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Why do healthcare workers adopt digital health technologies - A cross-sectional study integrating the TAM and UTAUT model in a developing economy

Onome Christopher Edo
Auburn University at Montgomery

David Ang
Auburn University at Montgomery

Egbe Etu Etu
San Jose State University, egbe-etu.etu@sjsu.edu

Imokhai Tenebe
San Jose State University

Solomon Edo
Auchi Polytechnic

See next page for additional authors

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Why do healthcare workers adopt digital health technologies - A cross-sectional study integrating the TAM and UTAUT model in a developing economy

Onome Christopher Edo[a,*], David Ang[a], Egbe-Etu Etu[b], Imokhai Tenebe[c], Solomon Edo[d], Oladapo Ayodeji Diekola[e]

[a] Department of Information Systems, Auburn University at Montgomery, Montgomery, Alabama, United States
[b] Department of Marketing and Business Analytics, Lucas College and Graduate School of Business, San Jose State University, United States
[c] Mineta Transportation Institute, San Jose State University, CA, United States
[d] Department of Agricultural Engineering, Auchi Polytechnic, Nigeria
[e] Department of Computer Information Systems, University of Houston, Victoria, Texas, United States,

A R T I C L E I N F O

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A B S T R A C T

Healthcare technology is a critical factor for effective management of patient care, resulting in enhanced effectiveness when adopted by healthcare professionals. However, the lack of acceptance can undermine its inherent benefits. This study aims to investigate the factors that influence the adoption of technology among healthcare professionals, using Nigeria as a case study. The dataset for the study was collected from a sample of 301 private and public healthcare professionals. The collected data were analyzed using structural equation modeling (SEM) and the results supported five of the proposed hypotheses, namely, perceived usefulness, perceived physical condition, technological anxiety, user innovativeness, and perceived availability which had a significant influence on Behavioral intention. However, Technological anxiety showed a negative influence on BI. The study sheds light on relevant factors for healthcare technology adoption. Psychological reengineering and human relation support and a reward system are required to further motivate technology adoption among healthcare workers.

1. Introduction

Technology provides a competitive edge concerning process improvement and strategic realization for various organizations, including the healthcare sector. The healthcare industry has undergone rapid transformation with manual operational systems being replaced by digital healthcare technologies such as personal health records, electronic prescriptions, smart health devices, wearable technologies, artificial intelligence-enabled patient relationship management, and telemedicine (Alolayyan et al., 2020; Chen et al., 2020; Kumar et al., 2023; Young & Steele, 2022).

Digital Health Technology (DHT) specifically refers to information, communication, and technological devices that enable patient care management in a computerized format; it includes but is not limited to, record management systems, health monitoring systems, medical dispensing devices, prescribing systems, and other software that support and improve patient care process management. DHT offers numerous benefits to both patients and practitioners including speedy and accurate access to patients' records, improved access to care, reliable diagnostics, and enables remote patient care to distant patients who might otherwise struggle to receive proper medical care (Ahsan & Siddique, 2022; Akwaowo et al., 2022; Babatunde et al., 2021; Grover et al., 2018).

However, there are challenges in adopting digital technologies in the industry (Moshood et al., 2022; Rajak & Shaw, 2021), and there are no consensus factors attributed to the behavioral deviations of adopting digital health technologies. Technology adoption studies categorized digital technology into two domains, development, and acceptance, the former being the process and activities of bringing new technology to the market and the latter behavioral tendencies for use of the new technology.

Given the significance of general technology adoption in organizations, F. Davis (1989) proposed a model for exploring the factors influencing adoption, and Venkatesh et al. (2003) improved on the theory by considering holistic factors of adoption such as perceived ease of use, perceived usefulness attitude, behavioral intention, and actual use. However, both model have not recorded significant research activities in the healthcare domain, especially in developing countries like African countries (Akwaowo et al., 2022; Gabriel Alobo et al., 2020),

* Corresponding author.
E-mail addresses: oedo@aum.edu (O.C. Edo), dang@aum.edu (D. Ang), egbe-etu.etu@sjsu.edu (E.-E. Etu), diekolao@uhv.edu (O.A. Diekola).

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where there are technological inconsistencies. For example, Nigeria, which is known as Africa's giant and the sixth most populated country in the world, records one of the world's worst healthcare indices and technology adoption index (Abubakar et al., 2022; Edo et al., 2022, and Ikechukwu et al., 2021). Moreover, the WHO reported that digital technologies for healthcare interventions in Africa remain at their pilot stage, and only a handful has documented the realities of such interventions.

Technology does not exist in isolation, and its availability does not translate into adoption but thrives on the acceptance and collaboration of the supposed users or process owners such as doctors, nurses, and medical personnel for the realization of its full potential (Akwaowo et al., 2022; Suha & Sanam, 2023; Udenigwe et al., 2022). Acceptance is a forerunner of technology adoption, which is founded on several factors, such as perception, attitudes, and behavior toward the deployment of technology (A.A. Alfalah, 2023; F.D. Davis, 1989; Venkatesh et al., 2003). Studies have identified factors impeding DHT adoption to be complexity, user capability, cognitive capacity, external and environmental factors, poor infrastructure, and anxiety (Jedwab et al., 2022; Ljubicic et al., 2020; Ngugi et al., 2021; Rajak & Shaw, 2021).

Most studies on technology acceptance have focused on developed continents, and the factors that have been identified in these countries may not necessarily be responsible for the deviations in developing continents, such as Africa, and by extension Nigeria. Furthermore, studies on technology acceptance in Nigeria have concentrated on resource and technical factors that affect the adoption and acceptance of DHT, with limited attention given to behavioral factors in this context. Specifically, the impact of social influence and perceived physical condition has not been documented in the Nigerian healthcare context. The failure to address technology adoption factors creates a gap in the healthcare space.

Therefore, this study aims to investigate behavioral impediments to technology adoption among Nigerian healthcare workers. The study is guided by the Technology Acceptance Model (TAM) and the Unified Theory of Use and Acceptance of Technology (UTUAT) model and seeks to address the following research questions (RQ):

a RQ-1: What factors influence the acceptance of DHT among Nigerian healthcare workers?
b RQ-2: What moderating variables affect technology adoption among Nigerian health workers?
c RQ-3: What is the impact of social influence and perceived physical condition on DHT adoption among Nigerian healthcare workers?

This paper is organized as follows: section.2 discusses the theory and hypothesis, section 0.3 outlines the research method, section.4 shows the results obtained from the analysis, Section 5 discusses the results and section.6 concludes the paper.

2. Theoretical framework and hypothesis development

Technology adoption intention is a well-established phenomenon in the domain of information systems. However, the findings from various studies suggest the need for a domain fit theory that can effectively explain the intentions for technology adoption. Several theories have been proposed to explain behavioral intent, including the theory of reasoned action (TRA) and planned behavior (Fishbein & Ajzen, 1975; Icek, 1991), which states that an individual's intention to perform an action at a particular time and place is influenced by the belief that they can successfully perform the task or action based on their perceived behavioral control which by extension is dependent the users' intent (A.A. Alfalah, 2023; Matar Alshahrani et al., 2023; Staats, 2004).

These theories draw on insights from human and psychological behavior to explain behavioral intentions, attitudes, beliefs, and subjective norms (Ajzen, 2011). In addition to these theories, Rogers (1962) developed the diffusion of innovation theory, which defines diffusion as the "process by which an innovation is communicated through certain channels over time among members of a social system". The theory suggests that the adoption of innovation is a function of its characteristics, and that adoption of a technology is predicted by its perceived innovation.

However, extant studies have expressed concerns about the applicability of these theories to investigate technology adoption in health information systems (LaMorte, 2019; Kippax, 1993). For example, adoption decisions are often influenced by contextual factors such as the environment, skills, prior experience, and other economic factors, which are not fully accounted for by the TRA and diffusion of innovation (LaMorte, 2019; Kippax, 1993). To address this limitation, the current study adopts the TAM and UTUAT as theoretical frameworks for investigating technology adoption in the Nigerian healthcare context.

2.1. Technology acceptance model

The TAM has gained widespread recognition for explaining adoption behavior in the domain of information systems. TAM supplements the theory of reasoned action and planned behavior originally put forward by Fred F. Davis in, 1989. TAM posits that the adoption of a new information system is influenced by attitude, which is a function of other factors (F.D. Davis, 1989)

The study specifically examines two factors, perceived usefulness, and perceived ease of use. F.D. Davis (1989) in his doctoral seminal paper defined perceived usefulness as "the degree to which a person believes that using a particular system would enhance their performance". In essence, adoption behavior is premised on the perceived utility and effectiveness of the system. Actual system usage is, therefore, a function of an individual's assessment of the system's contribution to task effectiveness and efficiency. It is worth noting, however, that this factor can vary among individuals and changes over time.

Perceived ease of use, on the other hand, "is the degree to which a person believes that using a particular system would be free from effort" (F.D. Davis, 1989). This factor limits the complexity of a system, and adoption decisions are likely to be positive based on the simplistic nature of the system. F.D. Davis (1989) found that these factors were highly significant and correlated in measuring technology adoption behavior. Further studies confirmed the validity and reliability of these constructs in predicting user intention (Adams et al., 1992; Hendrickson et al., 1993; Subramanian, 1994; Workman, 2007) (Fig. 1).

2.1.1. Unified theory of use and acceptance of technology

TAM has been a widely used model for explaining technology use. However, research has highlighted its limitations in predicting behavioral intentions, social influences, and facilitating conditions (Napitupulu, 2017; Torres & Gerhart, 2019), indicating the need for a more robust model. Consequently, Venkatesh et al. (2003) proposed the unified theory of use and acceptance of technology (UTUAT).

Unlike the TAM, UTUAT focuses on continuous usage and is based on four principal variables: performance expectancy, effort expectancy, social influence, and enabling conditions. Performance expectancy is similar to perceived usefulness, which is the degree of value anticipated from using a technology (Venkatesh et al., 2003), whiles effort expectancy is related to the ease of use associated with adopting and continuously using a technology (Davis & Venkatesh, 2004; Venkatesh et al., 2003). Social influence is premised on the perception of using a system based on beliefs and peer influence. The efficacy of the UTUAT model has been demonstrated in previous studies such as Hamzat and Mabawonku (2018), Mensah (2019), Eckhardt et al. (2009), Schretzlmaier et al. (2022) (Fig. 2).

Based on the sufficiency exhibited in prior literature and the validity of the TAM and UTUAT models, this study adopts a dual-model approach complimented by both theories. In addition to the constructs contained in both models, this study extends the model by incorporating perceived resource availability as a construct and including significant constructs

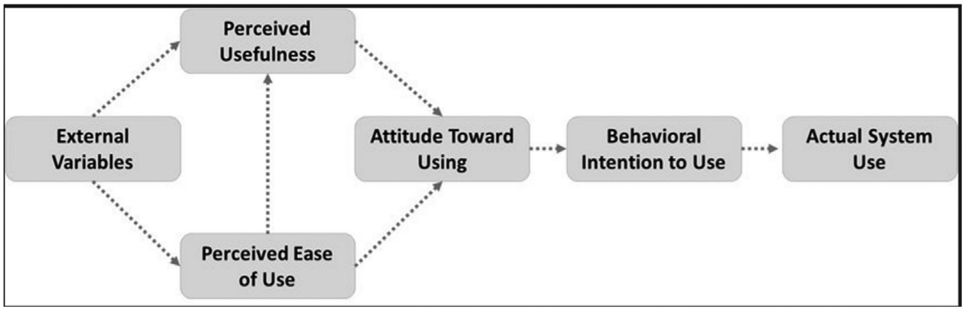

Fig. 1. Technlogy acceptance model. Adapted from F.D. Davis (1989).

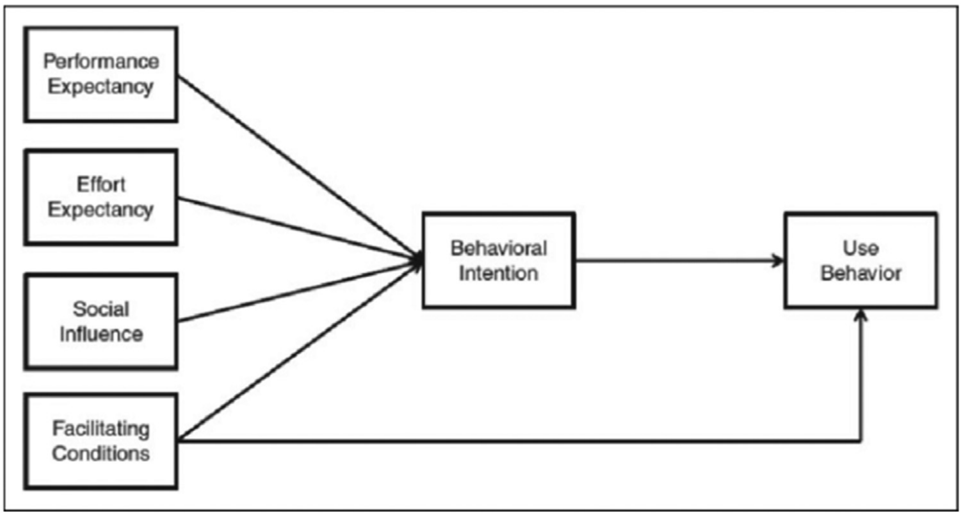

Fig. 2. UTUAT Model. Adapted from Venkatesh et al. (2003).

from previous studies, such as resistance to change, technology anxiety, technical skills, and personal innovativeness (see Table 1).

These variables were integrated into the model to provide a comprehensive understanding of behavioral intention. The reason for this approach is rooted in the fact that availability and reliability of resources are relative to the region, and the African region is particularly affected by this phenomenon. Therefore, it is essential to include the impact of these variables in the evaluation of healthcare technology adoption in the region. The constructs are derived from previous theories and studies (Table 1). Furthermore, the author developed items 2 and 3 of technology skills. Item 2 pertains to perceived availability and item 4 pertains to behavioral intention (see Table 1).

2.2. Technology adoption and perceived ease of use

F.D. Davis (1989) defined perceived ease of use as the extent to which individuals perceive a technology infrastructure or service to be easy to use. The degree of ease is a key aspect of usability, which can be evaluated based on the speed of task completion, the degree of error encountered, access to resources that guide the user in completing a task, time savings, or minimal effort required to use a technology system. According to Kar (2020) Adoption of digital services is frequently influenced by the perceived ease of use.

Previous studies have emphasized the relevance of perceived ease of use in evaluating user behavior (Choi & Tak, 2022; Jimma & Enyew, 2022; Ljubicic et al., 2020b; Rochmah et al., 2020). Understanding the individual perception of ease of use is critical, as it shapes behavior, which in turn influences acceptance. The importance of ease of use is well-documented in previous literature. For example, Choi and Tak (2022) investigated the behavioral intention of 206 Korean nurses to use a virtual simulation technology and found that behavior was significantly influenced by their perception of ease of use. However, this study was conducted only in one hospital and considered only nursing professionals.

In another study, Ebenso et al. (2021) investigated the factors that promote digital technology acceptance in maternal and childcare services in Nigeria. Data was collected from 294 healthcare workers across 126 hospital facilities, and the result showed that ease of use had a strong influence on user acceptance. Several studies have reported the impact of ease of use across various fields (Alexandra et al., 2021; Ali Alhur, 2023; Nguyen et al., 2020), leading to the inference that perceived ease of use is a crucial factor in technology adoption.

H_1: *Perceived ease of use significantly affects DHT adoption behavior.*

2.2.1. Technology adoption and perceived usefulness

The concept of usefulness is an extension of the concept of utility, which refers to the degree of satisfaction derived from the use of a service or technology. According to F.D. Davis (1989), usefulness can be defined as the extent to which an individual perceives the technology contributes to job performance. Perceived usefulness has been identified as a critical variable in technology acceptance behavior in various fields, such as mobile payment adoption (Ullah et al., 2022), e-learning (Al-Mamary, 2022a, 2022b), and social media (Grover et al. 2018; Hanaysha, 2022).

Adoption studies have reported similar findings, for example, Turan and Koc (2022), investigated technology acceptance among 174 Turkish physicians and found that perceived usefulness strongly impacted behavior. Similarly, Hicks et al. (2021) studied the acceptability of e-health tools among health workers in Nigeria using a semi-structured questionnaire and observation and found that perceived usefulness significantly influenced technology adoption behavior. Several other studies have reported similar results linking perceived usefulness and adoption (Ali Alhur, 2023; Cho et al., 2021; Choi & Tak, 2022; Rouidi et al., 2022). The perception of usefulness is a crucial factor in

Table 1
Summary of constructs, measures, and sources.

Constructs	Measurement (Response 1- Strongly disagree to 5 Strongly Agree) Items	Sources
Perceived Ease of Use		
PEU1	Learning to use health information systems would be easy for me	(Davis, 1986, F.D. 1989; Zhaohua, 2013)
PEU2	It will be easy for me to become skillful in using technology in my job	
PEU3	Interacting with Healthcare technology would require a lot of mental effort	
Perceived Usefulness		(Zhaohua, 2013)
PU1	Using technology at work would enhance my effectiveness at work	
PU2	I would find technology useful in healthcare practice	
PU3	I think healthcare information technology is useful for my job	
Perceived Physical Condition		
PPC1	Using computers and other information system technology would require me to exert more effort to perform my daily task at work	(Min-Ho, Seongcheol & Euehun, 2009)
PPC2	Using Computers and other Information Systems at work would limit the kind of activities I can perform	
PPC3	Using Health information technology and systems would cause some difficulties in performing my daily task	
Technology Anxiety		(Zhaohua, Mo, & Liu, 2014)
TA1	Using computers and associated technology makes me nervous	
TA2	Using computers and other systems makes me worried	
TA3	Using computers and other technology gadgets for work may make me uncomfortable	
Social Influence		
SI1	People who influence my behavior think I should use Health electronic systems	(Zhaohua, Mo & Liu, 2014)
SI2	My colleagues and peers think it is a good idea to use Healthcare information technology	
SI3	My peers and colleagues use health information technology and have encouraged me to adopt technology	
Technology Skills		
TS1	I have received formal training on healthcare information technology	(Ifinedo, 2018)
TS2	I have received support and training on healthcare information technology at my workplace	(Author)
TS3	I am aware of platforms and resources for healthcare technology training	(Author)
Personal Innovativeness		
UI1	If I heard about new information technology, I would look for ways to experiment with it	(Agarwal & PrasadJ, 1989; Yi et al., 2006)
UI2	Among my peers, I am usually the first to try out new information technologies	
UI3	In general, I am not hesitant to try out new information technologies	
Resistance to Change		(Bhattacherjee & Hikmet, 2008)
RTC1	I don't want electronic health technology to change the way I deal with patient disease	
RTC2	I don't want electronic health information technology to change the way I keep the health records of patients	
RTC3	I don't want electronic health technologies to change the way I interact with doctors and other hospital staff	
Perceived Availability		
PSA1	My place of work has limited information systems	
PSA2	There are no up-to-date information systems at my place of work	(Author)
Behavioral Intention		
BI1	I intend to use Health information technology in the future	(F. D. Davis & Venkatesh, 2004; Papa et al., 2018)
BI2	I will always try to use Health information technologies	
BI3	I plan to continue to use Health Information Systems frequently	
BI4	If I have the resources, Knowledge, and ability, I will use Health information systems	(Author)

technology adoption, as individuals are less likely to use a technology if they do not perceive that it will significantly improve their job performance. This study, therefore, aligns with previous literature and posits the following hypothesis:

H_2: *Perceived usefulness significantly affects DHT adoption behavior.*

2.2.2. Technology adoption and perceived physical condition

Perceived physical condition stems from an individual's ability to perform tasks effectively. It is linked to the individual's fitness and capacity for a particular task, and this is often influenced by age, which affects the individual's biophysical and psychosocial strength (Rajak & Shaw, 2021). However, the decline in perceived physical condition with age may not be solely due to aging, but may also be associated with other factors such as cognitive overload, information overload, or technostress, which can negatively impact an individual's ability to function optimally and limits their overall well-being, regardless of age (Asad et al., 2023; Kim et al., 2022; Singh et al., 2022).

Various studies in different IS domains have explored the impacts of these factors on adoption behavior. For example, Khlaif et al. (2022) examined the influence of age and technostress on the intention to use mobile technology among 367 teachers and found that technostress negatively affected usage attitude and perceived usefulness. Similarly, Alshurafat et al. (2022) found that the perceived physical condition of auditors was influenced by technostress, which, in turn, impacted the acceptance decision of blockchain technology.

Despite these findings, no study has explored the impact of perceived physical conditions on the adoption of technology among Nigerian health workers, given the conflicting definitions of the construct. Consequently, the study posits that perceived physical condition is a crucial factor that affects adoption behavior, based on its significance in prior research.

H_3: *Perceived physical condition significantly affects DHT adoption behavior.*

2.2.3. Technology adoption and technology anxiety

Anxiety is the emotional state characterized by feelings of fear and perceived frustration, particularly in situations involving challenging tasks or uncertainty. Technophobia refers to the fear or dislike of new or complex innovations, especially information and communication devices and applications that impact organizational behavior

(Rahmani et al., 2023). This often stems from the lack of familiarity with and the perceived complications of using technology (Maduku et al., 2023) and can manifest in the forms, including negative thoughts, and apprehension (Lee et al., 2021; Yuan et al., 2022).

Numerous studies conducted in the IS domain have demonstrated the influence of anxiety on technology adoption. For example, Rajak and Shaw (2021) investigated healthcare technology acceptance in India, with a sample of 289 participants, and their data analysis using SEM revealed that anxiety had a negative impact on technology adoption. Other studies have similarly shown that technology anxiety hinders technology adoption (Alqudah et al., 2021; Kwak et al., 2022; Rahmani et al., 2023), thereby reducing the likelihood of accepting technological innovations. Based on the results of these study, the following hypothesis is proposed.

H_4: *Technology anxiety significantly affects DHT adoption behavior.*

2.2.4. Technology adoption and social influence

Social influence refers to both intentional and unintentional efforts by others to affect an individual's thoughts, emotions, or behavior (Riva et al., 2022). Given the significant role of the social environment in shaping technology adoption intention (Rajak & Shaw, 2021), individuals are likely to conform to prevailing norms in their environment, particularly when the actors in the environment wield some level of respect and knowledge. Individuals often seek to associate themselves with knowledgeable groups, and the desire for affiliation can influence their attitudes and actions.

Peer opinions and views of revered individuals can significantly impact an individual's preferences and decisions (Wei et al., 2019), particularly when the opinions reflect perceived usefulness and ease of use (Rajak & Shaw, 2021). Moreover, studies have shown that social circles in the workplace can be instrumental in shaping attitudes and perceptions and can serve as an enabler or catalyst for technology adoption (Jedwab et al., 2022; Ljubicic et al., 2020; Rajak & Shaw, 2021; Yadav et al., 2022). Building on previous investigations, the current research proposes the following hypothesis.

H_5: *Social influence significantly affects DHT adoption behavior.*

2.2.5. Technology adoption and technical skill

Adopting digital technology requires individuals to possess digital competence, given that it involves the use of diverse technology that are constantly evolving. The individual's level of technological proficiency and comfort can significantly impact their performance on both simple and complex tasks in an environment where computers and associated technical services are used (Rahmani et al., 2023; Taha et al., 2014). Inadequate resources for developing an understanding of these technologies may present a major impediment to adoption decisions (Lyles et al., 2020), resulting in limited capacity and frustration (Rajak & Shaw, 2021). Thus, providing adequate resources and the necessary support to help further learning and continuous training is crucial.

The lack of technological skills and the unwillingness to expand one's knowledge on the use of DHT can have a significant impact on user adoption decisions (Lyles et al., 2020). Technical skills are directly linked with an individual's attitude toward adoption, which is based on personal innovativeness. Personal innovativeness refers to the capacity or willingness to use or manage technological gadgets. The degree of technology adoption is perceived to increase among individuals who express positive attitudes towards a new system, irrespective of the perceived challenges encountered during its use (Agarwal & Prasad, 1998). Previous studies have shown that technical skills and personal innovativeness with respect to technology adoption (Afrizal et al., 2019; Berihun et al., 2020; Choi & Tak, 2022; Rahmani et al., 2023; Sampa et al., 2020; Wubante et al., 2022; Yadav et al., 2022). Based on the preceding discussion, the study proposes the following hypothesis:

H_6: *Technical skills significantly affect DHT adoption behavior.*

H_7: *Personal Innovativeness influences DHT adoption behavior.*

2.2.6. Technology adoption and resistance to change

According to Piderit (2000), resistance to change as a tripod attitude that involves affective, behavioral, and cognitive components. These components are expressed in three dimensions: feelings, the effect of behavior, and beliefs or knowledge. An individual assesses a situation or object based on their feelings (McGuire, 1985), which translates into actions supported by one's beliefs or level of knowledge on the subject (Oreg, 2007). In most cases, people tend to align their behavior with old pre-existing norms.

Therefore, individuals must evaluate their intention considering this. Switching to a new habit can be challenging, but continuous changes are expected in the context of innovation. Several studies have investigated the relationship between resistance to change and technology adoption, with varying findings. For instance, while Hossain et al. (2019) found that resistance to change was not significant in explaining technology adoption behavior among Bangladeshi healthcare workers, other studies reported that resistance to change impedes technology adoption (Harahap et al., 2022; Yadav et al., 2022). Therefore, the following hypothesis is proposed.

H_8: *Resistance to change affects DHT adoption behavior.*

2.2.7. Technology adoption and perceived availability

Perceived availability refers to the readiness of an IT resource to accomplish a task on request (Tang, 2021). In the healthcare setting, the perception of a system's availability and reliability at the time of use is crucial. However, deficiencies in technological resources and basic amenities in certain geographical contexts, such as erratic unstable power supply, passive internet connection, and inadequate technical support (Adenuga, 2020; Agbata, 2021, and Edo et al., 2020), can negatively affect the adoption of technology, as shown by Consul et al. (2021) in a study of 150 hospital staff to evaluate the adoption of electronic technology in Nigeria. Archer et al. (2021) held that technological inadequacies were predominant in low resources countries such as Egypt, India, Kenya, and Nigeria, this impacted utilization, thus negatively affecting technology adoption. Other studies that point to the effect of perceived availability on technology adoption are Alanezi (2021) and Olorunfemi et al. (2020). Based on this, the following hypothesis is proposed:

H_9: *Perceived availability affects DHT adoption behavior.*

3. Research methodology

3.1. Study design

This study aims to investigate the factors that influence the adoption of technology in Nigeria's healthcare sector. The study considers observable variables established by major theories such as TAM and UTUAT and includes a construct on perceived availability to test the impact of resource constraints in the Nigerian healthcare environment. The study employs quantitative methodology and relies on all an . questionnaire for data collection. Structural equation modeling (SEM) is used to measure and evaluate the relationship between the latent variables, which is commonly used to validate the conceptual model of primary research (Al-Mamary, 2022b). The PLS-SEM is preferred for predicting and analyzing dependent variables in a study of this nature to account for maximum variation (Hair et al., 2018; Kock & Hadaya, 2018).

3.2. Questionnaire design

A series of questions from reviewed research is used in this study, with a few minor modifications to better resonate with healthcare workers in Nigeria. The questions were adapted from existing literature and are deemed reliable for this study (Rajak & Shaw, 2021). The construct for perceived availability was self-developed, and the questions were pre-tested by 30 healthcare workers and a panel of doctors and nurses in private and public hospitals to eliminate ambiguity. The questionnaire was designed on Surveyplanet.com and the link was sent to IT directors of hospitals and healthcare professional associations in Nigeria. The questionnaire contained 10 sections, including a section on demographic questions, and sections aligned with the respective study constructs.

3.3. Population and sample

To achieve the objectives of the study, an online survey was developed in August 2022. Before developing the survey questions, it was crucial to determine the appropriate survey respondents to provide accurate estimations and perceptions of the variables. As a result, survey participants were selected based on their profession; specifically, those working in health-related organizations such as public hospitals, primary healthcare hospitals, private hospitals, laboratories, pharmacies, and related care facilities. The participants included healthcare workers such as doctors, nurses, healthcare associates, pharmacists, therapists, and related healthcare practitioners, who were further categorized based on their job experience and active service. To ensure the study's validity and reduce resource requirements (Rajak & Shaw,2021), a judgmental sampling procedure was adopted, which is commonly used when certain qualities and experiences are expected from a target population.

3.4. Data collection

Data were collected through an online survey hosted on www.surveyplanet.com. The survey link was shared across social media platforms and sent to various healthcare facilities, including the administrative department of a general hospital in Ifako ijaiye, Lagos, Federal Medical Center, Asaba, Delta State. Health insurance board, Nigeria Medical Association, Delta State branch, and individuals working in the healthcare sector.

However, since collecting sufficient data only through the online survey proved to be challenging, a hardcopy survey was generated and distributed to participants who were skeptical about the surveys and the incidence of fraud. The hardcopy and online surveys were identical, and responses from the hardcopy survey were subsequently digitized to facilitate data analysis. Of the 300 hard copies circulated among the possible respondents, only 125 participants completed the survey to be included in the study. From the online survey, 179 completed responses were retrieved. Biased responses were identified and eliminated. In addition, three incomplete responses were eliminated.

3.5. Reliability analysis

To confirm the validity and reliability of the questionnaire, a pre-test was conducted using a questionnaire with 10 variables, distributed to 30 healthcare workers. The Cronbach alpha was used to assess the validity and reliability of the variables. The internal consistency coefficient of Cronbach's Alpha ranged from 0.723 to 0.893 which falls within the minimum acceptable threshold for a study of this nature (Hair et al., 2016, 2018, 2019). This suggests that the results were reliable and had consistency above the norm (see table below).

Reliability analysis

Reliability analysis

Constructs	Cronbach alpha
Perceived Ease of Use	0.751
Perceived Usefulness	0.893
Perceived Physical Condition	0.760
Technology Anxiety	0.859
Social Influence	0.768
Technology Skills	0.819
User Innovativeness	0.723
Resistance to Change	0.858
Perceived Availability	0.764
Behavioral Intention	0.852

4. Data analysis

To account for maximum variation and predict and investigate the dependent variables, this study used PLS-SEM, a widely recommended prediction technique (Roldán & Sánchez-Franco, 2012). It has been identified as the optimal method for the analysis of complicated path models, and is capable of handling both measurement (external) and structural (internal) models successively (Hair et al., 2016). PLS-SEM is effective with small sample sizes and sophisticated models (Kock & Hadaya, 2018), making it a suitable methodology for this study. Moreover, the PLS-SEM approach has been gaining popularity due to its potential advantages in management and behavioral research (Cepeda-Carrion et al., 2019; Bari et al., 2020).

4.1. Common method bias

The issue of common method variance (CMV) bias in the survey samples is a major concern that arises when data are acquired from a single source (Podsakoff & Organ, 1986). To assess whether CMV existed among constructs, a single-factor test was conducted according to Harman's (1976) approach. The results indicated that amongst all elements of the model, the first factor amongst the 10 pre-grouped factors, accounts for only 25.012% of the total variance (see Table 2). This falls below 50% of the cut-off criteria (Hair et al., 2016). Additionally, a thorough collinearity assessment test was conducted using Smart PLS, a method that has been shown to be efficient and concise according to Kock (2015). The VIF values of all the constructs were below the predetermined threshold of five, indicating that common method bias is not a significant concern in this study.

4.2. Measurement model evaluation

The present study used a measurement model to assess the reliability and validity of the measurements 10 latent variables as presented in Fig. 3. According to Hair et al. (2016), the evaluation of the measurement model focused on the reliability of the indicators and the convergent and discriminant validity of the constructs. To assess the reliability of the measurements, the indicator loading, and Cronbach's alpha (Ca) were examined.

Table 2 presents the reliability of each item, which was determined by the factor loadings of the items on the relevant constructs. Items with factor loadings of at least 0.6 and deemed significant (Hair et al., 2014), were retained in the model. All constructs exhibited Cronbach's alpha values larger than 0.7, indicating acceptable levels of reliability (Hair et al., 2016).

Because it is generally acknowledged that composite reliability is a more useful instrument for quantifying reliability than Cronbach's alpha, the composite reliability of the constructs was also evaluated. The reliability of all variables was further strengthened by the composite reliability scores for all constructs above 0.7. Convergent Validity assesses whether constructs measure or fail to measure what they claim. The average variance extracted (AVE), which determines whether the chosen items can explain concept variation, was used in this research to assess convergent validity (Fornell & Larcker, 1981). As shown in Table 3, the AVE values of all constructs are higher than the specified limit, and Hair et al. (2014) suggest that the cutoff value for the average variance retrieved is 0.5. This shows that the measurement model was valid and convergent (Fig. 3).

Additionally, three techniques—HTMT ratios, Fornell-Larcker criteria, and cross-loadings were used to assess the discriminant validity of the proposed model (Hair et al., 2016). The findings based on the Fornell-Larcker criterion, revealed that discriminant validity was validated since the correlation of each column's highest value was maximal (Fornell & Larcker, 1981; Hair et al., 2016). However, Henseler et al. (2015) proposed a new approach for evaluating discriminant validity, arguing that the Fornell-Larcker criteria were effective

Table 2
Common method bias.

Total Variance Explained						
	Total	% of Variance	Cumulative%	Total	% of Variance	Cumulative%
1	2.501	25.012	25.012	2.501	25.012	25.012
2	1.348	13.477	38.489	1.348	13.477	38.489
3	1.272	12.719	51.208	1.272	12.719	51.208
4	1.204	12.038	63.246	1.204	12.038	63.246
5	0.870	8.705	71.951	0.870	8.705	71.951
6	0.748	7.476	79.428	0.748	7.476	79.428
7	0.708	7.077	86.505	0.708	7.077	86.505
8	0.563	5.625	92.130	0.563	5.625	92.130
9	0.515	5.148	97.278	0.515	5.148	97.278
10	0.272	2.722	100.000	0.272	2.722	100.000

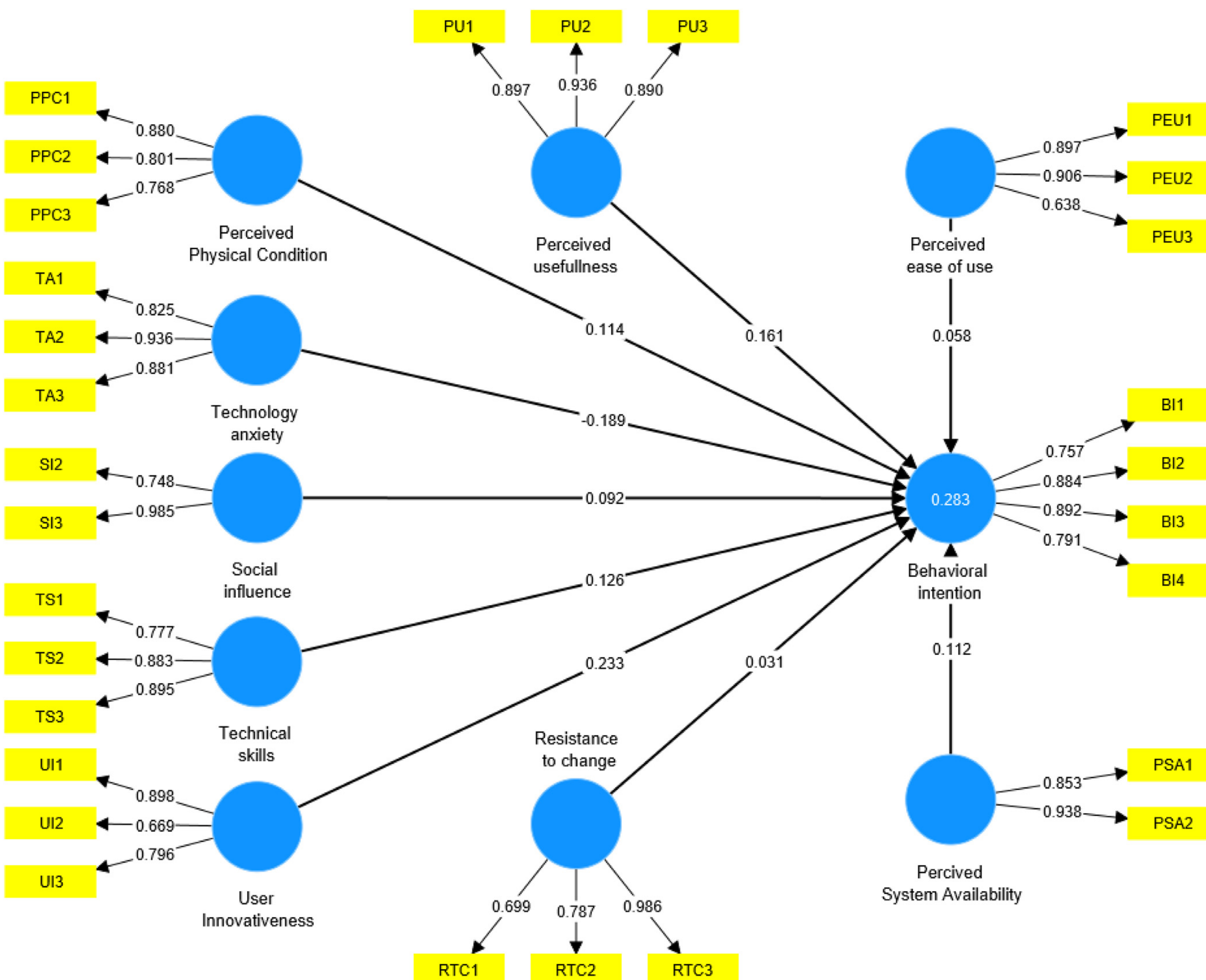

Fig. 3. Structural Model.

but could not detect the lack of discriminant validity. Therefore, the HTMT ratio was employed to assess the validity of discrimination, with the conditions that all variables' HTMT values should be less than 0.85 (Hair et al., 2016). The results showed that all the measures' HTMT values were less than 0.85, proving the discriminant validity of each variable in the study. Finally, cross-loadings were used to evaluate discriminant validity, and the findings demonstrated that all the data met the requirements, with high loadings (>0.6) on their identified factors but low loadings on others, supporting the discriminant validity of the model. The results of discriminant validity are presented in Tables 4 and 5.

4.3. Structural model evaluation

The evaluation of the structural model in the second stage of PLS-SEM analysis involved assessing multicollinearity, predictive ability,

Table 3
Measurement model results.

Constructs	Items	Loadings	Ca	CR	AVE
Perceived Ease of Use			0.751	0.860	0.677
PEU1	Learning to use health information systems would be easy for me	0.897			
PEU2	It will be easy for me to become skillful in using technology in my job	0.906			
PEU3	Interacting with Healthcare technology would require a lot of mental effort	0.638			
Perceived Usefulness			0.893	0.934	0.825
PU1	Using technology at work would enhance my effectiveness at work	0.897			
PU2	I would find technology useful in healthcare practice	0.936			
PU3	I think healthcare information technology are useful for my job	0.890			
Perceived Physical Condition			0.760	0.858	0.668
PPC1	Using computers and other information system technology would require me to exert more effort to perform my daily task at work	0.880			
PPC2	Using Computers and other Information Systems at work would limit the kind of activities i can perform	0.801			
PPC3	Using Health information technology and systems would cause some difficulties in performing my daily task	0.768			
Technology Anxiety			0.859	0.913	0.777
TA1	Using computers and associated technology makes me nervous	0.825			
TA2	Using computers and other systems makes me worried	0.936			
TA3	Using computers and other technology gadgets for work may make me uncomfortable	0.881			
Social Influence			0.768	0.865	0.765
SI1	People who influence my behavior think I should use Health electronic systems				
SI2	My colleagues and peers think it is a good idea to use Healthcare information technology	0.748			
SI3	My peers and colleagues use health information technology and have encouraged me to adopt technology	0.985			
Technology Skills			0.819	0.889	0.728
TS1	I have received formal training on healthcare information technology	0.777			
TS2	I have received support and training on healthcare information technology at my workplace	0.883			
TS3	I am aware of platforms and resources for healthcare technology training	0.895			
User Innovativeness			0.723	0.834	0.629
UI1	If I heard about new information technology, I would look for ways to experiment with it	0.898			
UI2	Among my peers, I am usually the first to try out new information technologies	0.669			
UI3	In general, I am not hesitant to try out new information technologies	0.796			
Resistance to Change			0.858	0.869	0.693
RTC1	I don't want electronic health technology to change the way I deal with patient disease	0.699			
RTC2	I don't want electronic health information technology to change the way I keep the health records of patients	0.787			
RTC3	I don't want electronic health technologies to change the way I interact with doctors and other hospital staff	0.986			
Perceived Availability			0.764	0.891	0.803
PSA1	My place of work has limited information systems	0.853			
PSA2	There are no up-to-date information systems at my place of work	0.938			
Behavioral Intention			0.852	0.900	0.694
BI1	I intend to use Health information technology in the future	0.757			
BI2	I will always try to use Health information technologies	0.884			
BI3	I plan to continue to use Health Information Systems frequently	0.892			
BI4	If I have the resources, Knowledge, and ability, I will use Health information systems	0.791			

empirical significance of the path coefficients, and the model's confidence level (Hair et al., 2016). The current research followed standard guidelines for analyzing the structural model and deriving conclusions from Hair et al. (2014).

To address concerns regarding collinearity in the model, the variance inflation factor (VIF) values were assessed. The data can be deemed free from collinearity issues if the inner VIF values are less than five (Hair et al., 2014). The results of the present analysis showed that the inner VIF values were lower than the cut-off level, indicates that the data employed in this study were not collinear and supported the fitness of the model. Next, the effect size (f2) findings further supporting the model's fitness (Hair et al., 2019), as the association values for f2 were lower to medium. In addition, the model contained one endogenous component, and the R2 and Q2 values for behavioral intention were found as R2=0.283 and Q2=0.182, respectively. The predictors may account for 28.3 of the variation in the dimensions mentioned above, indicating adequate predictive relevance, as values of Q2 higher than 0 desirable. The results are presented in Table 6.

In the subsequent stage, the structural model was analyzed for hypothesis testing. A bootstrap resampling approach with 5000 resamples was used to determine the significance of direct relationships according to Ringle et al. (2005) . The results of the hypotheses for direct effects are shown in Fig. 4 and Table 7.

Table 4
Discriminant validity.

Heterotrait-monotrait ratio (HTMT)	1	2	3	4	5	6	7	8	9	10
1. Behavioral intention										
2. Perceived Physical Condition	0.161									
3. Perceived ease of use	0.395	0.047								
4. Perceived usefulness	0.447	0.102	0.846							
5. Perceived System Availability	0.184	0.086	0.261	0.238						
6. Resistance to change	0.091	0.100	0.066	0.064	0.189					
7. Social influence	0.096	0.184	0.047	0.013	0.049	0.188				
8. Technical skills	0.206	0.085	0.086	0.121	0.202	0.111	0.090			
9. Technology Anxiety	0.289	0.064	0.267	0.368	0.079	0.299	0.058	0.112		
10. User Innovativeness	0.428	0.061	0.375	0.386	0.132	0.098	0.063	0.403	0.151	

Fornell-Larcker criterion	1	2	3	4	5	6	7	8	9	10
1. Behavioral intention	0.833									
2. Perceived Physical Condition	0.140	0.818								
3. Perceived ease of use	0.317	0.032	0.823							
4. Perceived usefullness	0.390	0.094	0.703	0.908						
5. Perceived System Availability	0.146	−0.023	0.186	0.196	0.896					
6. Resistance to change	0.035	0.068	0.030	0.063	0.167	0.833				
7. Social influence	0.102	0.182	0.021	−0.011	0.024	−0.095	0.875			
8. Technical skills	0.186	0.042	0.059	0.108	−0.148	0.070	−0.084	0.853		
9. Technology anxiety	−0.259	0.054	−0.221	−0.331	0.063	0.206	−0.043	0.094	0.882	
10. User Innovativeness	0.375	−0.010	0.301	0.338	0.077	0.021	−0.033	0.318	−0.134	0.793

Finally, a novel method for calculation the predictive relevance of the study model, particularly for PLS-prediction-oriented SEM, was created by Shmueli et al. (2019). It is necessary to first determine the Q2 of the LVs, then determine the items if the Q2 value is larger than zero (Shmueli et al., 2019). When the value of the PLS-LM of all items is higher, it indicates no predictive power, and when the value of the PLS-LM of all items is lower, it indicates a stronger or higher predictive ability(Shmueli et al., 2019). Table 8 shows that all items had lower PLS-LMs and stronger predictive power, with the Q2-predict being larger than zero.

5. Discussion

The study investigated digital technology adoption factors among healthcare workers, drawing on the TAM and UTUAT frameworks and conducting quantitative analyses of the constructs. The study tested nine hypotheses, and the empirical results confirmed six of them. The findings revealed the perceived ease of use (PEU) did not significantly predict healthcare workers' behavioral intention (BI) to adopt DHT, which contradicts prior literature suggesting that PEU is a significant factor influencing adoption (Alexandra et al., 2021; Choi & Tak, 2022; Ljubicic et al., 2020). However, the result corroborates the findings of Ebnehoseini et al. (2020), de Benedictis et al. (2020), and Yehualashet et al. (2021), which report that PEU is found to be a significant factor in developing countries (Rajak & Shaw, 2021). However, this is not the case in Nigeria. As Nigeria exhibits a high level of technology literacy and self-efficacy, especially among the younger generation, which renders PEU insignificant in predicting technology adoption, and H1 was rejected.

On the other hand, perceived usefulness (β=0.161, p<0.05) is found to significantly influence healthcare workers' intention to adopt digital technology. The finding is consistent with prior studies (Ali Alhur, 2023; Cho et al., 2021; Choi & Tak, 2022; Rouidi et al., 2022), and confirms the importance of cost-benefit and utility of adopting innovative systems to benefit from improving healthcare provision and cost-effectiveness. Specifically, the study of (Hicks et al., 2021) is important to consider since the study was conducted in Nigeria. The study reported that healthcare workers and policy stakeholders considered usefulness as a prime factor for digital technology adoption pointing toward these benefits. The current study supports this assertion and submits that healthcare professionals are aware of the cost-benefit and utility derived from adopting digital healthcare technology, and they are willing to adopt innovative systems if they are perceived to influence the trajectory of their work output and effectiveness over time. Consequently, H2 was accepted.

Perceived physical condition (β=0.114, p<0.05) significantly influenced healthcare workers' BI to adopt technology. The results obtained showed health workers' cognitive capacity has an impact on the acceptance and use of technology, given that cognitive capacity is a conduit for skills, learning, and development. Although this study is the first to examine this factor within the Nigerian context, the result agrees with studies in other information systems domains (Alshurafat et al., 2022; Khlaif et al., 2022). and leads to accepting H3.

As per technology anxiety, the results showed that BI decreases with the presence of anxiety (β=−0.189, p<0.001). The outcome corroborates the findings of Alqudah et al. (2021), Kwak et al. (2022), and Rahmani et al. (2023). Technology anxiety is reported to be prevalent in developing countries (Rajak & Shaw, 2021; Yadav et al., 2022). A possible reason for this may be connected to the work environment which is often reported to be harsh and unfriendly and thus instills the fear of errors which may influence the individual to resonate with the acceptance of the use of the technology. Specifically, in Nigeria, public healthcare facilities provide the opportunity for training and often give a specified time for workers to catch up with the use of these technologies. However, this may not be the same in private healthcare facilities where human relations policies are unfriendly and may lead to termination of service. Consequently, the hypothesis that technology anxiety affects DHT adoption behavior is supported.

Prior literature showed that social influence had a significant influence on DHT adoption (Barchielli et al., 2021; Jedwab et al., 2022; Rajak & Shaw, 2021; Yadav et al., 2022). Surprisingly, social influence was not significantly related to behavioral intention in the current study (β=0.092, p = 0.218). The apriori expectations were premised on the borderline of peer influence on BI. However, the results revealed the contrary. In Nigeria, technological education is a prerequisite for college education, and given that a large part of the participants were educated beyond college degrees, this confirms the weakness of social influence on the study participants. Therefore, the hypothesis is rejected.

Table 5
Cross loadings.

	Behavioral intention	Perceived ease of use	Perceived Physical Condition	Perceived System Availability	Perceived usefulness	Resistance to change	Social influence	Technology anxiety	Technical skills	User Innovativeness
BI1	0.757	0.273	0.087	0.216	0.291	0.087	0.095	−0.156	0.100	0.233
BI2	0.884	0.272	0.118	0.116	0.335	−0.006	0.052	−0.255	0.141	0.357
BI3	0.892	0.286	0.167	0.059	0.336	−0.021	0.118	−0.253	0.218	0.367
BI4	0.791	0.225	0.084	0.120	0.338	0.079	0.073	−0.184	0.146	0.274
PEU1	0.287	0.897	0.026	0.140	0.657	−0.006	0.020	−0.247	0.036	0.284
PEU2	0.285	0.906	0.035	0.136	0.657	0.033	0.027	−0.251	0.072	0.276
PEU3	0.202	0.638	0.013	0.201	0.383	0.059	−0.001	0.000	0.037	0.167
PPC1	0.147	0.029	0.880	−0.049	0.119	0.016	0.154	0.054	0.082	0.003
PPC2	0.091	0.029	0.801	−0.045	0.046	0.068	0.126	0.048	0.009	−0.020
PPC3	0.090	0.018	0.768	0.058	0.044	0.109	0.168	0.026	−0.017	−0.017
PSA1	0.101	0.186	−0.013	0.853	0.174	0.188	0.016	0.050	−0.136	0.106
PSA2	0.153	0.156	−0.026	0.938	0.179	0.125	0.025	0.062	−0.133	0.045
PU1	0.333	0.655	0.099	0.190	0.897	0.061	−0.005	−0.282	0.044	0.274
PU2	0.382	0.651	0.100	0.191	0.936	0.018	−0.010	−0.345	0.082	0.319
PU3	0.344	0.611	0.057	0.152	0.890	0.097	−0.016	−0.272	0.169	0.326
RTC1	0.009	−0.001	0.048	0.114	0.037	0.699	−0.069	0.226	0.077	0.109
RTC2	−0.002	−0.016	0.075	0.119	0.019	0.787	−0.130	0.261	0.101	0.046
RTC3	0.037	0.033	0.068	0.164	0.062	0.986	−0.096	0.189	0.065	−0.001
SI2	0.029	0.049	0.059	−0.033	−0.008	−0.181	0.748	−0.043	−0.009	0.006
SI3	0.112	0.012	0.199	0.036	−0.011	−0.065	0.985	−0.040	−0.097	−0.041
TA1	−0.161	−0.103	0.049	0.074	−0.219	0.195	−0.046	0.825	0.062	−0.054
TA2	−0.262	−0.197	0.065	0.070	−0.312	0.178	−0.033	0.936	0.033	−0.123
TA3	−0.241	−0.258	0.029	0.029	−0.327	0.181	−0.039	0.881	0.152	−0.160
TS1	0.096	−0.001	−0.027	−0.170	0.060	0.062	−0.127	0.017	0.777	0.245
TS2	0.170	0.056	0.078	−0.180	0.103	0.085	−0.080	0.093	0.883	0.272
TS3	0.186	0.074	0.031	−0.059	0.102	0.038	−0.039	0.103	0.895	0.294
UI1	0.405	0.307	0.012	0.020	0.340	0.043	0.000	−0.133	0.316	0.898
UI2	0.178	0.156	−0.030	0.054	0.124	−0.011	−0.064	−0.027	0.300	0.669
UI3	0.236	0.211	−0.027	0.144	0.283	−0.006	−0.046	−0.133	0.136	0.796

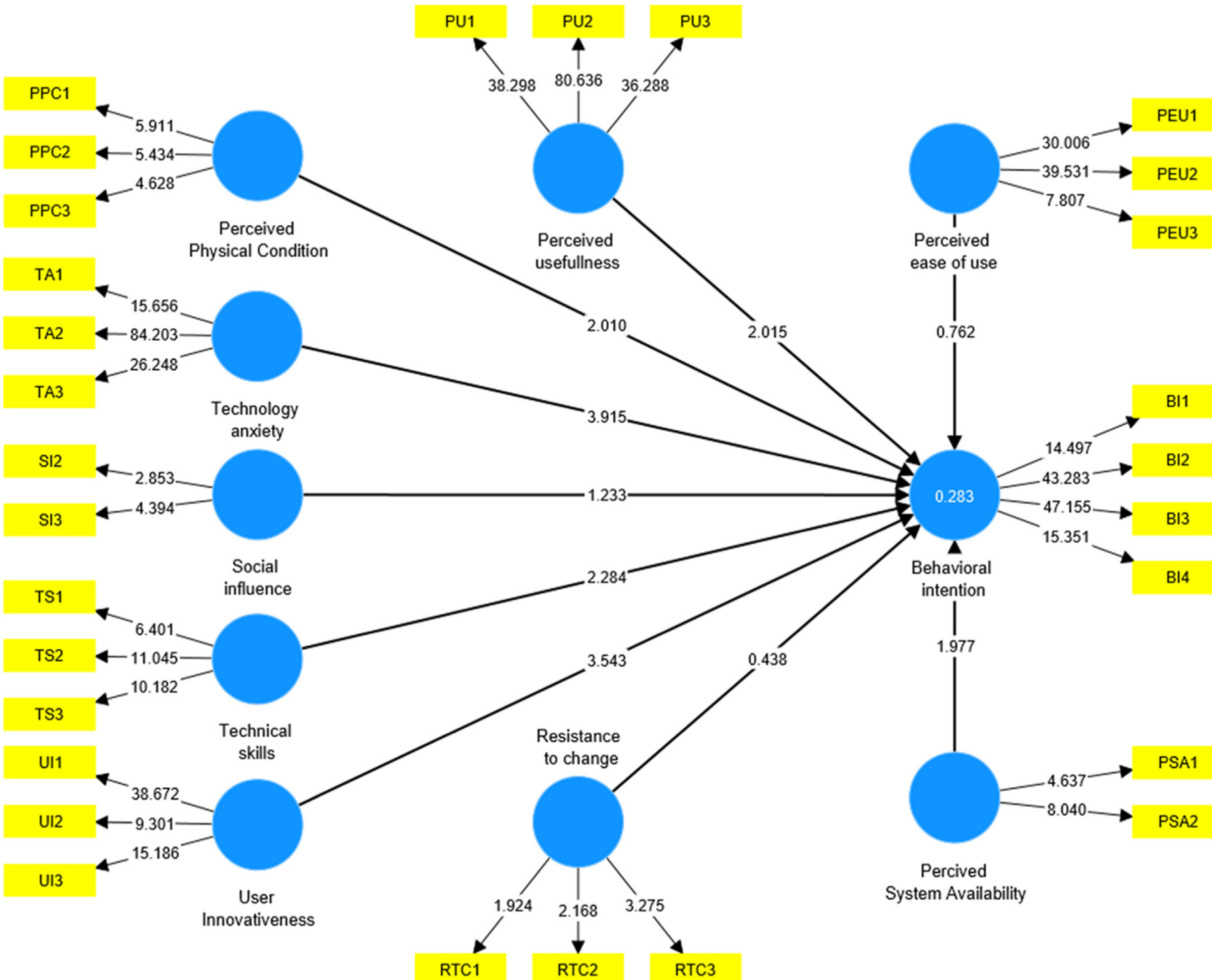

Fig. 4. Structural Model.

Table 6
VIF, F-square, R-square and Q-square.

	VIF Behavioral intention	F-square Behavioral intention	R-square Endogenous construct	SSO Endogenous construct	SSE	Q^2 (=1-SSE/SSO)
Behavioral intention			0.283	1204.000	984.603	0.182
Perceived Physical Condition	1.070	0.017				
Perceived ease of use	2.019	0.002				
Perceived usefulness	2.300	0.016				
Perceived System Availability	1.141	0.015				
Resistance to change	1.102	0.001				
Social influence	1.060	0.011				
Technical skills	1.205	0.018				
Technology anxiety	1.252	0.040				
User Innovativeness	1.272	0.059				

Technical skills (β =0.126, p<0.01) were positively and significantly linked to BI. The results show that when the rate at which people acquire technical skills grows by one unit (e.g., from disagree/low to agree/high or from agree/high to strongly agree/very high), their likelihood of adopting that technology will increase. This result aligns with that of Ljubicic et al. (2020) and Wubante et al. (2022). In particular, the study of Berihun et al. (2020) is pertinent to consider, the study found that healthcare professionals who had computer skills were ready and confident to adopt DHT, which is a possible connection in the Nigerian context. In the Nigerian context, most respondents had a college degree, which happens to be a requirement for entry into healthcare-related professions, and contingent upon requisite curriculum, computer technology happens to be a requirement for completion of a college degree. In addition, the younger population exhibits more prowess in ICT, which can be factored into their careers. As such, this study confirmed this hypothesis.

The findings show a significant association between User Innovativeness (β=0.233, p<0.001) and BI. The results show that inno-

Table 7
Hypotheses results.

Hypotheses	Relationships	Path Coefficient	Standard deviation	Bias corrected confidence intervals BCI-LL	BCI-UL	T statistics	P values	Conclusion
Hypotheses 1	Perceived ease of use→ Behavioral intention	0.058	0.076	−0.088	0.210	0.762	0.446	Insignificant
Hypotheses 2	Perceived usefullness→ Behavioral intention	0.161	0.080	−0.007	0.309	2.015	0.044	Significant
Hypotheses 3	Perceived Physical Condition→ Behavioral intention	0.114	0.057	0.004	0.226	2.010	0.044	Significant
Hypotheses 4	Technology anxiety→ Behavioral intention	−0.189	0.048	−0.289	−0.098	3.915	0.000	Significant
Hypotheses 5	Social influence→ Behavioral intention	0.092	0.075	−0.078	0.224	1.233	0.218	Insignificant
Hypotheses 6	Technical skills→ Behavioral intention	0.126	0.055	0.027	0.237	2.284	0.022	Significant
Hypotheses 7	User Innovativeness→ Behavioral intention	0.233	0.066	0.108	0.365	3.543	0.000	Significant
Hypotheses 8	Resistance to change→ Behavioral intention	0.031	0.071	−0.124	0.133	0.438	0.662	Insignificant
Hypotheses 9	Percived System Availability→ Behavioral intention	0.112	0.057	0.012	0.228	1.977	0.048	Significant
Control effects		Path Coefficient	Standard deviation	BCI-LL	BCI-UL	T statistics	P values	Conclusion
+	Age → Behavioral intention	0.058	0.041	−0.024	0.141	1.397	0.163	Insignificant
+	Education → Behavioral intention	−0.009	0.049	−0.105	0.086	0.186	0.853	Insignificant
+	GENDER → Behavioral intention	0.085	0.076	−0.062	0.233	1.119	0.263	Insignificant

Table 8
PLS-predict.

	Q^2predict	RMSE PLS-SEM_	PLS-SEM_MAE	LM _RMSE	LM_MAE	PLS-LM RMSE	MAE
BI1	0.099	0.883	0.612	0.942	0.651	−0.059	−0.039
BI2	0.158	0.718	0.537	0.741	0.556	−0.023	−0.019
BI3	0.186	0.778	0.565	0.812	0.585	−0.034	−0.02
BI4	0.114	0.751	0.537	0.784	0.56	−0.033	−0.023

vativeness positively influences DHT usage. This result aligns with prior investigations Gu et al. (2021), Hossain et al. (2019) and Turan and Koç (2022). The finding is, however, contrary to the study of Ebnehoseini et al. (2020). An important point to note is the fact that technical skills are strongly linked with personal innovativeness. Personal innovativeness increases as technical skills increase. Further reflection on the demographics revealed that a large proportion of the participants were below the age of 40 years. This age group tends to be self-motivated and are eager to try new technologies. Thus, this hypothesis that user innovativeness influences DHT adoption is accepted.

Surprisingly, resistance to change did not affect BI (β=0.031, p = 0.662), contrary to the findings of Cho et al. (2021), Graves et al. (2018), Renukappa et al. (2022), Yusif et al. (2022). However, a possible reason for this result can be traced to the Nigerian working environment. Workers are not saddled with the burden of making strategic decisions or contributions, such as the deployment of a new information system. This phenomenon differs across regions. While workers may have input in the technology development process in other countries, the same cannot be said for the Nigerian working space. Similarly, it is worth mentioning that workers choose to use an organizational working system. Individuals must adhere to the working conditions and ethos of the organization they belong to, and this includes adopting rules and practices of the organization; thus, resisting innovation can attract sanctions and be termed as a dereliction of duty. Our results align with that of Rajak and Shaw (2021), Hossain et al. (2019), and Yadav et al. (2022).

The coefficient representing the effect of the perceived availability of technology (β=0.112, p<0.05) was positive and indicated statistically significant influence on technology adoption decisions., This aligns with the study of Consul et al. (2021), Archer et al. (2021), and Alanazi et al. (2020). Specifically, the results show that when the rate at which people perceive a particular technology to be reliable and available, their likelihood of adopting that technology will increase. Nigerian healthcare sector currently suffers from inadequate health information technology infrastructure, especially in public healthcare facilities. A consequence of this phenomenon is the inability of healthcare workers to adopt technology. However, workers are more willing to adopt DHT when they perceive that it is available and reliable. Thus, the hypothesis that perceived availability influences DHT adoption behavior is accepted.

5.1. Contribution

The main contribution of this study is to the healthcare industry, policy administrators, and healthcare institutions with respect to digital healthcare technology adoption. Given the fact that the subject is of global interest and especially in developing continents like Africa. Specific criteria, according to the research, are important for successfully adopting digital healthcare technologies.

Research on DHT adoption specifically focuses on developed continents. Although, studies exist within developing countries. However, pertinent variables have been ignored. The research adds to the existing body of literature by first closing the literature gap in DHT studies in developing countries.

Second. the study adapted existing models from studies in developed countries and replicated the same in Nigeria to close the existing gap, in doing this, the study took cognizance of other variables such as perceived physical condition, perceived availability, and social influence, the impact of which was not well documented in the African context and by extension Nigeria. Nine variables were tested bases on the extraction from TAM and UTUAT models and Prior studies, The findings contribute to a better understanding of the factors that influence DHT adoption in Nigeria.

5.2. Practical implications

The results of this study provide insights into the causal factors that impede and influence health information technology adoption. Barriers influencing adoption decisions were identified (technology anxiety and facilitating conditions), from which it was could be understood that Nigerian healthcare workers are driven by negative emotions towards technology adoption, and this factor consequently fuels some skepticism about its full utilization. In other words, individuals fear sanctions resulting from a failure to use systems effectively, and there are no support conditions that counter this emotion.

Surprisingly, perceived ease of use, technology skills, and resistance to change had no significant influence on behavioral intention. This study confirms a high level of technology proficiency among the sample population, which is traceable to their academic background. Evidence from this study reveals that perceived usefulness, social influence, personal innovativeness, and perceived availability are positive factors that motivate individual adoption decisions. The findings can be considered to provide directions for policymakers within the hospital management space to develop effective policies and strategies to counter the negative tendencies and further encourage factors that influence technology adoption.

5.3. Limitations and area for further research

While the importance of this study cannot be overemphasized, it is pertinent to mention that it is not free of limitations. First, the data gathered represents the perception of healthcare workers in private and public health facilities in Nigeria. It is pertinent to mention that the work ethics and human relations policy differs in both segments and as such some factors may be more prevalent therefore study recommends a comparative analysis between the private healthcare and public healthcare.

Secondly, the responses from the envisaged population is another consideration for further study, it is pertinent to mention that while the study aims to capture the opinion of professional health worker in the Nigerian medical space. It was difficult to get most of the professionals to commit to responding to the survey which gave rise to the sample used for the study. Moreso, nurses represented a larger respondent of the study totaling about 41%, and doctors 17%, this was due to the inability to obtain sufficient responses from other healthcare professionals. Consequently, the result showcases a significant opinion of nurses and doctors. Although research indicates that a study of this kind might be conducted with samples ranging from 150 to 300. However, for future studies, a larger sample size across considering various healthcare professional is advised since it will assist expose the influence of control factors such as age, gender, and educational background and profession.

Finally, the study examined the impact of social factors and perceived physical condition, and to the best of our knowledge, this is the first to consider this factor in the Nigerian context. However, it is believed that there are more variables that exert influence on BI, and as such, the study recommends including further variables for future research.

6. Conclusion

This study aimed to investigate the factors influencing DHT adoption in the Nigerian healthcare sector using a quantitative survey gathered from healthcare workers in public and private practice in Nigeria. Doctors, nurses, pharmacists, and other hospital staff were included in the study. TAM and UTUAT frameworks were adopted to probe the causal factors. nine constructs were adapted to understand workers' behavioral intention, and a structural equation modeling technique was adopted to test the effect between the dependent variable (behavioral intention) after gathering data from respective health workers and the independent variables (PU, PEU, TA, SI, TS, UI, RCH, PA, and FC).

The study unravels the limiting factors of DHT adoption. After conducting the empirical analysis, the result supported six hypotheses namely (PU, PPC, TA, TS, UI and PA). However, three of the variables were not supported by the analysis, namely (PEU, RCH and FC). The findings inform policymakers, healthcare personnel, and private and public healthcare service providers about the critical factors to consider when introducing DHT.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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