ISSN 2664-4150 (Print) & ISSN 2664-794X (Online)
South Asian Research Journal of Engineering and Technology
Abbreviated Key Title: South Asian Res J Eng Tech

| Volume-7 | Issue-1 | Jan-Feb- 2025 | **DOI: https://doi.org/10.36346/sarjet.2025.v07i01.003**

Review Article

Assessing Adopting Emerging Digital Technologies in Developing Country Medical: A (Push-Pull-Mooring Model) Framework

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Article History
Received: 13.01.2025
Accepted: 17.02.2025
Published: 22.02.2025

Abstract: The current study aims to identify adopting Emerging Digital Technologies in developing country Medical. Was model study the, goal this achieve to order in designed starting from the factors influencing the adoption of the emerging digital technologies, up to the intention to adopting Emerging Digital Technologies in developing country Medical, based on the theory that supports technology represented by of adoption the (Push-Pull-Mooring Model) PPM, as according to extracted were factors influencing the that theory represented by the variable of push effects, which included dimensions of (low flexibility, limited scalability, low compatibility, and dissatisfaction). As for the variable of attraction effects, it included dimensions of (low cost, ease of maintenance, attractive alternatives, and expected value). As for the effects of awarding, it included two dimensions (expected risks, inertia), and the variable of behavioral intent to adopt emerging digital technologies., which the on relied study, the reached is that result a represents the and, implementation its for method survey analytical for tool a as studies previous on based designed was questionnaire data collection, as it was disseminated online. There were (203) responders out of the entire study population (575) individuals, and fourteen hypotheses emerged from the study model. The data was analyzed using the (SPSS) (AMOS) program to describe the variables of the study and test its hypotheses statistical the method modeling equations structural the using a significant effect of is there that showed results to the results of the study, the push effects represented by (low flexibility, limited scalability, and low compatibility), have a significant effect on dissatisfaction with the adoption of emerging digital technologies, and that low compatibility has a major impact on the behavioral intend to adopt emerging digital technologies. That the effects of attraction (low cost, ease of maintenance, and attractive alternatives) significantly affect the expected value of adopting emerging digital technologies. Researcher suggested the need to pay attention to adopting emerging digital technologies through the implementation of more studies, to define what emerging digital technologies are and to encourage people and companies to embrace these technologies, highlight their significance and the advantages they offer emerging digital technologies in their organizations.

Keywords: Emerging Digital Technologies, Health Sector, PPM.

1. INTRODUCTION

Perhaps one of the most important things that all hospitals and health centers seek to achieve is to develop performance and provide the best services according to the latest developments and the latest findings of modern science, as improving and developing the health service, or searching for new services is one of the prominent features in the work of health sectors. In order to keep pace with the speed of scientific and technical change in the health field, which makes some methods of providing health services obsolete over time, and with the increase in the number of patients and the demand for rapid response to their requirements and needs, in addition to the increase in improving the medical health services provided to them, all of this made it imperative for those in charge of managing health services to use and transfer data from data centers to its final location on the other side of the cloud, which led to the need to adopt emerging digital technologies in the health sector. The adoption of emerging digital technologies in the healthcare sector of developing countries is a critical area of research and practice. As these nations strive to modernize their medical systems and improve healthcare outcomes, understanding the factors that drive or hinder the uptake of innovative digital solutions becomes paramount. One framework that has shown promise in examining technology adoption in developing contexts is the Push-Pull-Mooring (PPM) model, PPM model posits that an individuals or organizations decision to adopt a new technology is influenced by three key sets of factors: push factors, pull factors, and mooring factors. Push factors are the forces that compel an entity to seek out and adopt a new technology, such as the need to improve efficiency or meet regulatory requirements. Pull factors, on the other hand, are the attractive features or benefits of the technology itself that draw the entity towards adoption. Mooring factors are the contextual elements, both internal and external, that can either facilitate or hinder the adoption process, such as organizational readiness, resource availability, or policy environments, By applying the PPM framework to the adoption of emerging digital technologies in the medical sector of developing countries, researchers can gain valuable insights into the complex dynamics that shape technology uptake in these unique settings. This introduction will provide an overview of the current state of digital technology adoption in developing country healthcare, highlight the relevance of the PPM model in this context, and outline the key objectives of a study that aims to empirically assess the factors influencing the adoption of emerging digital technologies in the medical sector of a developing country.

2. Theoretical Background

2.1. Emerging Digital Technologies

2.1.1. Definition of Emerging Digital Technologies

Emerging technologies are those technologies that are emerging and developing rapidly at the present time, and are innovative and promise new and exciting possibilities. These technologies are considered pivotal in transforming the world and influencing various fields, including industry, medicine, communications, energy, agriculture, and others(Shadiev *et al*., 2023). A group of smart and innovative technologies, such as big data analyses, the Internet of things, and cloud computing, that make it possible to achieve connectivity and automation, and thus enable organizations to transform their current product or service model into a smart one, to become more viable, competitive and achieve competitive advantages(Astuti *et al*., 2021) A group of technologies that include artificial intelligence, big data, robots, digital platforms, social media, blockchain, and 3D printing, which are reshaping human work (Bailey *et al*., 2019) The technologies that work to enhance organizational and individual results, which include artificial intelligence, blockchain, virtual reality, robots, the Internet of things, cloud computing, and big data, and what these technologies provide and achieve in terms of significant improvement and progress in the performance of organizations (Rippa & Secundo, 2018) It is a set of technologies that can be understood by defining their features that appear with the emergence of emerging digital technologies, namely (rapid growth - coherence - significant impact - uncertainty and ambiguity) and setting a framework for emerging technologies based on the proposed features (Rotolo *et al*., 2015) Through the aforementioned, the researcher proposes a procedural definition of emerging digital technologies, represented by a group of smart technologies that are still in stages of continuous development and are characterized by relatively rapid growth and a certain degree of continuous interdependence with time, with the possibility of a significant impact on organizational performance.

2.1.2. The Importance of Emerging Digital Technologies

Technical developments have brought about continuous changes to this day, which affects the availability of more favorable opportunities to benefit from them and their applications at all levels and in all sectors and organizations, because of their positive impact on doing business and its final results. (Brou & Janssen, 2015) indicated that the importance of emerging digital technologies lies on the levels (strategic - tactical - operational), which are as follows:

- Strategic importance through improved forecasting and trend analysis and enhancing transparency, scalability and inclusion.
- Tactical significance: Improving planning, improving health and safety measures and data privacy, and improving system efficiency.
- Operational significance: improving service efficiency, improving effectiveness and resilience of services, and enhance real-time monitoring.

Based on the aforementioned, the researcher believes that its importance is rooted in creating change in organizations' policy and objectives and improving planning processes, which contributes to improving internal operations and adding flexibility in business, eliminating routine, and improving decision-making, and thus the reflection of all of this on enhancing organizational performance.

2.1.3 Types of Emerging Digital Technologies

Emerging digital technologies have varied in recent years, which are among the most important outputs of the fourth industrial revolution. The most prominent of these technologies are the Internet of things, cloud computing, and big data. The researcher will focus on the importance of these technologies and their integration in order to enhance organizational performance, as follows:

1- The Internet of Things

The first appearance of the term internet of things was in the beginning of the twenty-first century, specifically in 1999 by the British scientist (Kevin Ashton), who is one of the pioneers in the technical field, who defined the internet of things as connected sensors that behave in a manner similar to the internet by conducting open and dedicated communications and sharing data freely, analyzing the results, and better understanding the surrounding environment. Although the concept of the internet of things has been addressed by specialists and researchers in their studies and research, there is no agreement about its concept due to their different orientations and interests. Gamundani (2015) defined it as a type of network to connect anything to the internet via the prescribed protocols, through information sensors to conduct information exchange to achieve intelligent perceptions and identify tracking, monitoring and management. While (Wang *et al*., 2013), An Internet of Things (IoT) based remote patient monitoring system can be an effective tool for medical services to remotely monitor pabents' health cond and provide timely interventions. The system can use a combination of sensors, wireless communication technology, and cloud computing to collect, store analyze patients data, and then transmit the information to healthcare professionals.(Rejeb *et al*., 2024) An IoT-based remote patient monitoring system for home healthcare. The system uses various sensors and a cloud-based platform for data storage and analysis. The authors' evaluation shows the system's reliability and efficiency in remote monitoring, making it a promising approach for improving healthcar delivery,The potential of lot technology in healthcare management, discussing applications and challenges are explored it high the importance of addressing security, privacy, IoT in healthcare has potential benefits such as improved patient outcomes, but also challenges such as interoperability and security(Sharma *et al*., 2020)

2- Cloud Computing:

Because of the tremendous evolution in the field of information technology and communication networks (the Internet), this development was reflected in the rapid growth in the volume of data and information, which limits the ability of organizations to deal, control and manage this data and information effectively. With the continued rise in storage costs, organizations are facing challenges in data retrieval and preparing backups. Hence the role of cloud computing stand out in dealing with these challenges, saving costs and reducing efforts in the environment of organizations. To clarify the concept of cloud computing, (Bradshaw, *et al*., 2010) refers to it as a model for providing information technology services, whether with hardware or software on demand, automatically over an independent network, regardless of the nature of the user's device or location. Digital ecosystems are generally run on clouds. (Flores *et al*., 2015) Cloud computing refers to the paradigm of delivering computational resources, including storage, processing power, and applications, as on- demand services over the internet. This model enables users to access and utilize these resources without the need for upfront infrastructure investments, allowing for flexible scalability and cost efficiency. Therefore, saving upfront investments for connection, individualized interfaces that cater to hospital's needs and are able to adapt to new developments. Cloud computing is characterized by its service models, namely Infrastructure as a Sevice (laas) (Putzier *et al*., 2024) Platform as a Service (PaaS), and Software as a Service (SaaS), which offer varying levels of control and management for users. This technology has gained significant traction due to its potential to revolutionize IT infrastructures and support various industries, such as healthcare, finance, and entertainment. Notably, cloud computing has been acknowledged for its role in facilitating resource sharing, improving accessibility and enabling collabora- tion among geographically dispersed users.

Currently, cloud computing is being used successfully in various areas of medicine: In the provision and processization of telemedicine services (Hsieh *et al*., 2013).

3- Big Data:

The impact of big data has become evident in the workflow of organizations and sectors whether for profit or service as a result of technical progress in the last decade of the twenty-first century. So there are many concepts and perspectives of researchers about what big data came in their research and studies. (Bomatpalli, 2016) defined it as it is a set of data that grows over time or with technical progress, and appears in applications that differ from each other. (Roy, 2016) indicated that big data is that of difficult to collect, analyze, store, and process within traditional systems, and it is a description of data of huge, diverse, and high-speed data. As for (Sanskruti & Patel, 2016), he indicated that it is a description of data that ranges from structured, semi-structured or unstructured data whose analysis leads to better decision-making and the development of a constructive strategy for the organization, which improves its performance. Creating (BD) apps has grown in importance in recent years. On the other hand, traditional data methodologies and platforms are less effective in light of the fact that many businesses across different industries rely on vast amounts of data (BD). Businesses now have a strategic advantage and unmatched potential to succeed because to the growth of (BD). The idea of big data business models, or (BDBMS), was born as a result of numerous companies starting to update or develop new business models in order to capitalize on the strategic economic prospects inherent in (BD) (Alshagathrh *et al*., 2018). Under the general heading of (digital health), the delivery of best practices in healthcare has become inextricable linked to disruptive inventions, advanced medical technology, and contemporary communication. Despite the fact that chronic sickness treatment is expensive, doctors. Global shortages are a real concern, and the intended reforms to the medical and healthcare system are not keeping pace with the quick development of the medical technology sector. The transformation is being slowed down by stringent regulations, healthcare stakeholders incapacity to adjust, and a disregard for the importance of societal changes and the human element in an increasingly technological world(Ghaleb *et al*., 2021). With increased access to and use of technology, the possibility of patients relying on an easily available yet uncontrolled technical approach to solve their health challenges is expected to rise. In, the authors explore how emerging advances assist and enhance the transformation of the old system of the paternalistic model of medicine into an equitable level relationship between patients and practitioners.

4- Artificial Intelligence:

Artificial intelligence technologies are one of the most important and dangerous outcomes of the technological revolution, as a result of the smart applications that have emerged from it, which have affected various aspects of life and contributed greatly to serving and advancing humanity. It is expected that artificial intelligence will open the door wide to limitless innovations and lead to more industrial revolutions that will radically change all fields (Mohammed *et al*., 2021). The rapid development of artificial intelligence technologies has changed the business landscape in various sectors at the global level, as these technologies have played a vital role in enhancing economic performance, improving the quality of services, providing innovative solutions to solve current problems, improving business efficiency and productivity, and even organizing people's lives. This has prompted many countries to compete in achieving the necessary technical maturity for these technologies and driving their adoption in a governed and responsible manner, in an effort by these countries to achieve leadership in the field of artificial intelligence at the national and global levels Artificial intelligence is considered one of the most time-changing technologies in the era of the Fourth Industrial Revolution (Kabalisa & Altmann, 2021). Artificial intelligence technology is not just a tool for advanced technologies, but it is considered a major driver of innovation in multiple fields, which is why many countries are using new technologies aimed at achieving high performance and competitive advantage (Borges *et al*., 2021), as the adoption and effective implementation of these technologies is a distinct set of challenges and opportunities(Abadie *et al*., 2023), and these opportunities include improving performance in various sectors such as health, education, agriculture, and public services. These technologies can contribute to improving the quality of life, increasing production efficiency.

2.2 Emerging Digital Technologies in Healthcare

There are several emerging digital technologies that are making an impact on health- care. These technologies use digital platforms, connectivity, and data to transform various aspects of healthcare delivery, patient engagement, and research. Regardless of the tech- nology, they all mainly aim to connect health workers and patients to enable a seamless flow of medical information between healthcare settings for informed decision-making purposes(Arafa *et al*., 2023) . Internet of medical things (IOMT). The (IOMT) refers to the interconnected network of medical devise, sensors, and wear- able technologies, such as smartwatches, fitness trackers, and glucose monitors. These devices collect and transmit instantaneous health data, allowing for remote patient monitoring, early disease detection, and personalized care, the (IOMT) framework- based digital healthcare includes several stages. Using smart wearable or implanted devices connected by a wireless sensor network or the patient's body, data is first gathered, then processed, and ultimately predictions are made. Healthcare providers, patients, or other medical devices can be automatically approached to be informed of the current medical condition or future potential health outcome. Finally, the (IOMT) provides real-time recom- mentation's about what should be conducted to manage the current medical condition and prevent future complications (Srivastava *et al*., 2022), Cloud Computing Cloud computing offers scalable and cost-effective storage and processing capabil- ities for healthcare organizations. It enables secure access to medical records, facilitates data sharing and collaboration, and supports telemedicine and remote monitoring,(Mehrtak *et al*., 2021) The implications of cloud computing in healthcare can be summarized in the following points: (1) relying on software, especially software as a service (SaaS), platform as a service (PaaS), and infrastructure as a service (IaaS); (2) providing security and interoperability; (3) performing clinical tasks; (4) supporting patient-centeredness; (5) facilitating collabora- tion; and (6) increasing service mobility and flexibility [19]. However, the lack of regulations, system outages, lack of control, and security issues remain potential challenges (Gao *et al*., 2018), Big Data Analytics Big data streams include various types of data: (1) clinical data from electronic med- ical records, hospital information systems, image centers, laboratories, and pharmacies; (2) biometric data from medical devices that monitor vital signs, body composition, etc.; (3) financial data, constituting records of relevant financial operations; (4) scientific re- search data; (5) patient data, including treatment preferences, satisfaction levels, self- administered information about their lifestyle and sociodemographic factors; and (6) social media data (Batko & Slezak, 2022), Artificial Intelligence (AI) Al and (ML) have the potential to revolutionize healthcare. They can analyze vast amount of medical data, including medical images, lab results, and patient records, to aid in the diagnosis of diseases. AI and (ML) can create individualized treatment regimens by evaluating patient data, taking into account lifestyle, genetics, and medical history. (AI)- powered monitoring devices can remotely track patient vital signs, symptoms, and adherence to treatment plans. (ML) algorithms can detect trends and anomalies, alerting healthcare providers to potential issues. Furthermore, (AI) can automate routine administrative tasks, such as appointment scheduling, documentation, and data entry, allowing healthcare professionals to focus more on patient care (Bajwa *et al*., 2021).

2.2.1 Theories and Models of Adopting Emerging Digital Technologies

Prominent researchers have formulated various theories and models related to technology adoption, such as the Technology Acceptance Model (TAM) developed by Fred Davis to explain the factors that influence individuals' acceptance of technology. The model focuses on two main variables: perceived usefulness and perceived ease of use (Davis, 1989). It can be used to analyze the benefits and ease of use of AI among individuals in developing countries, and whether this affects the acceleration of the adoption process. The Diffusion of Innovations Theory (DOI) was developed by Everett Rogers, and this theory focuses on how innovations (new technologies) spread across segments of society. The model includes factors such as innovation, comparative advantage, complexity, trialability, and observability (Rogers *et al*., 2014) to analyze how AI technologies spread across different sectors in developing countries and whether these factors help or hinder their diffusion, and the Unified Theory of Acceptance and Use of Technology (UTAUT) This theory combines several models and theories, and includes factors such as performance expectation, effort expectation, social influence, and ease of use. This model can be used to analyze the social and organizational factors that encourage or hinder the adoption of AI, and is considered a comprehensive model (Venkatesh *et al*., 2003). The Technology Readiness Model (TR) focuses on readiness for technology, and includes elements such as optimism, innovation, insecurity, and skepticism. It is useful in assessing the readiness of individuals or organizations in developing countries to adopt AI based on their attitudes and concerns about technology. The Model of Computer Use (MPCU) creates a framework for studying innovation in a wide range of application situations theoretically (Thompson *et al*., 1991). The Institutional Model of Technology Adoption (TOE) was developed to study technology adoption from a tripartite perspective that includes technology, organization, and environment. This model can be applied to analyze the environmental, organizational, and technological factors that influence AI adoption in developing organizations (Baker & Predicting Our Digital Society, 2012). Cost-Benefit Analysis In developing countries, technology adoption is often linked to evaluating the cost of implementing AI against the expected benefits. Technology Acceptance Theory (TAM2) is an extension of the original Technology Acceptance Theory (TAM) developed by Fred Davis, and is designed to explain the factors influencing individuals' acceptance of technology more broadly (Venkatesh & Davis, 2000). Technology Acceptance Theory (TAM3) is a further development of the original Technology Acceptance Theory (TAM) and its updated model (TAM2). TAM3 focuses on enhancing the understanding of the factors that influence technology acceptance by using additional factors for analysis, (Venkatesh & Bala, 2008).

2.2.2. Discussing the Theory Adopted In the Study (Push, Pull and Mooring) PPM Model

The push-pull and model (PPM) originated from studies of human migration, specifically by (Ravenstein, 1977) to describe human migration. In the 1990s, (Moon, 1995) proposed the effect of mooring in the Push and Pull Model (PPM) in terms of the three dominant perspectives on society represented by social factors, personal factors and cultural factors, but it was applied by (Bansal, 2005) as a theoretical basis in his study in a useful way to explain the determinants of the behavior of individual users towards a particular technology and the transition to a better technology. The model consists of the following:

1- Push Effects:

Effects that push individuals to move to new information technology that provides better services, and this motivation is generated by negative factors of current information technology, and push effects arise from the dissatisfaction variable represented by dimensions (low flexibility, limited scalability, and low compatibility).

2- Effects of Attraction:

Effects that attract individuals towards the new information technology. These effects are created by the positive factors of the new technology. They consist of a variable (expected value) represented by the dimensions (low cost, ease of maintenance, and attractive alternatives).

3- Mooring Effect:

Mooring effects are generally personal or circumstantial factors that either contribute to keeping individuals using current information technology, or affect the behavioral intention of the individual to adopt new information technology. The mooring effects measure includes (inertia and expected risks).

4- Behavioral Intention to Adopt Emerging Digital Technologies

Adoption intention is the degree of probability of an individual making conscious plans to perform a specific future behavior, and the behavior of individuals towards new information technology is predicted by behavioral intention. Figure (1) shows the PPM model adopted in the current study.

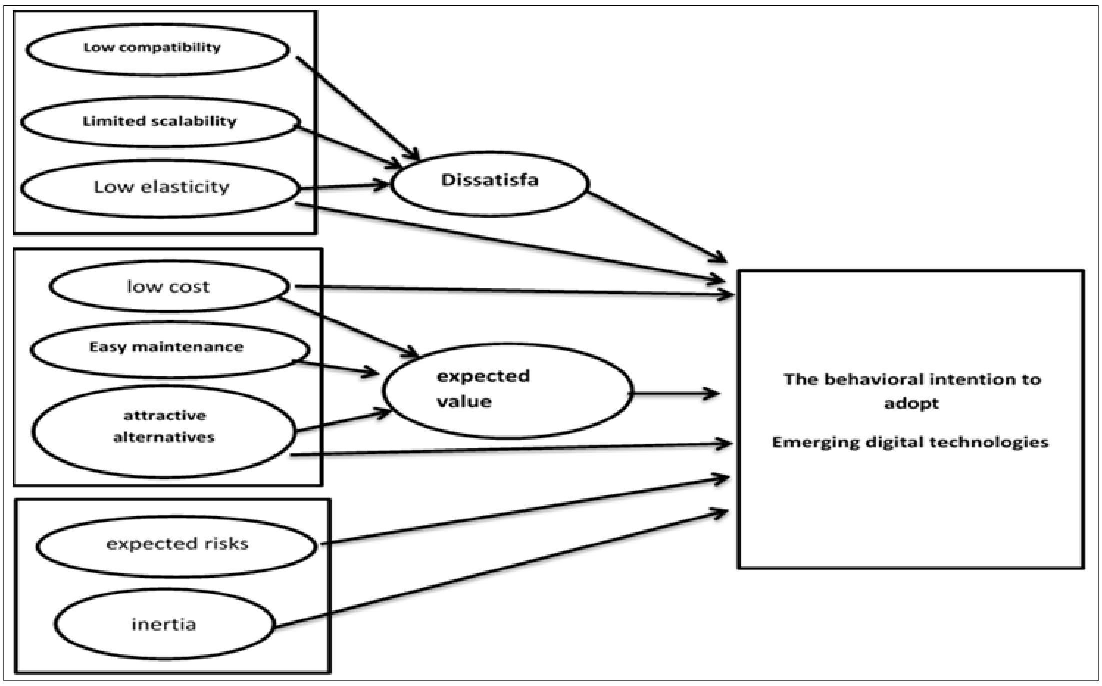

Figure 1: PPM Study Model

3. Research Model and Hypotheses

As demonstrated below, the research technique comprises establishing the study's direction, the elements pertaining to the research topic, it is significance and goals, the study model, and the development of it is hypotheses.

3.1. Research Problem

The remarkable and continuous progress in the field of information technology that the world has witnessed, especially in the recent times of the twenty-first century, has made huge changes and impacts in the daily lives of individuals, and even went beyond that to include organizations and sectors in various fields and specializations, which led to a rush towards adopting emerging digital technologies on a large scale especially in the health sector (Liu *et al*., 2022). However, the adoption of information technology is often hindered by the unwillingness of individuals to accept or use it for reasons related to the behavior of individuals, including personal and psychological ones, or factors related to the characteristics of the technology itself. (Zhang *et al*., 2009) found that individual satisfaction, attractive alternatives, ease of maintenance and cost and compatibility with the work environment can greatly affect the individual's intention to adopt emerging digital technologies. Despite the existence of many studies in the areas of adopting emerging digital technologies in developed countries, the study of the motives of adoption by individuals in developing countries is still limited (Al-Khouri, 2012). Given the persistence of this problem, this current study came to fill the research gap. On the other hand, the researcher conducted a survey study in the researched organization and found that the organization suffers from a weakness in adopting emerging digital technologies in its operations, and therefore. The main problem of the study can be articulated through a set of research questions as follows:

- Do the study sample individuals have a clear perception about the study topics (the adoption of emerging digital technologies)?
- Do the factors of adoption have an effect emerging digital technologies on the behavioral intend to adopt emerging digital technologies?
- Does the impact of the behavioral intend to adopt emerging digital technologies?

3.2. The Importance of Research

A- The significance of the study seems from a theoretical point of view, which can be shown in the following aspects:

- It dealt with the issue of adopting emerging digital technologies, as most studies indicated the lack of studies that dealt with this topic, especially in the Iraqi environment, and this study reveals the factors that affect the individual's intention to adopt emerging digital technologies in the researched organization.
- This study provides organizations with answers to their questions about the benefits achieved by adopting emerging digital technologies.
- The study deals with highlighting the role of emerging digital technologies in supporting and improving work in the researched organization, and accomplishing tasks and duties quickly, efficiently and effectively.
- B- Scientific importance, which can be shown in the following aspects:

- The study is one of the studies based on the latest important trends in information technology sciences based on published scientific research that indicated the need to keep pace with developments by adopting emerging digital technologies.
- The study crystallized on the experimental measures of the results, and the measure of adoption that was built according to the theories that support technology.

3.3. Research Objectives

- Presenting a theoretical framework that includes a presentation of what has been written about the variables of the study (adopting Emerging Digital Technologies in developing country Medical,) to clarify the intellectual foundations and variables of these topics.
- Measuring the correlation and impact of adopting Emerging Digital Technologies in developing country Medical.
- Presentation and analysis of the reality of using emerging digital technologies and their role in the researched organization.

3.4. The Research Model and It Is Hypotheses

The hypothetical research scheme was designed based on the importance and objectives of the research, and a set of hypotheses will be formulated, as shown in the hypothetical research scheme below.: To complete the requirements of the study methodology, a study plan model was built as shown in Figure (2) to address the problem of the study, as the model that was developed for this study relies on the theory of (push-pull-mooring), to accept and use emerging digital technologies (Bilson, 2005, 43), a theory that states that changing the behavior of the individual towards a technology depends on push, pull and mooring factors, which are as follows:

- Push effects: that push individuals to migrate and leave information technology that does not achieve their level of satisfaction, and the trend towards adopting new information technology.
- Attraction effects: These are the effects that attract individuals towards new information technology services.
- Mooring effects: personal or circumstantial factors that affect the behavioral intention to adopt information technology in an individual

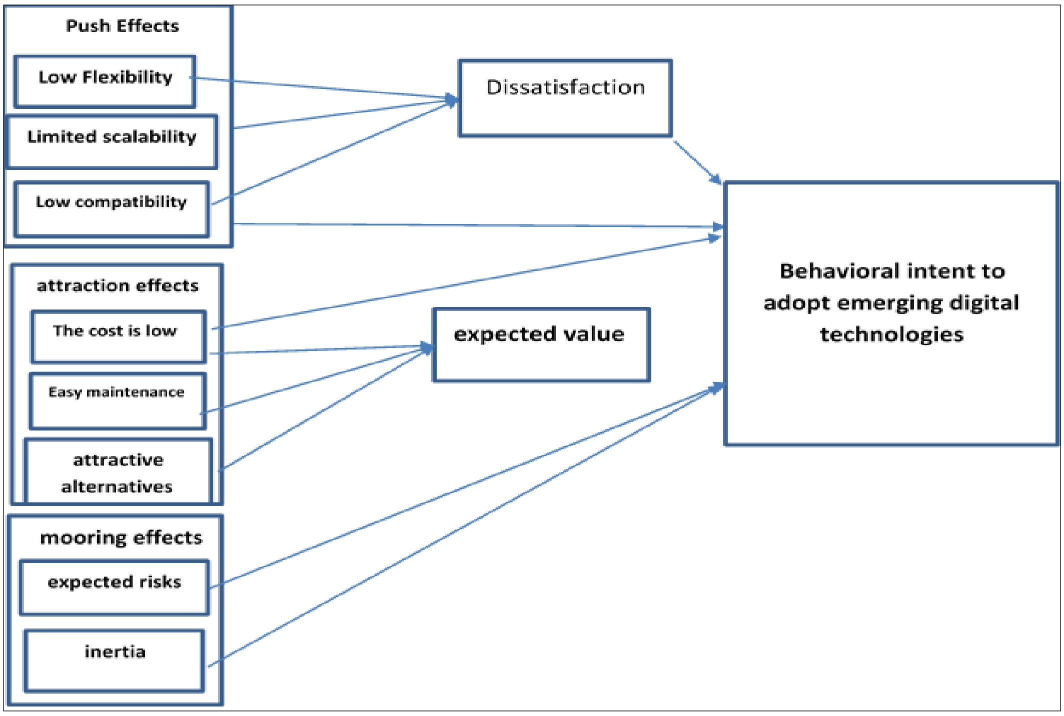

Fig. 2: PPM Study Mode

3.5. Research Hypotheses

The Main Hypothesis:

There is a statistically significant effect relationship between technical capabilities and the dimensions of creative performance at the macro level, and the following sub-hypotheses emerge from this hypothesis:

Hypothesis H1: Low flexibility significantly affects dissatisfaction with the adoption of emerging digital technologies.
Hypothesis H2: Limited scalability significantly affects dissatisfaction with the adoption of emerging digital technologies.
Hypothesis H3: Low compatibility significantly affects dissatisfaction with the adoption of emerging digital technologies.

Hypothesis H4: Low compatibility significantly affects behavioral intention to adopt emerging digital technologies.
Hypothesis H5: Dissatisfaction negatively affects behavioral intention to adopt emerging digital technologies.
Hypothesis H6: Low cost significantly affects the behavioral intention to adopt emerging digital technologies.
Hypothesis H7: Low cost significantly affects the expected value of adopting emerging digital technologies.
Hypothesis H8: Ease of maintenance significantly affects the expected value of emerging digital technologies.
Hypothesis H9: Attractive alternatives significantly affect the expected value of adopting emerging digital technologies.
Hypothesis H10: Attractive alternatives significantly affect the behavioral intention to adopt emerging digital technologies.
Hypothesis H11: Expected value significantly affects behavioral intention to adopt emerging digital technologies.
Hypothesis H12: Expected risks negatively affect behavioral intention to adopt emerging digital technologies.
Hypothesis H13: Inertia negatively affects behavioral intention to adopt emerging digital technologies.
Hypothesis H14: Testing the sub-hypotheses of the study model in an integrated manner.

4. Study Approach and Model

In line with the directions of the study, the researcher distributed the electronic questionnaire form to the study sample represented by doctors working in government hospitals under study, and (203) valid forms for analysis were obtained. The study sample was characterized according to the data provided by its members through their answers to the first part (respondent data) shown in table (3) of the questionnaire, with the following characteristics:

Table 1: Demographic characteristics of the study sample individuals

Item	Variables	property distribution	Repetition	Ratio
1	Gender	Male	112	55.8
		Female	91	44.2
	Total		**206**	**100%**
2	Age	20-30 year	63	30.6
		31-40 year	70	34
		41-50 year	46	22.3
		51-60 year and more	27	13.1
	Total		**206**	**100%**
3	Career years of service	1-5 year	61	29.6
		6-10 year	48	23.3
		10-15 year	24	11.7
		15-20 year	42	20.4
		20 and more year	31	15
	Total		**206**	**100%**
4	Qualification	Bachelor's	148	71.8
		Diploma	14	6.8
		Master	10	4.9
		Doctorate	34	16.5
	Total		**203**	**100%**

Source: prepared by the researcher based on the data of the study sample and the results of the statistical program (SPSS.V.25).

4.2. Measurement Model Test (Confirmative Factor Analysis)

The aim of this test is to diagnose the validity of the construction of the study scale and its suitability for the hypothetical study model, depending on the confirmatory factor analysis, which is one of the applications of Structural Equation Modeling (SEM). When developing a hypothetical model based on the existence of correlations between the potential variables and the observed variables in the light of previous theoretical knowledge, the confirmatory factor analysis allows testing this model statistically. Our current study relied on the application of confirmatory factor analysis, which is one of the (SEM) applications, on the unweighted Least Squares (ULS) method, which is one of the analysis methods within the statistical program (AMOS), and the method (Maximum Likelihood) (ML) was not adopted in the analysis, because the (ML) method requires the availability of the following conditions.

1. Randomness (i.e.: the data collected should be random).
2. The sample size should be relatively large (the sample size should be five or ten times greater than the number of observed variables).
3. Communicability (the dependent variable must be a continuous variable).
4. The condition of moderation in the two variables, the dependent and the random error (i.e.: that the probability distribution for them should be normal distribution, bearing in mind that the data is distributed in an abnormal distribution in terms of the value of: Assessment of normality: Multivariate/ 1098.897 - CR = 76.395
5. Its application requires that the determinant of the matrix be (positive).

6. The model must be accurately defined.

5. Data Analysis and Discussion

5.1. Testing the Quality of the Measurement Tool Data

The researchers employed statistical tests of validity and reliability to evaluate the tool data's quality.

- **Validity Test:**

To confirm the questionnaires efficacy in measuring research variables, it was presented to academic experts for a test of apparent validity. This was done to get their feedback on the questionnaires capacity to measure the variables and guarantee the accuracy of the findings.

- **Reliability Test:**

Indicates that if the survey is re-distributed with identical terms and conditions, it yields identical findings. With a minimum acceptable threshold value of (0.70) for Cronbach's coefficient, Cronbach's alpha, is one of the most popular techniques for assessing dependability. Table (2) displays the reliability test results using Cronbach's Alpha:

Table 2: Results of the scale stability test (Alpha Cronbach)

Scales	**Dimension**	**Items**	**Cronbach Alpha**	**Alpha coefficient for the combined dimensions**
Push effects	Dissatisfaction	DI1-DI5	0.880	0.920
	Low Elasticity	LF6-LF10	0.870	
	Limited Scalability	LS11-LS15	0.920	
	Low Compatibility	LC16-LC20	0.850	
Pull Effects	Expected Value	EV21-EV25	0.920	
	Low Cost	LO26-LO30	0.970	
	Easy Maintenance	EM31-EM35	0.950	
	Attractive Alternatives	AA36-AA40	0.950	
Mooring Effects	Inertia	IN41-IN45	0.930	
	Expected risks	ER46-ER50	0.940	
Intent to embrace emerging digital technologies		II51-II55	0.910	

Source: prepared by the researcher based on the data of the study sample and the results of the statistical program (SPSS.V.25).

Its clear from table (2) that the variables satisfied the accepted reliability ratio because all Cronbach's alpha values were greater than (0.70), indicating the stability and dependability of the assessment of the fundamental components of the study model.

5.2. Testing of the Study Hypotheses

5.2.1 Hypothesis Testing for the Push Effects Variable:

Hypothesis H1: Low flexibility significantly affects dissatisfaction with the adoption of emerging digital technologies.
Hypothesis H2: Limited scalability significantly affects dissatisfaction with the adoption of emerging digital technologies.
Hypothesis H3: Low compatibility significantly affects dissatisfaction with the adoption of emerging digital technologies.
Hypothesis H4: Low compatibility significantly affects behavioral intention to adopt emerging digital technologies.
Hypothesis H5: Dissatisfaction negatively affects behavioral intention to adopt emerging digital technologies.

In order to verify and confirm the authenticity of these hypotheses, the values of the tests included in this form, which guide us to accept or reject the hypothesis, as shown in Table (3):

Table 3: Analysis values for hypotheses (H1, H2, H3, H4, H5)

The independent variable	**direction of the effect**	**dependent variable**	**Estimate**	**Lower**	**Upper**	**P-value Significant**	**Result**
Low flexibility LF	→	Dissatisfaction	0.913	0.873	0.947	0.016	accepting
limited scalability LS	→	Dissatisfaction	0.802	0.732	0.872	0.007	accepting
Low compatibility LC	→	Dissatisfaction	0.833	0.759	0.869	0.032	accepting
Low compatibility LC	→	intention to adopt	0.034	0.028	0.047	0.005	Accepting
Dissatisfaction D.I	→	intention to adopt	1.031	1.023	1.044	0.006	Accepting

Source: Prepared by the researcher based on the results of the statistical program (AMOS.V.24))

The results od Table (3) show that the low degree of flexibility in discontent has a direct and significant impact, as indicated by the (Estimate) standard regression coefficient value of (0.913). This effect is significant according to the (p-value) of (0.016), which is less than (0.05). The standard regression coefficients value falls within the bottom and upper bounds of the confidence intervals (0.947 – 0.873), as confirmed by the same result. The hypothesis is accepted since it is evident from watching this time that it excludes the value (zero) between its bounds, demonstrating the importance of the independent variables influence consequently, the hypothesis is accepted about the dependent variable.

Regarding limited scalability, Table (4) data show that limited scalability has a direct and significant impact on dissatisfaction, as indicated by the standard regression coefficients (estimate) value of (0.802). This effect is significant according to the (P- value) of (0.007), which is less than (0.05), and the same result validates the lower and upper confidence limits for the standard regression coefficient value (0.872 – 0.732). The hypothesis is accepted because it is evident from watching this time that it excludes the value (zero) between its bounds, which shows a strong impact of the independent variable on the dependent variable, so the hypothesis is accepted.

As for the dimension of low compatible, the data of table (4) indicate that there is a direct and significant effect of low compatible on dissatisfaction, through the value of The standard retrogression measure (Estimate) of (0.833), and this effect is significant in terms of the (p-value) of (0.032), which is lower than (0.05), and the same result confirms the confidence limits for the value of the standard retrogression measure, which are in it is lower and upper limits (0.869 – 0.759). From observing this period, it is clear that it does not include the value (zero) between it is limits, and this is substantiation of the significance effect of the independent variable on the dependent variable, so the thesis is accepted.

As for the dimension of low compatibility, the data of table (4) indicate that there's a direct and significant effect of low comity in the behavioral intention to borrow arising digital technologies, through the value of the standard retrogression measure (Estimate) of (0.034), and this standard significant in terms of the probability (p-value) amounting to (0.003), which is lower than (0.005), and the same result confirms the confidence limits for the value of the standard retrogression measure in it is lower and upper limits (0.047 – 0.028). Form observing this period its clear that it does not include the value (zero) between it is limits, and this is an substantiation of the significance of the effect of the independent variable on the dependent variable, and therefore the thesis is accepted.

As for the dimension of dissatisfaction, with a standard regression coefficient (Estimate) of (1.031) the data in table (4) show that dissatisfaction has a negative impact on behavioral intention to adopt emerging digital technologies. This effect is detrimental, as indicated by a probability value (P- value) of (0.006), which is below the threshold of (0.05). the same result also supports the confidence limits for the standard regression coefficient value, which are in the lower and upper limits (1.044 – 1.023). it is evident by looking at this interval that it excludes the value (zero) between its bounds which shows that the independent variable has a negative impact on the dependent variable, that is, the lower the dissatisfaction, the greater the desire for the intention to adopt, and thus the hypothesis is accepted.

5.2.2 Hypothesis Testing for the Attraction Effects Variable:

Hypothesis H6: Low cost significantly affects the behavioral intention to adopt emerging digital technologies.
Hypothesis H7: Low cost has a significant effect on the expected value of adopting emerging digital technologies.
Hypothesis H8: Easy maintenance significantly affects the expected value of adopting emerging digital technologies.
Hypothesis H9: Attractive alternatives significantly affect the expected value of adopting emerging digital technologies.
Hypothesis H10: Attractive alternatives significantly affect the behavioral intention to adopt emerging digital technologies.
Hypothesis H11: Expected value significantly affects behavioral intention to adopt emerging digital technologies.

In older to verify and confirm the authenticity of these hypotheses, the values of the tests in this form, which guide us to accept or reject the hypothesis, have been clarified, as shown in table (4).

Table 4: Analysis values for hypotheses (H6, H7, H8, H9, H10, H11)

Independent variable	Impact Direction	Dependent variable	Estimate	Lower	Upper	P-Value	Result
Low cost	→	Intention to adopt	-0.027	-0.081	0.029	0.456	Rejection
Low cost	→	Expected value	0.972	0.937	1.011	0.009	Acceptance
Easy maintenance	→	Expected value	0.870	0.805	0.919	0.009	Acceptance
Attractive alternative	→	Expected value	0.892	0.826	0.947	0.007	Acceptance
Attractive alternative	→	Intention to adopt	0.052	-0.002	0.126	0.116	Rejection
Expected value	→	Intention to adopt	0.655	0.460	0.791	0.016	Acceptance

Source: prepared by the researcher based on the results of the statistical program (AMOS.V.24).

The data of Table (4) demonstrate that the standard regression coefficient (Estimate) of (- 0.027) and the P-value of (0.456) do not significantly correlate low cost with the intention adopt new digital technologies. The same result confirms the lower and upper bounds of confidence for the traditional regression coefficient value (0.029- 0.081), and it is more than (0.05). It has the value (zero) between its bounds, as we can see from monitoring this time, so the hypothesis is rejected.

Low cost on the expected value of adopting emerging digital technologies, this effect is significant according to the (p-value) of (0.009), which is less than (0.05), as indicated by the standard regression coefficient (Estimate) value of (0.972). The same result validates the confidence limits for the standard regression coefficient value, which are in its lower and upper limits (1.011 – 0.937). Its evident by looking at this time frame that it excludes the value (zero) between it is bounds, so the hypothesis is accepted.

As for the easy maintenance dimension, the data in the table (4) show that there is a substantial and direct impact of easy maintenance in the expected value of adopting emerging digital technologies, this effect is significant according to the probability value (p-value) of (0.009), which is less than (0.05), as indicated by the standard regression coefficient (Estimate) value of (0.870). The same result validates the confidence limits for the standard regression coefficient value, which are in it is lower and upper limits (0.919 – 0.805). Its evident by looking at this time frame that it excludes the value (zero) between it is bounds, and thus the hypothesis is accepted.

As for the dimension of attractive alternatives, with a non-standard regression coefficient (Estimate) of (0.892), the tables (4) data show that attractive alternatives have a direct and significant impact on the expected value of adopting emerging digital technologies. This effect is significant according to the probability value of (0.007), which is less than (0.05), and the same result validates the confidence limits for the non- standard regression coefficients value, which are in its lower and upper limits (0.947- 0.826). It is evident by viewing this period that the value (zero)between its bounds is not included. and thus the hypothesis is accepted.

The standard regression coefficient (Estimate) of (0.052) in table (4) shows that there are no immediate and noteworthy impact of attractive alternatives on the behavioral motive to adopt emerging digital technologies. The effect is not significant according to the (P-value) (0.116), which exceeds (0.05), and the same results validates the lower and upper bounds of confidence for the standard regression coefficient value (0.126 _ -0.002). It is evident from looking at this time frame that it encompasses the value (zero) in between its boundaries, and thus the hypothesis is rejected.

As for the expected value dimension, tables (4) data show that the expected value has a direct and significant impact on the behavioral intention to adopt emerging digital technologies, as indicated by the estimated standard regression coefficient value of (0.655). This effect is important according to the p-value, or probability value, of (0.004), which is below (0.05). The same outcome also supports the lower and upper bounds of confidence for the standard regression coefficients value (0.791 – 0.460). It is evident by looking at this time frame that it excludes the value (Zero) between it is limits, and thus the hypothesis is accepted.

5.2.3 Hypothesis Testing for the Attraction Effects Variable:

Hypothesis H12: Expected risks negatively affect behavioral intention to adopt emerging digital technologies.

Hypothesis H13: Inertia negatively affects behavioral intention to adopt emerging digital technologies.

In order to verify and confirm the authenticity of these hypotheses, the values of the tests included in this form, which guide us to accept or reject the hypothesis, as shown in table (5):

Table 5: Analysis values for hypotheses (H12, H13)

Independent variable	Impact direction	Dependent variable	Estimate	Lower	Upper	P-value	Result
Expected risks	→	Intention to adopt	0.645	0.527	0.753	0.012	Acceptance
Inertia	→	Intention to adopt	0.571	0.433	0.718	0.008	Acceptance

Source: Prepared by the researcher based on the results of the statistical program (AMOS.V.24)

The data of Table (5show that the intention to adopt emerging digital technologies is negatively impacted by expected risks, as indicated by the estimation of the standard regression coefficient value of (0.645). This effect is important according to the (p-value) of (0.012), which has the same outcome and is less than (0.05) validates the range of confidence for the standard regression coefficient value, which are in the lower and upper bounds (0.753 – 0.527). Upon examining this time frame, we discover that it excludes the value (zero) that lies between its boundaries. So the hypothesis is accepted.

As for the inertia dimension, with a standard regression coefficient (Estimate) of (0.571), the table (6) data show that inertia has a negative impact on behavioral to adopt emerging digital technologies. This effect is significant, as indicated by a probability value (P-value) of (0.008), which is less than (0.05). The same result also supports the confidence limits for the standard regression coefficients value in its lower and upper limits (0.718 – 0.433). it is evident by looking at this time frame that it excludes the value (zero) between its limits, and thus the hypothesis is accepted.

Hypothesis H14: Testing the sub-hypotheses of the study model in an integrated manner.

Table 6: Analysis Values of the Integrated Model of Hypotheses (H14)

Independent variable	Impact direction	Approved variable	Estimate	Lower	Upper	P-value	Result
Low Flexibility	→	Dissatisfaction	0.927	0.798	1.035	0.018	Acceptance
Limited scalability	→	Dissatisfaction	1.165	1.010	1.396	0.005	Acceptance
Low compatibility	→	Dissatisfaction	0.992	0.866	1.139	0.011	Acceptance
Low cost	→	Estimated Value	0.937	0.813	1.081	0.012	Acceptance
Easy maintenance	→	Estimated Value	0.975	0.854	1.163	0.009	Acceptance
Attractive Alternatives	→	Estimated Value	1.037	0.898	1.242	0.005	Acceptance
Low compatibility	→	Intention to adopt II	0.000	-0.044	0.060	0.916	Rejection
Low cost	→	Intention to adopt II	-0.100	-0.176	-0.044	0.012	Rejection
Attractive Alternatives	→	Intention to adopt II	-0.010	-0.085	0.050	0.749	Rejection
Expected risks	→	Intention to adopt II	1.067	0.891	1.314	0.009	Acceptance
Inertia IN	→	Intention to adopt II	1.201	0.965	1.593	0.004	Acceptance
Dissatisfaction	→	Intention to adopt II	0.857	0.694	1.004	0.006	Acceptance
Expected value	→	Intention to adopt II	0.991	0.828	1.186	0.007	Acceptance

Source: Prepared by the researcher based on the results of the statistical program (AMOS V.23)

It is clear from the data of table (8) that there is no significant effect of the low compatibility in the behavioral intention to adopt emerging digital technologies regarding the p-value, or probability value, of (0.916), which is greater than 0.05, and there is no significant effect of the low cost in the behavioral intention to adopt emerging digital technologies in terms of the p-value of (0.012), which id higher than (0.05), and there is no significant effect of attractive alternatives on the behavioral intention to adopt emerging digital technologies according to the p-value of (0.749) and the value exceeds (0.05).

Discuss the Results of Testing the Study Model and Its Hypotheses

Hypothesis H1:

The results of the statistical analysis indicated that there is a significant effect of low flexibility in dissatisfaction, and prior studies supported this, including the study of (Ramaraj, 2010), which indicated the need for information technology to have sufficient flexibility in response to the personal needs of individuals and their job requirements efficiently and effectively.

Hypothesis H2:

The results of the statistical analysis indicated that there is a significant effect of scalability in dissatisfaction, and the study (Delone & Mclean, 2004) indicated that scalability in the context of information technology is the ability of technology to expand, develop and grow, and its ability to be absorbed in processing more volume of business transactions does not affect its expansion in the quality of the information and the quality of the service provided.

Hypothesis H3:

The results of the statistical analysis indicated that there is a significant effect of low compatibility in dissatisfaction, and preceding studies, such as the study, supported this (Rogers, 2003), which indicated that low compatibility is the extent to which beneficiaries consider that information technology is not suitable for business processing.

Hypothesis H4:

The results of the statistical analysis indicated that there is a significant effect of low compatibility in the intention to adopt emerging digital technologies. Information technology improves an individual's image or position in the social system.

Hypothesis H5:

The results of the statistical analysis indicated the that there are negative impact of dissatisfaction in the impulse for a adoption emerging digital technologies, and earlier research supported this, including the study (Zhang *et al*., 2012), which indicated that dissatisfaction is the feeling that follows a failure of expectations among the beneficiaries of information technology, and that dissatisfaction is closely related to changing the behavioral intentions of individuals.

Hypothesis H6:

The results of the statistical analysis of this hypothesis indicated that there is no significant effect of the low cost in the intention to adopt emerging digital technologies. By reviewing earlier studies, including the study (Buttell, 2010), this showed that there was little to on assistance from management dissuades people from staying and continuing with the status situation, which impacts people’s attitudes regarding their intention to adopt emerging digital technologies.

Hypothesis H7:

The results of the statistical analysis of this hypothesis indicated that there is a significant impact of the low cost on the expected value of adopting emerging digital technologies, and by reviewing earlier research, such as the study (Sweeney & Soutar, 2001), which showed that the low cost can affect and enhance the expected value, which may be (emotional value - social value - quality value - price value), which significantly affects the expected value of information technology.

Hypothesis H8:

The results of the statistical analysis of this hypothesis indicated that there is a significant effect of ease of maintenance in the intention to adopt emerging digital technologies by reviewing earlier research, such as the study that showed that (Rohit, 2010), which showed that the ease of maintenance of information technology is a process that does not require time and great effort to modify and correct it to adapt to the work environment and the desire of individuals.

Hypothesis H9:

There is a significant effect of attractive alternatives on the expected value of adopting emerging digital technologies. By reviewing previous studies, including the study of (Zengyan *et al*., 2009), which described attractive alternatives as a conceptual perception that describes the positive characteristics and features of alternative technology, which when individuals realize that the main features of alternative technology are better than the current technology, they are likely to be attracted to replace it.

Hypothesis H10:

The results of the statistical analysis indicated that there was no significant effect of attractive alternatives on the behavioral intention to adopt emerging digital technologies, and previous studies corroborated this, including the study of (Sun *et al*., 2017) and (Zhang *et al*., 2012), as it is unlikely that Individuals are attracted to information technology if its financial costs are high, or it may take time and effort to learn it, and it does not provide comfort at work due to the complexity of its use.

Hypothesis H11:

There is a significant effect of the expected value in the behavioral intention to adopt emerging digital technologies. Through a review of earlier studies, such as the study of (Keaveney, 1995), which showed that the expected value is the degree to which the individuals expects that the adoption of information technologies will achieve value by processing business with high accuracy and speed in a way that ensures efficiency at the functional and administrative level and enhances organizational performance as a whole, which is an important factor that attracts individuals towards their willingness to adopt emerging digital technologies.

Hypothesis 12H:

The results of the statistical analysis of this hypothesis indicated that there is a significant effect of the expected risks in the behavioral intention to adopt emerging digital technologies. By reviewing previous studies, including the study of (Xue & Xin, 2016), the expected risks are a group of Beliefs, negative feelings, and fears related to data privacy and security that are generated by individuals when seeking a satisfactory result of adopting cloud-based information technology, that is, the lower the expected risks, the greater the individual's desire to intent to adopt, and the higher the risks, the greater the negative impact in the intent to adopt.

Hypothesis H13:

The results of the statistical analysis of this hypothesis indicated that there are is a negative effect of inertia on the behavioral intention to adopt emerging digital technologies. By reviewing previous studies, including the study of (Sun *et al*., 2017), which defined inertia as, situational or personal factors that explain the extent to which individuals relate to current patterns and behaviors (the status quo), as individuals tend not to change their behavior due to their personal and emotional attachment and their adherence to current technology, which negatively affects the intention to adopt.

Hypothesis H14:

There is no significant effect of low compatibility in the behavioral intention to adopt emerging digital technologies, and this was confirmed by the study (Low & Chen, 2011), as it indicated that there was no effect of low compatibility in the intention to adopt emerging digital technologies, nor is a significant effect of the low cost in the behavioral intention to adopt emerging digital technologies, as the study (Wang *et al*., 2021) indicated that individuals are concerned about not knowing the actual material cost that is uncertain in the process of adopting information technology and that it may expose individuals to a non-material cost from the psychological cost, the cost of time, training, and effort spent in learning new technology, and the cost of research and evaluation. So they are hesitant in making the adoption decision.

6. CONCLUSIONS, PROPOSALS AND FUTURE STUDIES

6.1. Conclusion and Suggestions

- Through the study, it became clear that there is an effect of the measures represented by (push effects - attraction effects - mooring effects) on the behavioral intention to adopt emerging digital technologies according to the theory of push-pull and mooring to accept the PPM technology (Push - Pull - Mooring Model) in the researched organization.
- According to the results of the study, the push effects represented by (low flexibility, limited scalability, and low compatibility) have a significant effect on dissatisfaction with the adoption of emerging digital technologies, and that low compatibility has a major impact on the behavioral want to adopt emerging digital technologies.
- The results of the study indicated that the effects of attraction (low cost, ease of maintenance, and attractive alternatives) significantly affect the expected value of adopting emerging digital technologies.
- The results of the study indicated that the effects of mooring (expected risks and inertia) negatively affect the intention to adopt emerging digital technologies
- The results of the study indicated that dissatisfaction negatively affects the behavioral intention to adopt emerging digital technologies.
- The results of the study indicated that the expected value possesses a substantiaAbdullah Mohammed l impact on the behavioral wish to adopt emerging digital technologies
- The results of the integrated study model show that there isn't any discernible impact of (low compatibility, low cost, and attractive alternatives) on the behavioral intention to adopt emerging digital technologies.

6.2. Proposals and Future Studies

- Working to raise awareness by administrations in health organizations about the importance of adopting emerging digital technologies because of their impact on improving the organization's operations and evaluating its performance.
- Senior management should provide the necessary support in helping individuals overcome the challenges that hinder the adoption of emerging digital technologies.
- We recommend hospital management in the health sector to apply the Balanced Scorecard (BSC) as a tool for measuring hospital performance and as a means to rationalize managers' decisions and direct their behavior to evaluate performance.

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