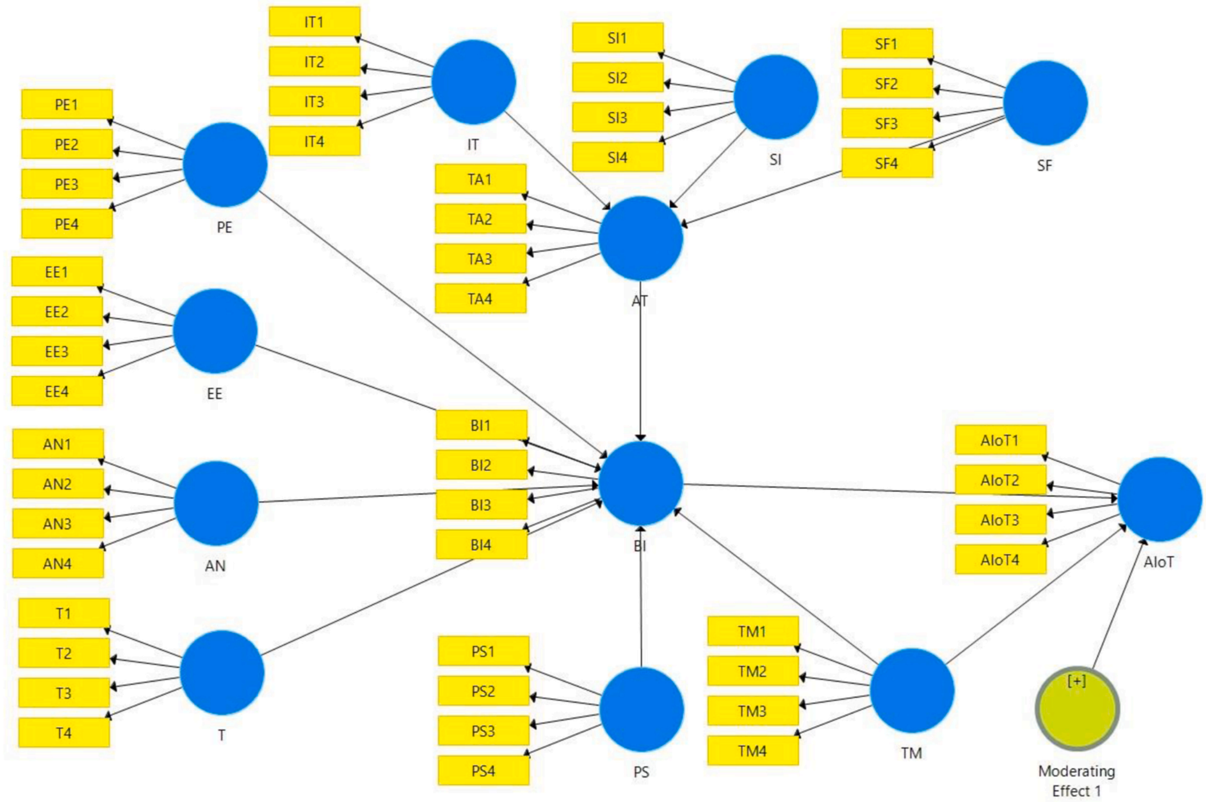

Fig. 6. PLS-SEM path diagram for study.

Table 11
Results of direct effects in study adoption.

Path	Beta	STDEV	T-Value	P-Value	Status
H1: EE→BI	0.228	0.100	0.221	0.825	Not Significant
H2: PE→BI	2.137	0.099	2.104	0.036**	Sig (p¡0.05)
H3: T→BI	2.598	0.143	2.473	0.014***	Sig (p¡0.01)
H4: AN→BI	0.486	0.067	0.496	0.620	Not Significant
H5: PS→BI	0.124	0.074	0.122	0.903	Not Significant
H6: AT→BI	0.464	0.041	0.041	0.485*	Not Significant
H7: IT→AT	5.458	0.088	5.676	0.000***	Sig (p¡0.01)
H8: SF→AT	0.280	0.089	5.111	0.000***	Sig (p < 0,01)
H9: SI→AT	3.420	0.106	3.445	0.014***	Sig (p < 0,01)
H10:BI→AIoT	5.372	0.041	4.99	0.00	Sig (p < 0,01)
H11:TM→BI	3.584	0.091	3.549	0.000***	Sig (p < 0,01)
H12:TM→AIoT	4.295	0.073	3.981	0.000***	Sig (p < 0,01)

T-Value >2,58, significant at 1 % (p < 0,01) T-Value >1,96, significant at 5 %.
T-Value >1,65, significant at 10 %(p < 0,10).
Notes: *** p-value< 0,01; ** p-value< 0,05; * p-value <0,10.

VAF values, there is no significant effect SF on BI and A IoT. Moreover EE, AN, PS, and SF do not have a significant effect on BI and A IoT. On another hand, there is a partial mediating effect of IT on AT and BI, and a fully mediating effect on SI, AT, PE, T, and TM on BI and AIoT.

6.8. Moderating effect (top management as a moderator)

According to Taherdoost [75] is defined as a qualitative variable such as sex, race, class, or quantitative variable. For example, the level of courage that influences the relationship between the independent and dependent variables is also considered a variable that increases the intensity of the interaction between a dependent variable and the independent variable. Therefore, the effect of the moderator variable can be on the strength or direction of independent and dependent variables.

Several studies, such as those conducted by Poltak et al. [76], have examined how top management support affects the relationship between independent and dependent variables. To confirm a moderator effect, two conditions must be met: first, the moderator

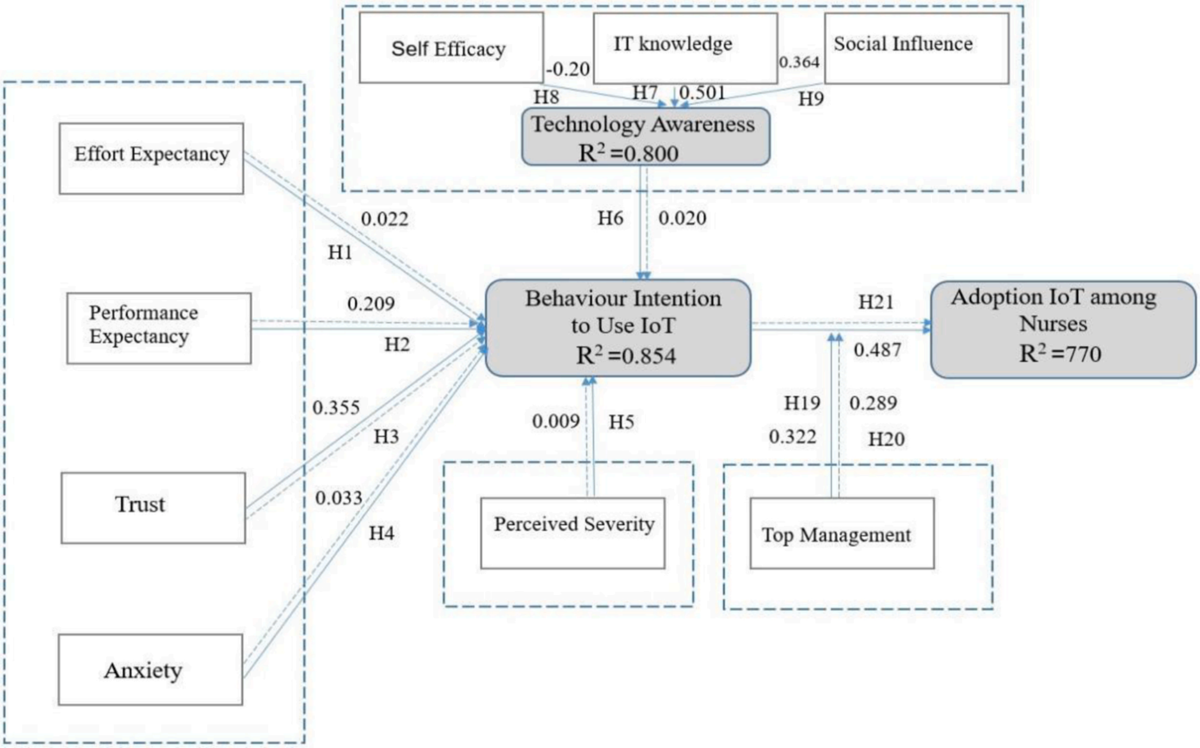

Fig. 7. Results of Direct Effects for Study Adoption. Value on path: standardized coefficients (β), R^2: Coefficiento f determination, $***p < 0{,}01$, $***p < 0{,}05$, $*p < 0{,}100$.

Table 12
Results of mediating effect for adoption.

Path	Standardized Beta (β)	Standard Error (SE)	T-Value	P- Value	VAF	Status
H13:IT→AT→BI	0.010	0.046	0.216	0.829	0.4	Partially Mediating
H14:SF→TA →BI	0.09	0.051	1.862	0.063	0.00	No Mediating
H15:SI→TA →BI	0.160	0.076	2.118	0.035	1.00	Fully Mediating
H16:EE→BI→AIoT	0.004	0.037	0.111	0.912	0.00	No Mediating
H17:PE→BI→AIoT	0.095	0.032	0.469	0.639	1.00	Fully Mediating
H18:T→BI→AIoT	0.009	0.019	0.468	0.640	1.00	Fully Mediating
H19:AN→BI→AIoT	−0.015	0.021	0.460	0.646	0.00	No Mediating
H20:PS →BI→AIoT	0.009	0.003	0.118	0.906	0.00	No Mediating
H21:AT→BI →AIoT	0.007	0.016	0.457	0.648	1.00	Fully Mediating
H22:TM→BI→AIoT	0.146	0.049	2.966	0.003	2.00	Fully Mediating
H23:IT→AT→BI→AIoT	0.005	0.010	0.460	0.646	1.00	Fully Mediating
H24:SI→AT→BI→AIoT	0.003	0.008	0.435	0.663	1.00	Fully Mediating
H25:SE→AT→BI→AIoT	−0.000	0.002	0.115	0.908	0.00	No Mediating

Fully Mediating if VAF > 0.8, Partially mediating if 0.2 < VAF < 0.8, Not Mediating if VAF < 0.2.

variable should be significant, and second, the moderator should either increase or decrease the intention. This research examines the moderating role of top management support on the connection between nurses' behavioral intentions to use IoT and the adoption of IoT among nurses. The results of the structural model, which was analyzed using the PLS method and bootstrapping technique, are presented in Table 13. The table shows that top management support has a significant positive impact on the adoption of IoT in nursing at a 99 % confidence level (Standardized estimate = 0.846, $p < 0{,}01$).

Additionally, Fig. 8 illustrates that top management support reduces the positive relationship of the healthcare sector with the adoption of IoT devices, particularly in nursing care, and enhances the adoption of IoT devices. On the other hand, the lack of top management support in the healthcare sector will reduce the adoption of IoT devices.

7. Discussion

According to the findings of this research, there is a need to find effective factors before the healthcare system is designed. Before finalizing the design of the system, these factors must be figured out in order to predict how well the system will work once it is built.

Table 13
Direct effect and moderating effects.

Path	Coefficient	T-Value	P-Value
Adoption of IoT among Nursing $R^2 = 0,861$			
Moderator Effect→AIoT	0.846	2.77	0.006 (p¡0.01)
TM→AIoT	0.289	3.098	0.002 (p¡0.01)
MT→BI	0.322	3.456	0.001 (p¡0.01)

T-Value >2.58, significance at 1 %.
T-Value >1.96, significance at 5%.

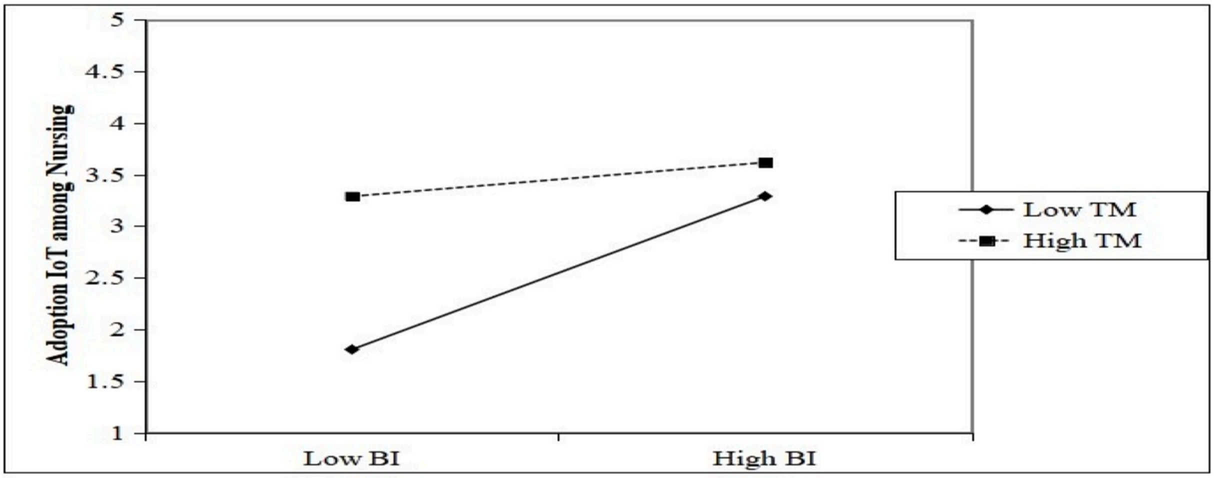

Fig. 8. Moderator effect (Top Management) on the relationship between Behavior Intention to use IoT and Adoption of IoT.

Effective factors are those that have an impact on how a system is used and how satisfied users are with it (Keikhosrokiani y et al., 2019). Furthermore, to ensure user interest in using a healthcare system, it is essential to determine their willingness to adapt to the system before finalizing the system design. A theoretical model was proposed to find the effective factors for the adoption of IoT in nursing care in Amman City comprising twelve constructs including Performance Expectancy (PE), Effort Expectancy (EE), Trust (T), Anxiety (AX), IT Knowledge (IT), Self-Efficacy (SE), Social Influence (SI), Technology Awareness (TA), Perceived Severity (PS), Top Management Support (TM), Behavioral Intention to Use (BI), and Adoption IoT among Nurses (A IoT) along with twenty-seven hypotheses. The results of this study were utilized to figure out the effective factors that influence the adoption of IoT devices in nursing care. The results are shown in Table 11. The results indicate that IoT devices in nursing care must have the ability to enhance nurses' performance and nursing srvices, and Trust is another factor that positively affects nurses' acceptance and intention to use IoT devices in their duties. IT Knowledge, Self-Efficacy, and Social Influence positively affect directly awareness about IoT devices in nursing care and indirectly the user intention to use IoT devices in nursing care services. Moreover, Top Management Support positively affects directly the intention to use IoT devices and adoption among Nurses, and Behavioral Intention to Use positively affects directly adoption of IoT among nurses. A total of 27 hypotheses were put forward regarding the adoption of IoT technology models, consisting of 12 general hypotheses, 13 hypotheses related to mediating effects, and 2 hypotheses concerning moderating effects. Over 50 % of the hypotheses have been deemed acceptable for this particular study. The findings of this study suggest that IoT devices, particularly those implemented in the context of nursing care, should be designed to fulfil the specific requirements of nurses, offer practical benefits to users, and enhance the quality of nursing services. The system is required to meet the patient's requirements for monitoring, assisting, and treating patients in the event of emergency data, with a significant emphasis on maintaining privacy.

On the other hand, the knowledge and ability of nurses to use the Internet is a crucial factor in speeding up the acceptance of IoT technology. Similarly, the nurses a perceptions of their ability to use IoT and the opinions of friends and colleagues are very important to accepting the use of IoT devices in carrying out nursing duties. Top management has a crucial role in facilitating the implementation of IoT technology in the nursing care sector.

Finally, the nurses a intention and acceptance are considered critical in the adoption process. Interpretation of the results is shown in Table 14. According to Table 11 the range of relationships between the variables of interest and their respective influences on Behavioral Intention (BI) and Adoption of the Internet of Things (AIoT). In the context of Effort Expectancy (EE) affecting BI, the first hypothesis (H1:$\beta = 0.228$, $p = 0.825$), did not reach statistical significance. Similarly, the influences of Anxiety (AN) on BI (H4: $\beta = 0.486$, $p = 0.620$), Perceived Security (PS) on BI (H5: $\beta = 0.124$, $p = 0.903$), and Technology Awareness (TA) on BI (H6: $\beta = 0.464$, $p = 0.485$) were also not statistically significant.

Nevertheless, a study by Arfi et al. [9] suggests that EE, possessing a significant influence ($\beta = 0.170$; $t = 2.298$), could play a crucial role. This viewpoint is further substantiated by research conducted by Dahri et al. [38] that establishes a significant correla-

Table 14
Interpretation of the results from this study.

Effective Factors	Effect	Features for system design from the results of Study
Performance Expectancy (PE)	Direct and Indirect	-Must be useful for the nurses and improve nursing duties -The system must fulfill expected services for monitoring, assisting and treatment of patients in case of emergency
Trust (T)	Direct and Indirect	-Data and privacy is very important
IT knowledge (IT)	Direct and Indirect	-The knowledge and ability of nurse's about using Internet is very important
Self-Efficacy (SE)	Direct and Indirect	- The nurseâs perceptions of his or her ability to use IoT is very important
Social Influence (SI)	Direct and Indirect	-Friends' and colleague's opinions are very important to motivate nurses to use IoT devices in their duties.
Top Management Support (TM)	Direct and Indirect	-Top management members have a crucial role to facilitate implement IoT technology in the nursing care sector
Behavior Intention to Use IoT	Direct	-Nurse's motivation and acceptance is very important in adoption process. -Top management members speed up the adoption process by preparing infrastru

tion between EE and BI. PE and BI ($T = 3.288$, $P = 0.000$)in the context of *M*-IOT wearable technology. Furthermore, research conducted by Humida et al. [77] substantiates that Anxiety exhibits significant predictive power ($\beta = 0.186$, $p < 0.01$) towards Behavioral Intention (BI) in the context of e-learning system utilization by students. This evidence indicates that student anxiety is a significant factor in their intention to use e-learning systems.

A separate study by Kwak et al. [78] establishes that Anxiety exhibits a positive correlation with a negative attitude towards Artificial Intelligence (AI), although this correlation is not statistically significant at the 0.05 level ($t = 1.65$ $p = 0.102$), while in the study conducted by Bhadauria y Chennamaneni [41] Anxiety is not significant in Adoption IoT devices. This suggests that heightened levels of anxiety may contribute to negative attitudes toward AI, but the evidence is not sufficiently strong to assert this as a statistically significant trend.

Additionally, the research executed by Upadhyay et al. [42] explains that Perceived Severity (PS) presents a significant influence ($\beta = 0.121$, $t = 2.053$, $p < 0.0001$) on consumers' behavioral intention and use behavior concerning mobile payment services during the COVID-19 pandemic. This finding underscores the essential role that perceived severity could play in shaping users' attitudes and subsequent behavioral intentions toward mobile payment services amid a global health crisis. Contrarily, hypotheses H2, H3, H7, H8, H9, H10, H11, and H12 exhibit significant results. Specifically, Performance Expectancy's (PE) impact on BI (H2:$\beta = 2.137$, $p < 0.05$), Trust's (T) effect on BI (H3: $\beta = 2.598$, $p < 0.01$), Intention Trust's (IT) effect on Attitude (AT) (H7: $\beta = 5.458$, $p < 0.01$), Social Factors' (SF) effect on AT (H8: $\beta = 0.280$, $p < 0.01$) Social Influence's (SI) effect on AT (H9: $\beta = 3.420$, $p < 0.01$), BI's effect on A IoT (H10:$\beta = 4.295$, $p < 0.01$), Top Management Support (TM) effect on BI (H11: $\beta = 3.584$, $p < 0.01$), and TM's effect on AIoT (H12: $\beta = 4.295$, $p < 0.01$) were all statistically significant at either the 1 % or 5 % level. On another hand, During the Bootstrapping analysis, the researcher investigated the mediating effects of TA on the relationship between the independent and dependent variables within the structural model. The first mediating variable, TA, demonstrated mediation effects between the independent variables of IT, SE, and SI, and the dependent variable of BI.

The second mediating variable, BI, exhibited mediation effects between the independent variables of EE, PE, T, AN, PS, and TA, and the dependent variable of Adoption of IoT In Nursing (AIoT). Table 12 displays the mediating effect analysis of the Variable Affecting Factor (VAF). The results obtained from the analysis of the VAF values indicate that Performance Expectancy (PE) exerts a direct influence on Behavioral Intention (BI), subsequently influencing the Adoption of IoT. This relationship is fully mediated, suggesting that individuals' perception of the favorable benefits and positive outcomes associated with utilizing IoT technologies strengthens their intention to adopt them, ultimately leading to a higher likelihood of actual adoption.

Similarly, Trust (T) directly influences Behavioral Intention and indirectly affects the Adoption of IoT. Trust in the technology or the entities promoting IoT positively influences individuals' behavioral intention to adopt IoT. When individuals have a higher level of trust, they are more likely to develop a positive intention, which, in turn, increases the likelihood of adopting IoT. Furthermore, the study reveals that Top Management Support (TM) influences the Adoption of IoT through its mediating effect on Behavioral Intention. Top management creates a positive organizational climate that fosters employees' intention to adopt and embrace IoT technologies. Technology Awareness (TA) has a direct influence on Behavioral Intention and indirectly affects the Adoption of IoT. Individuals' awareness of the technology, including its functionalities and potential applications, positively influences their intention to adopt IoT. This mediating effect signifies the crucial role of awareness in shaping individuals' likelihood of actual adoption.

Moreover, Social Influence (SI) indirectly influences the adoption of IoT through its mediation via technology awareness and behavioral Intention. Social factors shape individuals' awareness of the technology, which, in turn, influences their behavioral intention to adopt IoT and subsequently impacts the likelihood of adoption. Additionally, IT Knowledge indirectly influences the Adoption of IoT through its mediation between Technology Awareness and behavioral Intention. Individuals with higher levels of IT knowledge possess a better understanding of IoT technology, which positively affects their behavioral intention and increases the likelihood of actual adoption.

These findings align with previous studies that highlight the positive impacts of Performance Expectancy, Trust, Top Management Support, Awareness Technology, Social Influence, and IT Knowledge on Behavioral Intention and the Adoption of IoT in various contexts. Studies conducted by Arfi et al. [9] Arfiet al. [9],Rajmohan y Johar [50], Alanazi y Soh [53], Hossain et al. [5], Abushakra y Nikbin [48], and Bukhari et al. [40] provide further support for the positive impacts of these factors on attitude and intention towards using IoT in eHealth. Furthermore, based on the analysis presented in Table 12, the significance of VAF becomes a critical factor in determining the presence and impact of mediating relationships.

Specifically, if the VAF is not found to be significant, it suggests that the mediating relationship may not exist or may not have a substantial influence on the relationship between the independent variable and the dependent variable. For instance, in the case of Self-Efficacy (SF), where the VAF between SF and Technology Awareness is not significant, it indicates that the mediating effect of Technology Awareness may not play a significant role in the relationship between SelfEfficacy and Behavioral Intention. Similarly, non-significant VAFs for Perceived Severity (PS), Effort Expectancy (EE), and Anxiety (AN) suggest that the mediating relationships may not hold significance in those cases. Several studies have examined the relationship between specific variables and Behavioral Intention to use IoT devices. Arfi et al. [9] found significant associations between EE and BI, suggesting that EE plays a crucial role in influencing individuals' intention to adopt IoT devices. Furthermore, Hossain et al. [5],Masmali et al. [79], and Rajmohan y Johar [50] revealed the significance of SE in shaping BI toward IoT device usage. In line with these findings, Chaulagain et al. [80] conducted a study that demonstrated the significant influence of PS on individuals' BI on to use of IoT devices.

Their results indicated that individuals' perception of the severity of consequences related to not using IoT devices significantly affects their intention to adopt them. Lastly, Bhadauria y Chennamaneni [41] conducted a study that revealed the significant impact of AN on BI towards IoT device usage. Their findings suggested that an individual's level of anxiety related to using IoT devices significantly influences their intention to adopt and utilize them.

According to Table 13, the analysis revealed significant moderator effects on the Adoption of IoT (A IoT).

The moderator variable demonstrated a coefficient of 0.846 ($t = 2.77$, $p < 0.01$), indicating a strong and positive influence on the Adoption of IoT. The significant T-value exceeding 2.58 (significance at 1 %) further strengthens the statistical significance of the moderator effect. Additionally, Top Management Support (TM) exhibited a coefficient of 0.289 ($t = 3.098$, $p < 0.01$), indicating a significant influence on the Adoption of IoT. The T-value exceeding 1.96 (significance at 5 %) highlights the statistical significance of this relationship. Furthermore, the analysis revealed that the moderator variable, Moderating Variable (MT), had a coefficient of 0.322 ($t = 3.456$, $p < 0.01$) on behavioral Intention (BI). The significant T-value emphasizes the significant influence of the moderator variable on Behavioral Intention. These findings provide evidence of the significant impact of the moderator variables on the Adoption of IoT and Behavioral Intention.

The statistical significance of the T-values supports the robustness and reliability of the observed relationships. These results suggest that the presence of the moderator variables plays a crucial role in influencing individuals' intentions and decisions related to the adoption of IoT. Further examination of these relationships can provide valuable insights into the factors that contribute to the successful implementation and adoption of IoT technologies.

Fig. 8 illustrates the impact of Top Management Support (TM) on the adoption of IoT devices. It shows that TM plays a moderating role by dampening the positive relationship between the healthcare sector, particularly the nursing care sector, and the adoption of IoT devices. This implies that the presence of strong Top Management Support in the healthcare sector positively influences the adoption of IoT devices.

Conversely, the absence or lack of Top Management Support in the healthcare sector leads to a decrease in the adoption of IoT devices. Previous studies have provided evidence supporting the significant effect of top management support on behavioral intention (BI) in adopting social commerce by SMEs. For instance, Abed [81] found a significant relationship between top management support and BI ($\beta = 0.32$, $p = 0.001$). Similarly, Hsu et al. [82] reported a significant result ($\beta = 0.34$, $t = 3.84$, $p < 0.001$), confirming the moderating role of top management support in influencing BI. These findings highlight the importance of top management support in fostering a positive environment for technology adoption and promoting the openness of organizations to embrace new technologies.

7.1. Implications and contributions

The main contributions of the research are the development of a theoretical framework model for the adoption of IoT in nursing care, and identifying the effective factors that impact the adoption of IoT among nurses in Amman City. According to the findings of the research, the contributions are summarized in two directions.

1 Empirical Contributions:

Define the list of effective factors. The effective factors influencing the adoption of IoT in nursing care in Amman City include Performance Expectancy (PE), Trust (T), Anxiety (AN), Technology Awareness (TA), IT knowledge (IT), Self-Efficacy (SE), Social Influence (SI), Top Management Support (TM), and Behavioral Intention to Use IoT. These factors play a vital role in shaping individuals' acceptance and utilization of IoT devices and systems in nursing care. Addressing these factors is essential for the successful implementation and integration of IoT technology, leading to improved healthcare practices and outcomes in the region.

The study develops a theoretical framework model for the adoption of IoT in nursing care.

The findings suggest that the adoption of IoT applications among nurses in Amman city can contribute to saving lives and improving the field of nursing. The study's results reveal that Performance Expectancy (PE), Trust (T), Anxiety (AN), Technology Awareness (TA), IT knowledge (IT), Self-Efficacy (SE), Social Influence (SI), and Top Management Support (TM) are significant factors impacting the Behavior Intention to Use IoT and adoption of IoT in nursing care.

2 Theoretical Contributions:

The proposed model of adoption of IoT in nursing care is adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT) and Health Belief Model (HBM) by adding ten main constructs and a moderator. The new model offers a more specific assessment model for adopting IoT in nursing care and can be expanded for use in different technology adoptions in nursing care and healthcare. Study II fills the gap in the literature by extracting the factors that impact the adoption of IoT applications in nursing care, addressing the gap between research and practice, which negatively affects the adoption of innovative technologies in the healthcare industry.

7.2. Limitations and future directions

There are several other limitations of the current study that future research could address. Firstly, the current study only focused on the assessment process of three hospitals in one city in Jordan, which limits the generalization of the findings to other healthcare settings. Future research could expand the study to include more hospitals and healthcare settings in Jordan and other countries to obtain a more representative sample. Secondly, the number of participants in this study is limited. Future research could increase the sample size to enhance the reliability and generalizability of the findings. Additionally, future research could investigate the perspectives of different stakeholders, such as patients, caregivers, and policymakers, to gain a more comprehensive understanding of the potential impact of IoT in healthcare.

Thirdly, the current study was conducted during the COVID- 19 pandemic, which may have influenced the adoption and implementation of IoT in healthcare. Future research could investigate the effective factors of IoT in healthcare in non-pandemic situations to provide a more comprehensive understanding of its application in healthcare.

Fourth, the present study solely explored the influential factors of IoT in nursing care, potentially overlooking the broader impact of IoT across other healthcare sectors. Future research endeavors could delve into the influential factors of IoT in various healthcare domains, including radiology, pharmacy, and primary care. Such investigations would offer a more holistic comprehension of IoT's potential influence in healthcare and pinpoint the healthcare sectors where IoT could prove most beneficial. Fifthly, the current study did not consider the potential impact of IoT on patient satisfaction and patient-provider relationships.

Future research could explore how IoT-enabled healthcare services affect patients' perceptions of care services affect patients' perceptions of care quality, trust in healthcare providers, and overall satisfaction with their healthcare experience.

We recommend future research involving physicians and other professional staff. Another consideration is the difficulty in implementing IoT security practices because of the difficulties in developing and implementing new security measures. Security issues should be included in business model frameworks for the IoT.

8. Conclusion

The findings of this research highlight the importance of identifying effective factors before the design of healthcare systems. These factors play a significant role in shaping system usage and user satisfaction. Moreover, it is crucial to ascertain users' intentions to adopt healthcare systems during the design phase to ensure user interest and engagement. Healthcare developers and organizations must be aware of potential obstacles and goals before proceeding with the design, testing, and implementation stages. On the other hand, examined effective factors from the perspective of nurses, emphasizing their importance in designing IoT healthcare systems for seamless adoption in nursing duties. Privacy, security, and alignment with users' tasks were identified as crucial considerations in system design to mitigate potential health effects.

Furthermore, the study underscored the significance of top management support in the nursing care sector for the successful utilization of IoT healthcare systems. The findings provide valuable insights for healthcare system developers, emphasizing the need for awareness, goal identification, and consideration of user needs. Professionals can benefit from healthcare IoT systems in their duties, while individuals, especially the elderly, can benefit from monitoring systems that prioritize prevention over cure.

Also, future-proofing healthcare facilities through advanced building engineering practices ensures they remain at the forefront of technological innovation. Moreover, User-centric design principles, highlighted in the individual awareness context, are crucial for the successful adoption of IoT among nursing professionals. Building engineers can prioritize ergonomic design, creating workspaces that facilitate the smooth incorporation of IoT devices into daily routines. This not only enhances user experience but also contributes to the overall efficiency and effectiveness of nursing care delivery.

The comprehensive model established by this study, integrating various behavioral and technological theories, emphasizes the interdisciplinary nature of IoT adoption in healthcare. This underscores the importance of collaborative efforts between healthcare professionals and building engineers. Long-term impacts include fostering a culture of collaboration where both fields work hand in hand to create innovative solutions that enhance patient care and facility management.

In conclusion, this research contributes to the understanding of effective factors and considerations in the design, testing, and implementation of healthcare IoT systems. The findings have practical implications for healthcare system developers, professionals, and individuals seeking improved healthcare outcomes through IoT technology. The long-term impacts extend beyond mere technological integration to shaping the very fabric of healthcare facilities, fostering adaptability, user-centricity, and resilience in the face of technological advancements.

Building engineers, armed with the insights from this study, can actively contribute to creating smart, efficient, and secure environments that elevate the standards of nursing care and healthcare delivery.

CRediT authorship contribution statement

Manal Al-Rawashdeh: Writing – Review & Editing, Writing – Original Draft, Visualization, Validation, Supervision, Software, Resources, Project Administration, Methodology, Investigation, Formal Analysis, Data collection, Conceptualization. **Pantea Keikhosrokiani:** Supervision. **Bahari Belaton:** Supervision. **Moatsum Alawida:** Supervision. **Abdalwhab Zwiri:** Review & Editing, Validation, Supervision.

Declaration of competing interest

This manuscript has not been published and is not under consideration for publication elsewhere. We have no conflicts of interest to disclose.

Data availability

The data that has been used is confidential.

References

[1] M. Alshamrani, Iot and artificial intelligence implementations for remote healthcare monitoring systems: a survey, Journal of King Saud UniversityComputer and Information Sciences 34 (8) (2022) 4687–4701.
[2] Bodur, Perceptions of Turkish health professional students toward the effects of the internet of things (iot) technology in the future, et al. Nurse Educ. Today. 79 (2019) 98–104.
[3] D. Hurley, G.H. Popescu, Medical big data and wearable internet of things healthcare systems in remotely monitoring and caring for confirmed or suspected covid-19 patients, American Journal of Medical Research 8 (2) (2021) 78–90, https://doi.org/10.22381/ajmr8220216.
[4] M. Javaid, A. Haleem, R.P. Singh, S. Rab, M.I.U. Haq, A. Raina, Internet of things in the global healthcare sector: significance, applications, and barriers, International Journal of Intelligent Networks 3 (2022) 165–175.
[5] M.I. Hossain, A.F. Yusof, A.S. Sadiq, et al., Factors influencing adoption model of continuous glucose monitoring devices for internet of things healthcare, Internet of Things 15 (2021) 100353.
[6] M. Mustafa, S. Alzubi, Factors affecting the success of internet of things for enhancing quality and efficiency implementation in hospitals sector in Jordan during the crises of covid-19, Internet of Medical Things for Smart Healthcare: Covid-19 Pandemic (2020) 107–140.
[7] AlZghoul, Towards nationwide electronic health record system in Jordan, et al., in: En: 2016 13th International Multi-Conference on Systems, Signals & Devices (SSD), IEEE, 2016, pp. 650–655.
[8] S.B. Junaid, A.A. Imam, A.O. Balogun, L.C. De Silva, Y.A. Surakat, G. Kumar, M. Abdulkarim, A.N. Shuaibu, A. Garba, Y. Sahalu, et al., Recent Advancements in Emerging Technologies for Healthcare Management Systems: A Survey. En: Healthcare, vol. 10, MDPI, 2022, p. 1940.
[9] W.B. Arfi, I.B. Nasr, T. Khvatova, Y.B. Zaied, Understanding acceptance of ehealthcare by iot natives and iot immigrants: an integrated model of utaut, perceived risk, and financial cost, Technol. Forecast. Soc. Change 163 (2021) 120437.
[10] Martınez-Caro, Healthcare service evolution towards the internet of things: an end-user perspective, et al. Technol. Forecast. Soc. Change. 136 (2018) 268–276.
[11] Masmali, Adoption of iot based innovations for healthcare service delivery in Saudi Arabia, et al., in: En: 2019 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE), 2019, pp. 1–9, https://doi.org/10.1109/CSDE48274.2019.9162390.
[12] F. Al-Turjman, M.H. Nawaz, U.D. Ulusar, Intelligence in the internet of medical things era: a systematic review of current and future trends, Comput. Commun. 150 (2020) 644–660, https://doi.org/10.1016/j.comcom.2019.12.030.
[13] M.I. Hossain, A.F. Yusof, A.R.C. Hussin, N.A. lahad, A.S. Sadiq, Factors influencing adoption model of continuous glucose monitoring devices for internet of things healthcare, Internet of Things 15 (2021) 100353, https://doi.org/10.1016/j.iot.2020.100353.
[14] R. Mieronkoski, I. Azimi, A.M. Rahmani, R. Aantaa, V. Terava, P. Liljeberg, S. Salantera, The internet of things for basic nursing careaa scoping review, Int. J. Nurs. Stud. 69 (2017) 78–90.
[15] Kang, Survey on the demand for adoption of internet of things (iot)-based services in hospitals: investigation of nurses' perception in a tertiary university hospital, et al. Appl. Nurs. Res. 47 (2019) 18–23.
[16] Carol Huston, The impact of emerging technology on nursing care: warp speed ahead, Online J. Issues Nurs. 18 (2) (2013).
[17] A. Koohang, C.S. Sargent, J.H. Nord, J. Paliszkiewicz, Internet of things (iot): from awareness to continued use, Int. J. Inf. Manag. 62 (2022) 102442, https://doi.org/10.1016/j.ijinfomgt.2021.102442.
[18] T. Osmonbekov, W.J. Johnston, Adoption of the internet of things technologies in business procurement: impact on organizational buying behavior, J. Bus. Ind. Market. (2018).
[19] Irfan, Internet of medical things: architectural model, motivational factors and impediments, et al., in: En: 2018 15th Learning and Technology Conference (L& T), IEEE, 2018, pp. 6–13, https://doi.org/10.1109/LT.2018.8368495.
[20] J. Abdullah, M.A. Marzukhi, M.H. Danial, M.K. Ghani, P. Kokchang, Technology adoption among town planners in Malaysia, International Journal of Sustainable Construction Engineering and Technology 14 (5) (2023) 161–169.
[21] Keikhosrokiani, Assessment of a medical information system: the mediating role of use and user satisfaction on the success of human interaction with the mobile healthcare system (iheart), et al. Cognit. Technol. Work. 22 (2) (2020) 281–305, https://doi.org/10.1007/s10111-019-00565-4.
[22] Kao, An exploration and confirmation of the factors influencing adoption of iot-based wearable fitness trackers, et al. Int. J. Environ. Res. Publ. Health. 16 (18) (2019) 3227.
[23] H. Taherdoost, A review of technology acceptance and adoption models and theories, Procedia Manuf. 22 (2018) 960–967.
[24] M.-T. Ho, P. Mantello, N. Ghotbi, M.-H. Nguyen, H.-K.T. Nguyen, Q.-H. Vuong, Rethinking technological acceptance in the age of emotional ai: surveying gen z (zoomer) attitudes toward non-conscious data collection, Technol. Soc. 70 (2022) 102011.
[25] M. Al-Rawashdeh, P. Keikhosrokiani, B. Belaton, M. Alawida, A. Zwiri, Iot adoption and application for smart healthcare: a systematic review, Sensors 22 (14) (2022) 5377.
[26] H. Gangwar, H. Date, A. Raoot, Review on it adoption: insights from recent technologies, J. Enterprise Inf. Manag. (2014).
[27] S.-L. Guo, L.-N. Han, H.-W. Liu, Q.-J. Si, D.-F. Kong, F.-S. Guo, The future of remote ecg monitoring systems, Journal of geriatric cardiology: JGC 13 (6) (2016) 528.
[28] Yang, An iot-cloud based wearable ecg monitoring system for smart healthcare, et al. J. Med. Syst. 40 (12) (2016) 286.
[29] Serhani, Ecg monitoring systems: review, architecture, processes, and key challenges, et al. Sensors. 20 (6) (2020) 1796.
[30] Ren, A novel cardiac auscultation monitoring system based on wireless sensing for healthcare, et al. IEEE journal of translational engineering in health and medicine. 6 (2018) 1–12.
[31] S.F. Khan, Health care monitoring system in internet of things (iot) by using rfid, in: En: 2017 6th International Conference on Industrial Technology and Management (ICITM), IEEE, 2017, pp. 198–204.
[32] J.H. Abawajy, M.M. Hassan, Federated internet of things and cloud computing pervasive patient health monitoring system, IEEE Commun. Mag. 55 (1) (2017) 48–53.
[33] B.S. Mostafa, A.H. Miry, T.M. Salman, Healthcare monitoring and analytic system based internet of thing, Iraqi Journal for Electrical And Electronic Engineering

(3RD) (2020).
[34] J.E. Shaji, B. Varghese, R. Varghese, A health care monitoring system with wireless body area network using iot, International Journal of Recent Trends Engineering & Research 3 (2017) 112–117.
[35] A. Kulkarni, M. Suchetha, N. Kumaravel, Iot based low power wearableecg monitoring system, Curr. Signal Transduct. Ther. 14 (1) (2019) 68–74.
[36] F.D. Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, MIS Q. (1989) 319–340.
[37] Venkatesh, A theoretical extension of the technology acceptance model: four longitudinal field studies, et al. Manag. Sci. 46 (2) (2000) 186–204.
[38] Dahri, An overview of ai enabled m-iot wearable technology and its effects on the conduct of medical professionals in public healthcare in Pakistan, et al. 3c Tecnol. 9 (2) (2020) 87.
[39] S. Gedam, S. Paul, A review on mental stress detection using wearable sensors and machine learning techniques, IEEE Access (2021), https://doi.org/10.1109/ACCESS.2021.3085502.
[40] S.A.A. Bukhari, F. Hashim, A. Amran, Pathways towards green banking adoption: moderating role of top management commitment, International Journal of Ethics and Systems 38 (2) (2022) 286–315.
[41] V.S. Bhadauria, A. Chennamaneni, Do desire, anxiety and personal innovativeness impact the adoption of iot devices? Information & Computer Security 30 (5) (2022) 730–750.
[42] N. Upadhyay, S. Upadhyay, S.S. Abed, Y.K. Dwivedi, Consumer adoption of mobile payment services during covid-19: extending meta-utaut with perceived severity and self-efficacy, Int. J. Bank Market. 40 (5) (2022) 960–991.
[43] Solangiet, An empirical study of internet of things (iot) abased healthcare acceptance in Pakistan: pilot study, et al., in: En: 2017 IEEE 3rd International Conference on Engineering Technologies and Social Sciences (ICETSS), IEEE, 2017, pp. 1–7.
[44] Zhu, Moderating factors influencing adoption of a mobile chronic disease management system in China, et al. Inf. Health Soc. Care. 43 (1) (2018) 22–41.
[45] Abubakar, The moderating effect of technology awareness on the relationship between utaut constructs and behavioural intention to use technology: a conceptual paper, et al. Aust. J. Bus. Manag. Res. 3 (2) (2013) 14–23.
[46] M. Zwilling, G. Klien, D. Lesjak, Ł. Wiechetek, F. Cetin, H.N. Basim, Cyber security awareness, knowledge and behavior: a comparative study, J. Comput. Inf. Syst. 62 (1) (2022) 82–97.
[47] Venkatesh, User acceptance of information technology: toward a unified view, et al. MIS Q.. (2003) 425–478.
[48] A. Abushakra, D. Nikbin, Extending the utaut2 model to understand the entrepreneur acceptance and adopting internet of things (iot), in: En: Knowledge Management in Organizations: 14th International Conference, KMO 2019, Zamora, Spain, July 15–18, 2019, Proceedings 14, Springer, 2019, pp. 339–347.
[49] Al-Momani, Factors that influence the acceptance of internet of things services by customers of telecommunication companies in Jordan, et al. J. Organ. End User Comput. 30 (4) (2018) 51–63.
[50] R. Rajmohan, M.G.M. Johar, Influence of social moderators on the internet of things of srilankan healthcare services, Int. J. Recent Technol. Eng. 9 (1) (2020) 2154–2164, https://doi.org/10.35940/ijrte.A2815.059120.
[51] O.M. Yigitbasioglu, External auditors' perceptions of cloud computing adoption in Australia, Int. J. Account. Inf. Syst. 18 (2015) 46–62.
[52] MacKinnon, How and for whom? mediation and moderation in health psychology, et al. Health Psychol. 27 (2S) (2008) S99.
[53] M. Alanazi, B. Soh, Behavioral intention to use iot technology in healthcare settings, Eng. Technol. Appl. Sci. Res. 9 (5) (2019) 4769–4774.
[54] C.-L. Hsu, J.C.-C. Lin, Exploring factors affecting the adoption of internet of things services, J. Comput. Inf. Syst. 58 (1) (2018) 49–57.
[55] C.-M. Chen, H.-W. Jyan, S.-C. Chien, H.-H. Jen, C.-Y. Hsu, P.-C. Lee, C.-F. Lee, Y.-T. Yang, M.-Y. Chen, L.-S. Chen, et al., Containing covid- 19 among 627,386 persons in contact with the diamond princess cruise ship passengers who disembarked in taiwan: big data analytics, J. Med. Internet Res. 22 (5) (2020) e19540, https://doi.org/10.2196/19540.
[56] Keikhosrokiani, Success factors in developing iheart as a patientcentric healthcare system: a multi-group analysis, et al. Telematics Inf. 35 (4) (2018) 753–775.
[57] J.W. Creswell, et al., Research Design: Qualitative and Mixed Methods Approaches, Sage Publications, London and Thousand Oaks, 2009.
[58] A.S. Al-Adwan, H. Berger, Exploring physicians' behavioural intention toward the adoption of electronic health records: an empirical studyfrom Jordan, Int. J. Healthc. Technol. Manag. 15 (2) (2015) 89–111.
[59] M.F. Ansari, A quantitative study of risk scores and the effectiveness of ai-based cybersecurityawareness training programs, International Journal of Smart Sensor and Adhoc Network 3 (3) (2022) 1.
[60] Silva, Internet of things: a comprehensive review of enabling technologies, architecture, and challenges, et al. IETE Tech. Rev. 35 (2) (2018) 205–220.
[61] M.-J. Wu, K. Zhao, F. Fils-Aime, Response rates of online surveys in published research: a meta-analysis, Computers in Human Behavior Reports 7 (2022) 100206.
[62] D. Strijker, G. Bosworth, G. Bouter, Research methods in rural studies: qualitative, quantitative and mixed methods, J. Rural Stud. 78 (2020) 262–270.
[63] N. Blunch, Introduction to Structural Equation Modeling Using IBM SPSS Statistics and AMOS, Sage, 2012.
[64] A. Maydeu-Olivares, C. Garcia-Forero, Goodness-of-fit testing, International encyclopedia of education 7 (1) (2010) 190–196.
[65] Gallagher, A journey into the unknown; taking the fear out of structural equation modeling with amos for the first-time user, et al. Market. Rev. 8 (3) (2008) 255–275.
[66] R.H. Hoyle, Handbook of Structural Equation Modeling, Guilford press, 2012.
[67] A. Karahoca, D. Karahoca, M. Aks oz, Examining intention to adopt to internet of things in healthcare technology products, Kybernetes (2017).
[68] H. Wang, D. Tao, N. Yu, X. Qu, Understanding consumer acceptance of healthcare wearable devices: an integrated model of utaut and ttf, Int. J. Med. Inf. 139 (2020) 104156, https://doi.org/10.1016/j.ijmedinf.2020.104156.
[69] L.M. Wolfle, Sewall Wright on the Method of Path Coefficients: an Annotated Bibliography, 1999.
[70] R. Sun, S. Zhang, T. Wang, J. Hu, J. Ruan, J. Ruan, Willingness and influencing factors of pig farmers to adopt internet of things technology in food traceability, Sustainability 13 (16) (2021), https://doi.org/10.3390/su13168861.
[71] S. Wright, The theory of path coefficients a reply to niles's criticism, Genetics 8 (3) (1923) 239.
[72] M.E. Sobel, Asymptotic confidence intervals for indirect effects in structural equation models, Socio. Methodol. 13 (1982) 290–312.
[73] E. Linder, G.J. Babu, Bootstrapping the linear functional relationship with known error variance ratio, Scand. J. Stat. (1994) 21–39.
[74] A.F. Hayes, Beyond baron and kenny: statistical mediation analysis in the new millennium, Commun. Monogr. 76 (4) (2009) 408–420.
[75] H. Taherdoost, What are different research approaches? comprehensive review of qualitative, quantitative, and mixed method research, their applications, types, and limitations, Journal of Management Science & Engineering Research 5 (1) (2022) 53–63.
[76] Poltak, The determinants of the effectiveness of internal audits with management support as the moderating variable, et al. International Journal of Multicultural and Multireligious Understanding. 6 (1) (2019) 33–51.
[77] T. Humida, M.H. Al Mamun, P. Keikhosrokiani, Predicting behavioral intention to use e-learning system: a case-study in begum rokeya university, rangpur, Bangladesh, Educ. Inf. Technol. 27 (2) (2022) 2241–2265.
[78] Y. Kwak, J.-W. Ahn, Y.H. Seo, Influence of ai ethics awareness, atitude, anxiety, and self-efficacy on nursing students a behavioral intentions, BMC Nurs. 21 (1) (2022) 1–8.
[79] F.H. Masmali, S.J. Miah, N.Y. Mathkoor, Internet of things-based innovations in saudi healthcare sector: a methodological approach for investigating adoption issues, in: En: 2020 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE), IEEE, 2020, pp. 1–5, https://doi.org/10.1109/CSDE50874.2020.9411588.
[80] S. Chaulagain, A. Pizam, Y. Wang, An integrated behavioral model for medical tourism: an american perspective, J. Trav. Res. 60 (4) (2021) 761–778, https://doi.org/10.1177/0047287520907681.
[81] S.S. Abed, Social commerce adoption using toe framework: an empirical investigation of saudi arabian smes, Int. J. Inf. Manag. 53 (2020) 102118.
[82] H.-Y. Hsu, F.-H. Liu, H.-T. Tsou, L.-J. Chen, Openness of technology adoption, top management support and service innovation: a social innovation perspective, J. Bus. Ind. Market. 34 (3) (2019) 575–590.