The Factors Influencing Internet of Things Adoption in Public Hospitals: A Pilot Study

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Abstract*—Incorporating Internet of Things (IoT) technologies in healthcare represents a significant leap forward, capable of transforming the delivery and management of medical services. As healthcare systems across the globe increasingly seek innovative solutions to improve efficiency, enhance patient outcomes, and reduce operational costs, IoT emerges as a key enabler of this transformation. Despite the widely recognized benefits of IoT, its adoption in the healthcare sector, particularly within public hospitals in developing countries, remains limited and is still in the early stages. Therefore, understanding the factors influencing its adoption is essential for supporting effective adoption and advancing digital healthcare initiatives. This study aims to assess the validity and reliability of the instrument designed to identify the factors influencing the adoption of IoT technology in Jordanian public hospitals. A structured survey instrument collected a preliminary dataset from forty decision-makers in Jordanian public hospitals. The survey items were developed based on constructs derived from the Technology-Organizational-Environment (TOE) framework and the Human-Organization-Technology fit (HOT-fit) model, supported by relevant literature. Descriptive statistics were performed using SPSS, while the reliability and validity of the instrument were assessed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results demonstrated that the measurement instrument had acceptable levels of reliability and validity, confirming its suitability for use in the main study. This study enriches the existing research and enhances the broader understanding of IoT adoption in healthcare organizations, offering insights that can be useful to both practitioners and researchers in this field.

***Keywords*—Internet of Things; adoption; Jordan; TOE**

I. Introduction

The advent of the Internet of Things (IoT) has marked the beginning of a transformative era, often known as the Fourth Industrial Revolution. This revolution is reshaping industries by enabling smart technologies and interconnected systems that influence how individuals live, work, and interact with their environment. The term IoT was first defined by Ashton [1] in 1999, within the context of supply chain management. Since then, the concept has evolved across various fields, reflecting its expanding applications. In general, IoT can be defined as a rapidly growing network of objects that are addressable and identifiable uniquely, where each of these objects connects to servers to transfer their data and extract valuable knowledge that efficiently provides appropriate services. What sets IoT apart from other technologies is its integration of smart features, sensors, and actuators that enable it to detect and collect data, communicate across systems, and perform real-time analysis of vast amounts of information from internal and external environments via a global network [2]. These remarkable capabilities of IoT have attracted the attention of various industries, including healthcare, manufacturing, transportation, agriculture, supply chains, and logistics, to adopt IoT. The healthcare industry has emerged as a highly attractive domain for IoT applications, with recent research increasingly emphasizing its implementation in healthcare settings [3]. IoT plays a vital role in enhancing various aspects of the healthcare system, including chronic illness management, elderly care, patient engagement, physician-patient interaction, remote patient monitoring, and authentication. Consequently, hospitals are increasingly encouraged to adopt IoT technology, as they have the potential to improve treatment outcomes, reduce errors, reduce treatment costs, and elevate the overall quality of the healthcare system [4].

However, the global population and rising life expectancies have substantially increased the demand for healthcare services, placing significant pressure on public health institutions worldwide [5]. As a result, hospitals and healthcare organizations are operating at nearly full capacity as they strive to meet the increasing demand for healthcare, particularly in terms of hospitalization. These challenges are particularly acute in developing countries, where public hospitals may struggle to provide quality, affordable, and accessible healthcare due to limited resources [6, 7]. Moreover, the emergence of the COVID-19 pandemic has brought attention to pre-existing issues within the healthcare system, particularly concerning shortages in the healthcare workforce and inequities in access to healthcare [8]. In response to these challenges, healthcare organizations continuously seek ways to enhance healthcare delivery quality. One promising avenue for improvement is the adoption of the IoT, which has demonstrated the potential to address various issues and challenges facing the healthcare system, as highlighted by research studies [9, 10].

While there is acknowledgment of the potential benefits of the IoT in enhancing public health efforts, its integration into the operations of these organizations is not yet widespread or fully mature [11]. According to Alifan, et al. [12], the current studies on health information technology in the Jordan context are still insufficient, and more comprehensive research is needed to better understand and address the unique challenges and opportunities in this area. Disruptive technologies, such as IoT, often emerge from edge markets, which may significantly change businesses and create value within any organization [13]. However, sector-wide implementation of these technologies presents significant challenges, as unexpected obstacles during the implementation process can result in project failure [14].

Organizations that are aware of the associated risks and adequately prepared for the changes brought by digital transformation are more likely to adopt emerging technologies successfully and avoid costly implementation failures [15]. Therefore, identifying and evaluating the factors that enhance organizational readiness is critical for facilitating the effective adoption of IoT in healthcare. According to Chang, et al. [13], considering the technical aspects of new technologies alongside an organization's internal and external resources will increase its readiness to adopt new technologies and avoid wasted resources and project risks.

In response to this gap, the present pilot study represents an initial effort to assess the validity and reliability of a measurement instrument developed to investigate the key factors influencing the adoption of the Internet of Things (IoT) in Jordanian public hospitals. The instrument is grounded in established theoretical foundations, drawing on constructs from both the Technology-Organization-Environment (TOE) framework and the Human-Organization-Technology Fit (HOT-Fit) model, which are widely used in technology adoption research. The questionnaire was administered to forty decision-makers and healthcare professionals across public hospitals in Jordan to evaluate the internal consistency, construct validity, and reliability of the proposed model using SPSS and Partial Least Squares Structural Equation Modeling (PLS-SEM). Given the highly regulated nature of Jordan's public healthcare sector and the national initiatives to advance healthcare technology and digital transformation, this study contributes to the limited body of literature on IoT adoption in this context and offers a foundation for future empirical investigations.

The remainder of this study is structured as follows. The next section presents the theoretical background and conceptual model underpinning the study. This is followed by a description of the research methodology and instrument development process. The subsequent section reports the findings from the pilot study, including statistical analyses and interpretation. Finally, the study concludes with a discussion of the study's implications, limitations, and suggestions for future research.

II. Theoretical Background

The adoption of Internet of Things (IoT) technologies in healthcare has been examined through several theoretical models that aim to understand and predict technology usage and acceptance. Among the most frequently employed are the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Theory of Planned Behavior (TPB), and Diffusion of Innovations (DOI). These models primarily address individual-level factors, such as perceived usefulness, ease of use, social influence, and facilitating conditions, and are typically tested through cross-sectional surveys targeting end-users like physicians or nurses [16]. While such approaches have significantly contributed to understanding user intentions, they fall short of capturing the organizational-level factors that influence technology adoption in healthcare institutions, particularly within the context of public hospitals in developing countries. In other words, models like TAM, UTAUT, and TPB do not account for the broader organizational and environmental conditions that influence technology adoption in public healthcare institutions. The adoption of IT innovations such as IoT is influenced by more than just user perceptions. While ease of use and usefulness are important, organizational factors often play a larger role. Factors such as leadership commitment, the availability of IT resources, existing infrastructure, regulatory mandates, and the organization's technical skills play a critical role in determining adoption readiness and implementation outcomes [17]. In many cases, especially in large institutions, the decision to adopt new technologies depends more on these internal capabilities than on individual user opinions. Since IoT adoption in public hospitals, particularly in developing countries like Jordan, remains an emerging research area, the focus of this research is on the organizational level, guided by the nature of IoT adoption in public hospitals, where decisions are typically made at the institutional rather than individual level.

This study adopts a theoretical lens approach to explore the factors influencing Jordanian public hospitals to adopt IoT. As defined by Creswell and Creswell [18], a theoretical lens approach involves applying established theories to investigate relatively new or under-researched topics. In this study, two complementary frameworks are used as guiding lenses: the TOE framework [19] and the HOT-Fit model [20]. Both models have been widely applied in technology adoption and health information systems research and provide a structured foundation for examining technological, organizational, environmental, and human factors that may shape IoT adoption in healthcare. Employing these theories as guiding lenses ensures that the research remains theoretically grounded while exploring an emerging issue within a complex healthcare environment.

The TOE framework has proven to be a practical tool for analyzing the adoption of various IT innovations, as noted by [21]. According to Salman et al. [22], the TOE model is suitable for measuring organizations' readiness to adapt to new work activities related to the use of new technology. Although the TOE framework was not originally developed for technology adoption in healthcare, its extensive use in prior healthcare studies has led to widespread acceptance, demonstrating its versatility. For example, Abdulaziz and Yasin [23] employed the TOE framework to understand the critical factors affecting the decision to adopt cloud computing within the healthcare industry; Yang, et al. [24] found that the TOE framework can be applied to identify the factors involved in the decisions made by integrated medical and healthcare organizations to adopt artificial intelligence (AI); and Anthony Jnr [25] indicated that the TOE framework is useful for identifying the critical factors that influence telehealth adoption. Similarly, Thyagaraj and Narayanan [26] used it to examine the adoption of IoT in the hospital context. These studies affirm the TOE framework's relevance and applicability, supporting its suitability for investigating IoT adoption in the healthcare industry. In contrast, In parallel, the HOT-Fit model was specifically designed to address the adoption and evaluation of health information systems (HIS), focusing on the interaction among human, organizational, and technological dimensions [20]. Its relevance lies in its healthcare-centered structure, which makes it highly applicable for studying IT adoption in hospital environments. According to Lian, et al. [27], human characteristics should be carefully considered when adopting technological innovations in the healthcare environment. Although previous research [28, 29] has underscored the significance of incorporating the human dimension when studying the adoption of IT within the healthcare domain. Nevertheless, the role of human behavior within hospital environments in shaping the adoption of information technologies has received limited attention in academic research [29]. Considering the substantial convergence between the TOE and HOT-fit models, this study integrates the TOE framework with the human dimension emphasized in HOT-Fit. Both models emphasize the significance of technological, organizational, environmental, and human readiness factors in driving innovation adoption. Consequently, integrating these models can encompass most of the readiness factors that impact the adoption of IoT in the healthcare sector. For these reasons, the integrated TOE–HOT-Fit model adopted in this study directly addresses the theoretical shortcomings identified in prior work, providing a more comprehensive framework for examining IoT adoption in public hospitals.

To effectively capture the combined influence of technological, organizational, environmental, and human factors on IoT adoption, researchers have proposed a formative construct known as "IoT Readiness". This construct serves as an integrative measure that reflects the overall preparedness of an organization to adopt IoT, based on the collective impact of these key dimensions [17, 30]. Each hospital or healthcare institution may face unique conditions, such as varying levels of technological infrastructure, organizational capacity, external support, and human resource readiness that shape their specific level of readiness. Therefore, IoT Readiness is not a singular or uniform concept; rather, it is shaped by the contextual variations across institutions and is essential for understanding how prepared a healthcare organization is to adopt and integrate IoT technologies. Cintrão [31] suggests that including technological readiness as a dependent variable of TOE determinants provides a unique perspective on the phenomenon of adopting new technologies. Similarly, Chang, et al. [13] argue that integrating IoT with the TOE framework and readiness perspectives allows for a comprehensive understanding of how technology readiness, organizational readiness, and environmental readiness collectively influence the effectiveness of IoT implementations. This combined approach enables a nuanced examination of these perspectives and offers a holistic approach to studying IoT adoption. Prior research has underscored the significance of these dimensions in evaluating readiness for adoption within healthcare contexts [15, 28, 32, 33], as well as in various other contexts [34-36]. These studies provided the foundational elements for establishing the initial integrated theoretical model for IoT readiness.

A. Technological Readiness

The technology context examines a technology's inherent characteristics and their impact on readiness to adopt IoT solutions. This includes factors such as relative advantage, compatibility, complexity, and security, collectively shaping technological readiness—an essential component of overall IoT readiness. Technological readiness refers to how individuals within an organization feel prepared and capable of adopting a new technology, such as the IoT, based on how they perceive its features and benefits [37]. This includes users' perceptions of whether the technology is compatible with existing systems, easy to use, secure, and advantageous. If organizational users view the technology as useful and appropriate for their work environment, they are more likely to be open and ready to adopt it [38].

1) Relative advantage. Among the technological readiness dimension factors is Relative advantage, which refers to the degree to which adopting a new technology, such as the IoT, in a hospital setting is perceived to provide tangible benefits over existing practices and technologies [27]. This study adopts the concept of relative advantage to investigate whether, and to what extent, the adoption of IoT in public hospitals is perceived as more beneficial than alternative technologies. These benefits include enhancing organizational competitiveness, reducing costs, improving operational efficiency, and streamlining work processes [39]. Relative advantage has been widely recognized as a critical determinant of technology adoption across various sectors, including healthcare [24, 40]. Previous studies have demonstrated that when healthcare institutions perceive clear advantages from IoT, they are more inclined to consider its implementation. This highlights the importance of evaluating relative advantage when assessing the potential for IoT adoption in hospital settings.

2) Compatibility. Compatibility is a critical technological factor identified in the Diffusion of Innovation (DOI) theory as a motivational driver for the adoption of new technologies. It refers to the extent to which a new technological solution, such as the IoT, is perceived to be consistent with existing values, cultural norms, knowledge, infrastructure, and operational requirements within an organization. In the context of healthcare, this includes the seamless integration of IoT with the hospital's current technological systems and healthcare workflows, both technical and managerial [26]. Organizations are more willing to embrace technologies that align with their established practices and strategic direction. Studies, such as Bhuiyan, et al. [41] and Karahoca, et al. [42], highlighted that compatibility among IoT devices is crucial for ensuring functional coherence and adaptability in healthcare environments. It is important to note that a lack of compatibility can cause concerns about the functionality of a system and its operational reliability.

3) Complexity. Complexity is a critical factor influencing an organisation's readiness to adopt new technology [43]. According to Rogers Everett [44], Complexity refers to "the degree to which an innovation is perceived as relatively difficult to understand and use". The perception of innovation complexity can vary among organisations based on their existing skills and knowledge. Some organisations may find an innovation complex due to a lack of necessary expertise, while others, with the required skills, may not perceive it as complex. Unlike other innovation characteristics, complexity often lacks a strong positive correlation with adoption [15]. In the context of IoT, higher perceived complexity has been found to influence adoption decisions negatively [40]. This issue is particularly pronounced in healthcare, where the environment is inherently complex, and the introduction of IoT can further amplify this complexity [45]. Consequently, healthcare organizations may resist adopting IoT if it is seen as complicating their management processes

4) Security. Although integrating IoT technology enhances an organization's productivity and efficiency, it also raises significant security and privacy issues. These concerns become more pronounced as the quantity and types of interconnected devices within organizations increase [46]. In the healthcare environment, ensuring security and privacy is a critical issue for both patients and is required by laws in many countries. Healthcare institutions must prioritize data security when utilizing IoT technology for storing and handling medical data [47]. Previous research has identified security and privacy as significant factors influencing the adoption of new technologies across various sectors. For instance, [48] found that these concerns significantly shaped hospital managers' intentions to adopt RFID technology. Similarly, Hawash et al. [49] reported a positive impact of security-related factors on IoT adoption in the oil and gas industry. Dewi et al. [36] and Sam and Chatwin [30] also examined security and privacy constructs to evaluate organizational readiness for Smart City and Big Data Analytics initiatives in Indonesia and China, respectively. These findings underscore the critical role of security and privacy in shaping organizational readiness for adopting emerging technologies like IoT.

B. Organizational Readiness

Organizational readiness is defined as the extent to which public hospitals can provide and manage all the resources necessary for the successful adoption and integration of IoT technologies into their operations [36]. It emphasizes the institution's internal capacity to support and sustain the implementation process. According to Yang et al. [17], the IT Infrastructure and Top Management Support emerge as two important organizational readiness factors for technology adoption.

1) Top management support. Top management support reflects the commitment of senior leadership to actively promote and enable the adoption of new technologies throughout the organization [50]. This includes their willingness to allocate the necessary resources, offer clear guidance, and remain actively involved in planning, evaluation, and supervision throughout the adoption process. In the context of IoT adoption in healthcare, strong commitment from top management is essential because it helps ensure that the organization is adequately prepared and motivated to embrace such innovations [51]. Without this support, efforts to adopt and implement IoT solutions may face resistance or lack direction. The transition from traditional Information Technology (IT) systems to Internet of Things technologies within healthcare organizations is not merely a technical upgrade but a carefully considered strategic decision. Therefore, the proactive involvement of top executives, especially their awareness of IoT's potential benefits, plays a crucial role in successful adoption [52]. In addition, as IoT technologies are often expensive and resources are limited, top management can create a conducive environment and allocate essential resources such as expertise and infrastructure [53]. Adequate resources are crucial for the successful implementation of IoT projects, and strong top management support has consistently been identified as a vital factor for the adoption and diffusion of large systems.

2) IT infrastructure. Besides top management support, a strong IT infrastructure is essential for successfully adopting IoT technology within the firm. It provides the foundation for seamless communication and data transfer between IoT devices. Technology infrastructure can be characterized as an integrated and interconnected system comprising computer hardware, software, networks, and tangible equipment that are essential to adopting new technologies [54]. IT infrastructure has been frequently used in literature to study the adoption of IoT in many contexts, including healthcare, where IT infrastructure stands out as a significant factor in the adoption of IoT technology in the healthcare environment [55, 56]. According to Abd El-Hamed et al. [57], organizations that plan to adopt IoT technologies should prioritize evaluating and enhancing their IT infrastructure to ensure it can support emerging technological requirements. Similarly, Rey et al. [58] highlight the significance of having reliable and ready technological systems before integrating IoT into business operations. Therefore, organizations with a well-developed and dependable technology infrastructure are more likely to adopt IoT solutions successfully.

C. Environmental Readiness

Environmental readiness refers to the organization's perception of external factors influencing its decision to adopt IoT. It reflects how hospitals respond to the environment in which they operate, including competitive pressure, government support, and the availability of vendor support. These external conditions shape how organizations carry out their activities during the adoption of new technologies.

1) Competitive pressures. Which arise from the threat of losing a competitive advantage in the industry to other competitors, prompt organizations to adopt new technologies to improve their competitiveness and enhance their productivity [59]. While competition is typically associated with the private sector, similar dynamics are increasingly observed in the public healthcare sector. As hospitals witness peer institutions integrating emerging technologies such as the IoT, the pressure to keep pace becomes a compelling motivator [26]. When hospital decision-makers believe that IoT adoption can improve operational efficiency and help them remain competitive, their willingness to invest in such technologies increases [52]. Several studies confirm that competitive pressure catalyzes technology adoption, especially when organizations trust that the innovation will enable them to outperform others [26, 32]. Therefore, the intensity of competition may significantly influence a healthcare organization's readiness to adopt IoT.

2) Vendor support. Given the complexity of IoT technology and the diverse range of devices involved, implementing an IoT system involves intricate features. Therefore, robust vendor support is essential during and after implementation to ensure a smooth deployment and continued operation [46]. Vendor support refers to the assistance and services provided by technology suppliers to their clients. This support typically includes technical assistance, problem-solving, maintenance services, training, and other resources aimed at helping clients effectively implement, use, and maintain the technology [60]. Previous studies [61, 62] have indicated that vendor support plays a significant role in influencing technology adoption in the healthcare environment. Hence, organizations with adequate vendor support for IoT implementation and operations will experience greater success in incorporating IoT technologies than those without such support.

3) Government support. Refers to the various forms of assistance provided by public authorities to foster the adoption of technological innovations [63]. Such support is vital for promoting IoT integration within the healthcare sector. Ahmetoglu et al. [64] emphasize that governmental pressure can significantly accelerate the adoption process of emerging technologies. Since healthcare institutions are primarily public or private entities that operate under strict government regulation and oversight, the role of government becomes especially influential. Therefore, governments often implement a range of financial and non-financial initiatives, such as funding programs, favorable policies, investment schemes, tax incentives, and educational or strategic interventions, to encourage innovation and digital transformation in healthcare [55, 65]. This form of government support can directly or indirectly facilitate the readiness and implementation of IoT solutions across public healthcare organizations.

D. Human Readiness

Focusing on the human aspects of IT innovations in healthcare is crucial because ultimately, end stakeholders should be able to utilize IT innovations effectively. According to Alharbi et al. [66], it is crucial to consider the human aspect before implementing any IT project, as it significantly influences the adoption of new technology. Hence, this research will apply some of the HOT-fit model concepts related to the human perspective to understand the decision to adopt IoT in the healthcare sector.

1) Technical competence. Refers to the capability of IS/IT staff to effectively understand, adapt, and implement technological innovations within their field [67]. Concerning technological advancement in the healthcare sector, previous studies have highlighted the importance of technical competence (the capability of IS staff) as a crucial factor that influences healthcare organizations to effectively adopt IT/IS innovations [27, 28, 67]. According to Lian [27], the availability of a robust Information Systems (IS) department, equipped with highly skilled staff, is crucial for solving business problems and seizing opportunities through the use of IT. When hospital IT staff are well-trained and knowledgeable about new technology, they feel more confident and assured when implementing it within the hospital setting. Regarding the IoT, technical competence is considered an essential indicator for decision-makers who want to adopt IoT technology [68, 69]. According to Savoury [70], organizations need to ensure the availability of skilled and knowledgeable staff before adopting and integrating IoT solutions into their business operations. This emphasizes the importance of having skilled staff who can handle the complexities of IoT technology, thus ensuring the successful adoption of IoT projects.

2) Employees' knowledge. Human resources are a critical asset in any organization, and their knowledge and skills play a significant role in the successful adoption of new technologies [67]. In addition to infrastructure investment, empowering employees with adequate IoT-related knowledge is essential for effective implementation and for gaining a competitive advantage. IT-proficient employees have been shown to play a key role in technology adoption, especially in healthcare settings [71]. For instance, Abugabah et al. [29] found that employee IT knowledge was a critical factor in adopting RFID technology in hospitals. Similarly, Liu [72] emphasized the need to evaluate IS/IT skills before implementing telecare systems. The introduction of IoT technologies in healthcare leads to significant changes in traditional workflows, including how data is collected, shared, and utilized across departments [73]. These changes can create challenges for staff who are accustomed to established routines and systems. As a result, ensuring that employees possess adequate operational knowledge and situational awareness becomes essential for the successful integration and effective use of IoT. Without proper understanding, even the most advanced IoT systems may be underutilized or mismanaged, ultimately hindering the intended improvements in efficiency and patient care.

E. IoT Readiness

Despite the potential benefits of IoT implementation, IoT is still in its early stages of development, and several adoption issues must be overcome before it can be widely adopted [74]. These issues extend beyond technological issues and encompass organizational and environmental factors, which can result in financial costs for the organization and may disrupt or impede the successful adoption of IoT initiatives [46]. According to Chang et al. [13], disruptive technologies, such as IoT, often emerge from edge markets, which may significantly differ from the core operations of established organizations. Consequently, when organizations are unprepared for the changes brought by the new technologies, implementing these technologies may fail to meet expectations. The authors emphasized that if organizations only consider the technical aspects of new technologies when adopting them, without considering their internal and external resources, it can result in wasted resources and project risks. Similarly, Dewi et al. [36] underscored that adopting Internet of Things technology involves inherent risks and uncertainties. Therefore, the willingness to embrace these challenges will significantly impact an organization's decision to adopt IoT. When an organization is adequately prepared and informed about the risks and uncertainties associated with adopting an innovation, the organization becomes more willing to adopt this innovation [15]. Therefore, Readiness for IoT adoption is a critical determinant that can shape an organization's intention to adopt IoT technologies. Consequently, hospitals with a higher level of preparedness are better positioned to implement and leverage IoT technologies effectively. Fig. 1 illustrates the initially proposed IoT readiness adoption model.

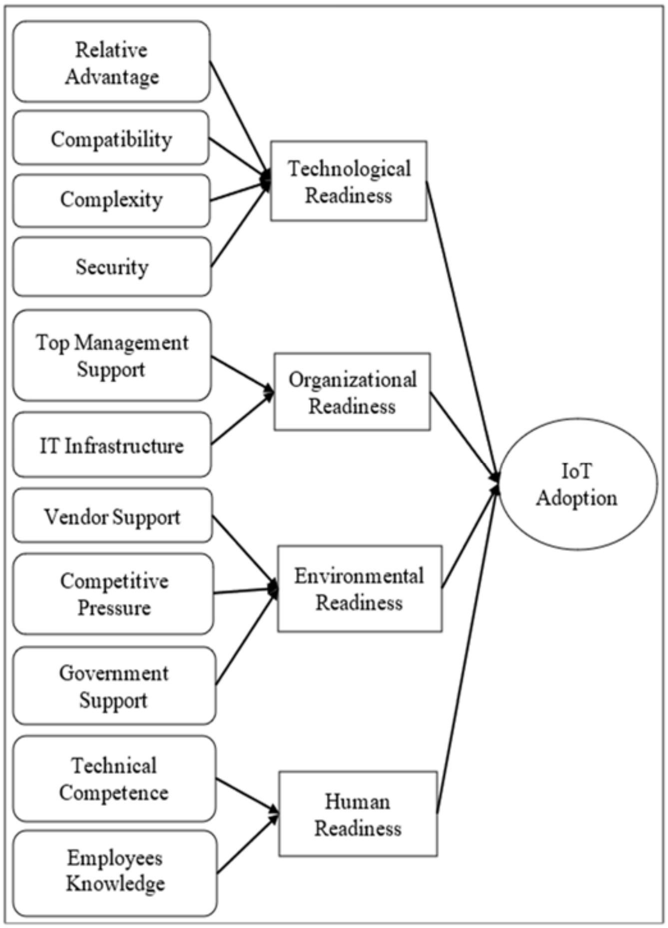

Fig. 1. Proposed research model.

III. Research Methodology

A. Instrument Design

A pilot study was carried out to assess the reliability and validity of the proposed IoT readiness adoption model. The survey instrument used in this study was carefully designed based on insights from previous literature, incorporating elements from both the TOE framework and the HOT-Fit model, which are commonly applied in healthcare technology adoption research. The development of the survey questionnaire was grounded in a review of existing literature, which provided a theoretical foundation for identifying the eleven key factors included in the proposed model. These factors are assumed to influence the adoption of IoT in hospital settings. Therefore, to accurately measure respondents' perceptions, it was essential to establish appropriate measurement scales for each factor. These scales ensure that each construct is represented by a set of items that reliably and validly capture the underlying concept related to IoT adoption in the healthcare context.

The questionnaire design followed three essential criteria: the clarity and formulation of questions, the strategic classification of variables, and the visual presentation of the instrument. The development process began with a comprehensive review of validated items from previous studies related to technology adoption and readiness. These items were then adapted to suit the specific context of IoT adoption in Jordanian public hospitals. The modifications ensured that the items were clear, contextually relevant, and appropriate for measuring the technological, organizational, environmental, and human dimensions that underpin this research. The survey instrument was organized into three sections. The first section introduced the study's purpose and emphasized the confidentiality of respondents' identities and responses. The second section collected demographic and background information. The third section gathered data for testing the proposed research framework by assessing the perceived influence of four readiness dimensions, Technology, Organization, Environment, and Human, on the intention to adopt IoT in Jordan's public hospitals. A five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree") was used. Table I provides an overview of the constructs, the number of items per construct, and supporting references.

TABLE I. Measurement of Constructs

Variables	No of Items	Source
Relative Advantage	4	[70, 75-77]
Compatibility	4	[70, 75, 77, 78]
Complexity	4	[33, 77, 79, 80]
Security	3	[61, 77, 81, 82]
Top Management support	4	[17, 75, 83, 84]
IT Infrastructure	4	[17, 85, 86]
Competitive Pressure	4	[17, 67, 87]
Vendor Support	4	[87, 88]
Government Support	5	[70, 75, 82, 89]
Employee Knowledge	4	[67, 77, 87]
Technical competence	3	[27, 67, 85, 88]
Intention to adopt IoT	4	[17, 30, 90]

B. Content Validity

Expert judgment was employed as a primary method to evaluate the relevance and clarity of the questionnaire items to establish content validity. Five experts specializing in Information Systems (IS) and health information technology were selected based on their academic expertise and familiarity with the study's context. According to Lynn [91], a panel of at least three experts is recommended for content validation, while more than ten is generally unnecessary. The selected experts were explicitly chosen for their knowledge of the IS domain and their understanding of the study's objectives, ensuring that their evaluations were aligned with the intended research focus. Each expert was asked to assess the questionnaire items regarding their relevance to the constructs being measured and the simplicity of their wording. This process allowed for the systematic evaluation of item appropriateness and linguistic clarity. Several revisions were made to enhance the instrument based on the feedback received. Some items were simplified to improve comprehension, while others were reworded to increase clarity and eliminate ambiguity. This content validation process helped to ensure that the questionnaire was conceptually sound and practically accessible to the targeted respondents, thereby strengthening its overall validity [92].

C. Pilot Study

A pilot study survey involves conducting a smaller-scale version of the actual data collection process to evaluate its feasibility. This preliminary step is typically performed before a large-scale study to determine if the research is practical and to avoid the full costs and effort of a comprehensive study [93]. The main goal of the pilot study is to determine whether the survey instrument requires modifications. By conducting a pilot study, researchers can identify potential issues in the study design, such as unclear questions, logistical challenges, or unexpected responses, and make necessary adjustments before proceeding to the main study. In this study, the pilot questionnaire was distributed to 40 participants from public hospitals in Jordan, including key stakeholders such as senior management (e.g., CEO, CIO, CMIO), middle management (e.g., department heads, project managers), IT and technical staff (e.g., IT managers, system administrators, system analysts), and senior medical professionals. These respondents were selected based on their direct involvement in healthcare services' day-to-day operations and strategic planning, and their potential roles in adopting and implementing technologies. To ensure that all participants had the same understanding of IoT applications and services in the healthcare context, a summarized definition was provided on the first page of the survey instrument. Participants were then asked whether they were familiar with such applications; only those who responded affirmatively were permitted to complete the survey.

The pilot study data were analyzed using SmartPLS 4.0 to assess the instrument's content validity and reliability. Expert evaluation ensured content validity, confirming that the survey items appropriately captured the constructs under investigation. Reliability testing was conducted to examine the instrument's internal consistency, including calculations of Cronbach's alpha, composite reliability, and indicator reliability. These tests helped to refine the questionnaire by identifying weak or ambiguous items. In addition, convergent and discriminant validity assessments were carried out to evaluate the instrument's construct validity and confirm the distinctiveness of the measured constructs. These procedures ensured that the instrument was valid and reliable for the full-scale study.

IV. Results and Discussion

A. Descriptive Analysis of Samples in Pilot Survey

The preliminary study used SPSS v.23 software to analyze the participants' demographic details. A total of forty questionnaires were distributed to respondents in Jordanian public hospitals as part of the pilot study. This sample size falls within the recommended range for pilot testing, as the literature typically advises using a small group of participants [77], with Hertzog [94] explicitly recommending a sample size of ten to forty for pilot studies. The pilot study was conducted to evaluate and refine the final data-collection process. Participant responses were analyzed to produce the frequency and percentage distributions presented in Table II, which outlines the demographic characteristics of the pilot study sample.

TABLE II. Frequency and Per cent of Demographic Variables in the Pilot Test

	Items	Frequency	Percent
Gender	Male	26	65%
	Female	14	35%
Age	Less than 30 years	0	0
	30-34 years	4	10%
	41-45 years	12	30%
	46-50 years	8	20%
	More than 50 years	2	5%
Education	Diploma	0	0
	Bachelor's Degree	26	65%
	Master's Degree	12	30%
	Doctoral Degree	2	5%
Position at Hospital	Senior Management	1	2.5%
	Middle Management	12	30%
	IT/Technical Staff	20	50%
	Healthcare Practitioners	7	17.5%
Experience in the current position	Less than 1 year	2	5%
	1-3 years	20	50%
	4-6 years	12	30%
	7-9 years	4	10%
	More than 10 years	2	5%
Experience in the Healthcare	Less than 5 years	2	5%
	6-10 years	19	47.5%
	11-15 years	8	20%
	21-25 years	1	2.5%
	26 years and above	4	10%
Knowledge about the Internet of Things	No information or knowledge	0	0
	Little information and knowledge	1	2.5%
	Some information and knowledge	2	5%
	Good information and knowledge	15	37.5%
	Excellent information and knowledge	22	55%

The sample consisted of forty respondents, with a majority being male (65%), and a relatively balanced representation across middle-aged groups, though no participants were under thirty. This may suggest a lack of younger professionals in decision-making or technical roles within public hospitals. The educational background was predominantly bachelor's degree holders (65%), indicating a solid academic foundation, with

35% having postgraduate qualifications, which could contribute positively to informed responses on technological topics such as IoT. From an organizational standpoint, 50% of respondents were IT or technical staff, which aligns well with the study's focus on IoT implementation, as these individuals are directly involved in deploying and managing such technologies. However, the limited representation from senior management (2.5%) may restrict insights from strategic-level decision-makers. In terms of work experience, half of the participants had one to three years in their current role, and nearly half (47.5%) had six to ten years of experience in the healthcare sector overall, suggesting a sample that combines both current role familiarity and broader sectoral expertise. Importantly, 92.5% of participants reported having good or excellent knowledge of IoT, indicating that the respondents were well-positioned to evaluate IoT adoption in healthcare, strengthening the reliability of the pilot findings.

B. *Construct Reliability*

In this study, the reliability of the research instrument was assessed using Smart PLS V4. Two main criteria were used: internal consistency and indicator reliability [95, 96]. To assess internal consistency, both Cronbach's alpha and composite reliability were employed. Cronbach's alpha evaluates reliability by examining the intercorrelations among observed indicators, while composite reliability considers the varying outer loadings of these indicators. In addition, indicator reliability was analyzed by evaluating the statistical significance of outer loadings, where a minimum threshold of 0.70 was deemed acceptable. This comprehensive approach ensured that all constructs in the research framework were reliably measured.

1) Internal consistency. Internal consistency was assessed using both Cronbach's Alpha (α) and Composite Reliability (CR), which are standard indicators for evaluating the reliability of latent constructs. Cronbach's Alpha evaluates the degree to which measurement items are correlated, assuming equal contribution of items, whereas CR accounts for the actual outer loadings of items, offering a more accurate estimation in SEM contexts [96]. A value above 0.70 is considered acceptable for both metrics. As shown in Table III, all constructs exceeded the recommended thresholds, with Cronbach's Alpha values ranging from 0.743 to 0.839 and Composite Reliability values from 0.844 to 0.892. These results demonstrate satisfactory internal consistency across all constructs. The high CR values indicate that the items within each construct reliably measure the same underlying concept, and the use of both metrics strengthens the credibility of the instrument. IT Infrastructure achieved the highest internal consistency ($\alpha = 0.839$; CR = 0.892), suggesting that this construct is both conceptually clear and consistently interpreted by respondents. This result likely reflects the tangible and well-established nature of IT infrastructure within hospitals, which may lead to more uniform responses.

In contrast, Security showed the lowest Cronbach's Alpha (0.743), and Compatibility reported the lowest CR (0.844), though both remained above the acceptable threshold. These slightly lower values may indicate more heterogeneous responses or measurement items that capture broader, more context-dependent perceptions. For Security, this could suggest variation in how respondents perceive threats and data protection standards in their institutions. For Compatibility, the modest reliability may reflect ambiguity in how well IoT systems are perceived to integrate with existing workflows, particularly in environments with varying levels of digital maturity. Taken together, the results confirm that the instrument demonstrates solid internal consistency across all constructs. The combination of high alpha and CR values provides strong empirical support for the reliability of the measurement model, laying a sound foundation for structural modeling and hypothesis testing in the next phase of the research. However, continued refinement of items with comparatively lower reliability will be important for improving the instrument's performance in future applications.

TABLE III. INTERNAL CONSISTENCY OF THE REFLECTIVE CONSTRUCTS

Constructs	Number Items	Cronbach's Alpha	Composite Reliability
Relative Advantage	4	0.796	0.866
Compatibility	4	0.758	0.844
Complexity	4	0.814	0.877
Security	3	0.743	0.854
Top management Support	4	0.799	0.867
IT Infrastructure	4	0.839	0.892
Competitive Pressure	4	0.802	0.870
Vendor Support	4	0.770	0.853
Government support	5	0.784	0.856
Technical competence	3	0.779	0.872
Employee Knowledge	4	0.768	0.852
Intention Towards IoT	4	0.815	0.879

2) Indicator reliability. Indicator reliability refers to the extent to which each observed variable (or item) accurately represents the latent construct it is intended to measure. This is assessed through the item's outer loading, which reflects the strength of the relationship between the observed variable and the construct. A commonly accepted threshold is 0.70, indicating that more than 50% of the variance in the item is explained by the underlying construct [97]. Items with loadings between 0.40 and 0.70 may be retained if they contribute to content validity, but those below 0.40 are generally recommended for removal unless strong theoretical justification exists[95].

As reported in Table IV, most items in this study achieved outer loadings above the 0.70 threshold, suggesting a high level of indicator reliability across the measurement model. This reinforces the internal consistency of the constructs and supports the appropriateness of the selected items. However, two items, GS3 (Government Support) and INTI4 (Intention Towards IoT) exhibited loadings of 0.240 and 0.366, respectively, falling well below the acceptable threshold. After identifying these problematic items, they were removed, and the measurement model was reassessed. The updated analysis showed that eliminating these two low-loading indicators improved the reliability and validity metrics, particularly the Average Variance Extracted (AVE), Cronbach's Alpha, and Composite Reliability values for their respective constructs. This process confirms the usefulness of empirical testing in refining the measurement instrument, even when items are initially retained for theoretical completeness or face validity. The need to remove GS3 and INTI4 also points to broader considerations in measurement design. While content validity remains crucial, ensuring all facets of a construct are represented, this must be balanced with empirical evidence to avoid retaining items that dilute the strength of the construct. Future research may benefit from revising these items for clarity, rephrasing them to better reflect the conceptual domain, or supplementing them with more targeted indicators.

TABLE IV. ITEM LOADING OF INDICATORS

Constructs	Items	Outer loading before deleting items	Outer loading after deleting items
Relative Advantage	RA1	0.753	0.753
	RA2	0.791	0.791
	RA3	0.804	0.804
	RA4	0.796	0.796
Compatibility	COMPA1	0.703	0.703
	COMPA2	0.771	0.771
	COMPA3	0.801	0.801
	COMPA4	0.757	0.757
Complexity	COX1	0.721	0.722
	COX2	0.881	0.881
	COX3	0.811	0.811
	COX4	0.785	0.785
Security and Privacy	SP1	0.797	0.798
	SP2	0.779	0.779
	SP3	0.862	0.862
Top management Support	TM1	0.792	0.792
	TM2	0.742	0.742
	TM3	0.791	0.791
	TM4	0.821	0.821
IT Infrastructure	ITI1	0.778	0.778
	ITI2	0.829	0.829
	ITI3	0.833	0.833
	ITI4	0.843	0.843
Competitive Pressure	CP1	0.747	0.747
	CP2	0.838	0.838
	CP3	0.823	0.823
	CP4	0.756	0.755
Vendor Support	VS1	0.760	0.760
	VS2	0.782	0.782
	VS3	0.741	0.741
	VS4	0.793	0.793
Government support	GS1	0.780	0.794
	GS2	0.740	0.754
	GS3	0.240	-
	GS4	0.801	0.800
	GS5	0.744	0.746
Technical competence	TC1	0.903	0.903
	TC2	0.768	0.768
	TC3	0.824	0.824
IoT Knowledge	EK1	0.729	0.729
	EK2	0.809	0.809
	EK3	0.821	0.821
	EK4	0.712	0.712
Intention Towards IoT	INTI1	0.838	0.849
	INTI2	0.759	0.782
	INTI3	0.865	0.892
	INTI4	0.366	-

Moreover, the high loadings across the majority of other items provide strong evidence of a well-developed measurement model. Constructs such as Technical Competence, IT Infrastructure, and Intention Towards IoT (after item deletion) showed particularly strong loadings, indicating that these concepts are well captured and perceived consistently by respondents. This strengthens confidence in the reliability of the data collected and the subsequent structural model outcomes. Overall, the analysis of indicator reliability confirms that the measurement model is robust, though it also underscores the importance of iterative testing and item refinement. In settings like public healthcare in developing countries, where technological adoption is shaped by complex institutional and environmental factors, measurement instruments must be both context-sensitive and empirically sound.

V. CONSTRUCT VALIDITY

Construct validity is concerned with how accurately a tool or questionnaire measures the concept it was designed to assess. In other words, it examines whether the items within the instrument truly reflect the theoretical idea they are intended to capture [92]. This involves empirical assessment, examining how well a measure correlates with external criteria based on empirical observations. In this study, construct validity was investigated through convergent and discriminant validity assessments.

1) Convergent validity. Convergent validity examines whether a construct effectively captures the variance of its associated indicators, ensuring that items measuring the same concept are indeed related. This is typically assessed through the Average Variance Extracted (AVE), which reflects the proportion of variance explained by the latent construct relative to measurement error. According to Fornell and Bookstein [98], a minimum AVE of 0.50 is recommended, suggesting that at least 50% of the indicator variance should be accounted for by the construct. As presented in Table V, all constructs in this study meet or exceed the 0.50 threshold, indicating satisfactory convergent validity.

TABLE V. CONVERGENT VALIDITY

Constructs	Number of Items	AVE
Relative Advantage	4	0.618
Compatibility	4	0.576
Complexity	4	0.643
Security and Privacy	3	0.662
Top management Support	4	0.620
IT Infrastructure	4	0.674
Competitive Pressure	4	0.627
Vendor Support	4	0.592
Technical competence	3	0.694
IoT Knowledge	4	0.592
Government support	4	0.598
Intention Towards IoT	3	0.709

This confirms that the measurement model generally performs well in representing the intended latent variables. However, a more nuanced examination reveals variation in the strength of convergent validity across constructs. For instance, Intention Towards IoT achieved the highest AVE (0.709), suggesting strong internal consistency and a high degree of shared variance among its indicators. Similarly, constructs like Technical Competence (0.694) and IT Infrastructure (0.674) exhibit robust convergence, indicating that these areas are conceptually well-defined and consistently measured in this study. Conversely, constructs such as Compatibility (0.576), IoT Knowledge (0.592), and Vendor Support (0.592), while above the threshold, have relatively lower AVE values. This may suggest potential areas for improvement in item formulation or conceptual clarity. Lower AVE values can sometimes reflect measurement items that are not strongly correlated, possibly due to broad or multidimensional definitions of the construct. Therefore, while the results support the use of these constructs in subsequent analysis, future studies might consider revisiting the measurement items for these constructs to enhance reliability and ensure tighter conceptual alignment. Overall, the results confirm acceptable convergent validity for all constructs, supporting the reliability of the measurement model.

2) Discriminant validity. Discriminant validity measures how a construct differs from others [95]. Discriminant validity was assessed using the Fornell-Larcker criterion, which requires that the square root of the AVE for each construct (shown on the diagonal in Table VI) be greater than its correlations with other constructs (off-diagonal values). This ensures that each construct shares more variance with its indicators than with other constructs, confirming that the latent variables are empirically distinct. The results support the discriminant validity of all constructs, as each diagonal value is higher than the corresponding off-diagonal correlations. For instance, the square root of AVE for Intention Towards IoT (ITI) is 0.821, exceeding its highest correlation with Security and Privacy (SP) at 0.672. Similarly, Technical Competence (TC) shows a strong distinction (0.833) despite moderate correlations with constructs like Employee Knowledge (EK) and Security and Privacy (SP).

However, some constructs demonstrate relatively high intercorrelations, particularly among Government Support (GS), Technical Competence (TC), and Security and Privacy (SP). For example, GS correlates at 0.705 with TC and 0.675 with SP, raising questions about potential conceptual overlap or shared variance due to external support mechanisms being tied closely to both technical readiness and data privacy policies. While the Fornell-Larcker threshold is met, such strong correlations suggest these constructs may be related in practice and should be more sharply delineated in future research. Overall, the model demonstrates acceptable discriminant validity, but the observed correlations warrant attention. These findings highlight the importance of refining construct definitions and measurement items in follow-up studies, especially in contexts like public healthcare, where institutional roles may blur the boundaries between support, competence, and data security.

TABLE VI. FORNELL-LARCKER CRITERION

	COMPA	CP	COX	GS	ITI	ATT	EK	RA	SP	TC	TM	VS
COMPA	**0.759**											
CP	0.443	**0.792**										
COX	-0.269	-0.299	**0.802**									
GS	0.458	0.481	-0.417	**0.774**								
ITI	0.257	0.287	-0.585	0.549	**0.821**							
ATT	0.290	0.069	-0.546	0.235	0.315	**0.842**						
EK	0.480	0.280	-0.308	0.712	0.313	0.210	**0.769**					
RA	0.243	0.251	-0.007	0.287	0.250	0.210	0.214	**0.786**				
SP	0.395	0.498	-0.398	0.675	0.672	0.397	0.552	0.453	**0.813**			
TC	0.578	0.398	-0.251	0.705	0.422	0.405	0.511	0.419	0.640	**0.833**		
TM	0.564	0.382	-0.361	0.560	0.427	0.346	0.416	0.193	0.486	0.629	**0.787**	
VS	0.125	0.467	-0.091	0.328	0.281	0.085	0.230	0.278	0.613	0.263	0.257	**0.769**

VI. Conclusion

This pilot study offers an empirically grounded validation of a comprehensive measurement instrument designed to assess IoT adoption readiness in Jordanian public hospitals, an area that remains underexplored despite the growing strategic importance of digital health technologies in developing countries. By integrating constructs from both the TOE framework and the HOT-Fit model, this study transcends traditional user-centric adoption theories and addresses the multidimensional complexity of institutional readiness. The results confirmed that the instrument demonstrates robust internal consistency, satisfactory indicator reliability, and strong convergent and discriminant validity, suggesting that it is both psychometrically sound and contextually relevant.

Practically, this study offers valuable insights for healthcare administrators, policymakers, and system developers aiming to promote digital transformation in public hospitals. The validated model identifies key dimensions—technological, organizational, environmental, and human readiness—that must be considered when planning for IoT implementation. Hospital leaders should ensure not only that technical infrastructure is in place but also that staff possess the necessary knowledge and competencies, and that sufficient management support and external resources (e.g., vendor and government support) are available. Moreover, this study demonstrates the importance of tailoring adoption models to the institutional realities of developing countries. The integration of both TOE and HOT-Fit constructs reflects the complex interplay of internal and external factors that shape readiness in public sector environments. As such, this pilot study contributes to a more context-sensitive approach to technology adoption in healthcare, especially within resource-constrained settings.

Building on this foundation, the next step involves deploying the validated instrument in a full-scale quantitative study to test the proposed model and examine the relationships between the readiness factors and the intention to adopt IoT. Structural equation modeling (SEM) can be employed to assess the model's explanatory power. In addition, future research may benefit from adopting a mixed-methods approach, incorporating qualitative techniques such as interviews or case studies to explore contextual nuances, user perceptions, and institutional dynamics that may not be fully captured through quantitative measures alone. Longitudinal studies could also offer valuable insights into how readiness and adoption progress over time, particularly as digital transformation efforts expand within Jordan's healthcare sector. In conclusion, the study provides a validated foundation for future empirical investigations and offers practical implications for stakeholders aiming to accelerate IoT adoption in the healthcare systems of developing countries.

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