

Using TAM to measure the factors affecting the use of eHealth services in Misurata City

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Abstract:

This research paper aims to identify the factors that influence the adoption of the eHealth system for enhancing healthcare services within the public health sector of Misurata city. However, numerous scholars have emphasized that the integration of technological solutions in healthcare should be preceded by user acceptance. Without this crucial step, the endeavor to incorporate technology into healthcare services is likely to be underutilized and ultimately unsuccessful.

In light of this concern, an extended model based on the Technology Acceptance Model (TAM) has been developed. This augmented model includes three additional external variables: Technology Anxiety, User Experience, and Technology Infrastructure. To gather comprehensive perspectives, an online survey was conducted, gathering data from 150 citizens and healthcare professionals in Misurata city, encompassing a diverse range of backgrounds.

The primary objective of this study is to expand upon the Technology Acceptance Model (TAM) to identify the factors that influence the effectiveness of utilizing the eHealth system as a tool for healthcare services in the Libyan public health sector. The findings of this investigation unveiled that the attitude toward usage significantly and directly impacts the intention to use the eHealth system. Furthermore, perceived usefulness, perceived ease of use, Internet User Experience, Technology Infrastructure, and attitude toward usage are all identified as significant indirect determinants of the intention to use the eHealth system. Conversely, Technology Anxiety was found to have an insignificant indirect impact on the intention to use the eHealth system.

Key words: Health data center, Technology Acceptance Model (TAM), perceived usefulness, perceived ease of use, technology anxiety, system interface, internet experience.

استخدام نموذج قبول التكنولوجيا (TAM) لقياس العوامل التي تؤثر على استخدام

خدمات الصحة الإلكترونية في مدينة مصراتة

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الملخص:

تهدف هذه الورقة البحثية إلى تحديد العوامل التي تؤثر في اعتماد نظام الصحة الإلكترونية لغرض تعزيز خدمات الرعاية الصحية داخل مدينة مصراتة. وفي هذا الإطار، أكد العديد من العلماء على أنه يجب أن يسبق دمج الحلول التكنولوجية في مجال الرعاية الصحية قبول المستخدم لهذه الحلول. بدون هذه الخطوة المهمة، قد يتم استخدام التكنولوجيا في خدمات الرعاية الصحية بشكل غير فعال، مما قد يؤدي في النهاية إلى فشل الجهود المبذولة لدمج التكنولوجيا في هذه الخدمات.

استناداً إلى هذا، تم تطوير نموذج موسّع مستند على نموذج قبول التكنولوجيا (TAM). يشمل هذا النموذج المعزز ثلاثة متغيرات خارجية إضافية: قلق التكنولوجيا، تجربة المستخدم، وبنية التكنولوجيا. لجمع وجهات النظر الشاملة، تم إجراء مسح عبر الإنترنت، حيث تم جمع البيانات من 150 مواطناً ومتخصصاً في مجال الرعاية الصحية من مدينة مصراتة، وشمل ذلك مجموعة متنوعة من الخلفيات.

الهدف الرئيسي لهذه الدراسة هو توسيع نموذج قبول التكنولوجيا (TAM) لتحديد العوامل التي تؤثر في فعالية استخدام نظام الصحة الإلكترونية كأداة لخدمات الرعاية الصحية في قطاع الصحة العامة في ليبيا. أظهرت نتائج هذه الدراسة أن الاتجاه نحو الاستخدام يؤثر بشكل كبير ومباشر على النية في استخدام نظام الصحة الإلكترونية. بالإضافة إلى ذلك، تم تحديد فائدة الاستخدام، وسهولة الاستخدام، وتجربة مستخدم الإنترنت، وبنية التكنولوجيا، والاتجاه نحو الاستخدام كمحددات غير مباشرة مهمة للنية في استخدام نظام الصحة الإلكترونية. ومن ناحية أخرى، تشير النتائج إلى أن قلق التكنولوجيا له تأثير غير مهم وغير مباشر على النية في استخدام نظام الصحة الإلكترونية.

الكلمات المفتاحية: مركز بيانات الصحة، نموذج قبول التكنولوجيا (TAM)، سهولة الاستخدام، قلق التكنولوجيا، واجهة النظام، تجربة النظام، تجربة الإنترنت.

Introduction:

The realm of medical informatics currently represents one of the largest domains of study, primarily centered around Artificial Intelligence and Information Systems (IS). Within the broader context of health networks, these IS play a pivotal role. Specifically, they are structured around medical records to facilitate the storage, retrieval, distribution, and exchange of patient data (Zarour & Zarour, 2012).

For Hospital Information Systems (HIS) to achieve optimal efficacy and facilitate timely, informed decisions, they must house information of utmost quality—pertinent, dependable, precise, and up-to-date. Furthermore, this information must be maintained, revised, and made accessible to various stakeholders within the healthcare system as needed. Among care providers, information stands as a strategic asset demanding mastery, as it significantly contributes to decision-making quality. The duty of HIS entails disseminating information to relevant parties, regardless of its nature. Functioning as a collaborative information system, HIS encompasses individuals such as clients, physicians, nurses, educators, researchers, and health insurance personnel, who collectively share patient data, including text, images, and multimedia content. Its purpose extends to enabling data utilization for diverse purposes, including patient care, administrative and operational management, assessment of medical services, epidemiological and clinical research, and resource allocation for medical services (Zou et al., 2007; Zarour & Zarour, 2012).

A personal health record is characterized as an "electronic tool allowing individuals to privately, securely, and confidentially access, oversee, and exchange their health data, along with that of authorized individuals." These systems embody an enticing and evolving technology within healthcare setups and applications, progressively gaining traction across various nations. Precisely, personal health record (PHR) systems are information frameworks designed to encompass data, utilities, and functionalities tailored for individual health. An alternate interpretation, put forth by the Markle Foundation (Markle Foundation, 2013), aligns with this perspective.

The growing utilization of digital medical data necessitates real-time accessible information storage capacities. This imperative compels most hospitals to continually expand their data repositories. Unfortunately, inadequate planning, as illuminated by Shawn (Shawn, 201X), often hampers

hospitals' ability to effectively scale their databases. As projected by Low et al. (Low & Hsueh Chen, 2012), the impending surge in information will likely see data housed in expansive global data centers, serving as access points for medical records catering to doctors, pharmacies, insurers, patients, and institutions. The absence of pertinent medical data could precipitate delayed or erroneous decisions.

According to Lejiang et al. (Lejiang et al., 2018, conventional medical data management confronts several challenges: (i) electronic file storage is constrained by hardware limitations in capacity and quality, (ii) escalating data volumes result in system deceleration due to channel access mode and bandwidth constraints, (iii) the current simplistic backup approach inadequately addresses security and long-term storage requisites for medical files, and (iv) the traditional data storage model impedes resource sharing. Consequently, comprehensive information sharing among all participants in the medical ecosystem throughout a patient's care journey is hindered. The adoption of mediation-based architectures (El Azami et al., 2012) can prove complex and financially burdensome.

The central focus of this paper revolves around the eHealth service, a subject that has garnered significant attention in recent times (Sánchez-Franco et al., 2009; Venkatesh et al., 2002; Ajzen & Fishbein, 1980). The selection of an eHealth system hinges on several factors: the utilized platform, the capability to provide advanced storage solutions, and the provision of adequate bandwidth. Consequently, any information integrated within an eHealth system must be swiftly accessible via high-speed internet connections, regardless of prevailing circumstances. Within the existing literature, the eHealth system is commonly referred to as a repository for patients' data (Saadé & Galloway, 2005; Tao et al., 2016). In the specific context of our research, the eHealth framework encompasses the primary location for a hospital's servers and storage infrastructure (Cisco, 2007).

The remainder of the objectives for this study pertains to the factors influencing the adoption of the eHealth service. Within this paper, we intend to assess the impact of various factors—namely, perceived usefulness, perceived ease of use, Technology Anxiety, Internet Experience, and

Technology Infrastructure—on the utilization of eHealth services within Misurata city.

2 REVIEW OF LITERATURE AND HYPOTHESES DEVELOPMENT

The objective of this investigation is to identify the elements that impact the adoption of eHealth services for the enhancement of healthcare within the public health domain of Misurata city. The research framework employed in this study is built upon the foundational TAM model, encompassing perceived ease of use, perceived usefulness, attitude towards use, and behavioral intention to use. Additionally, the model incorporates three external factors—Internet Experience, Technology Anxiety, and Technology Infrastructure. This proposed model comprises a total of seven constructs and nine hypotheses, as depicted in Fig 1.

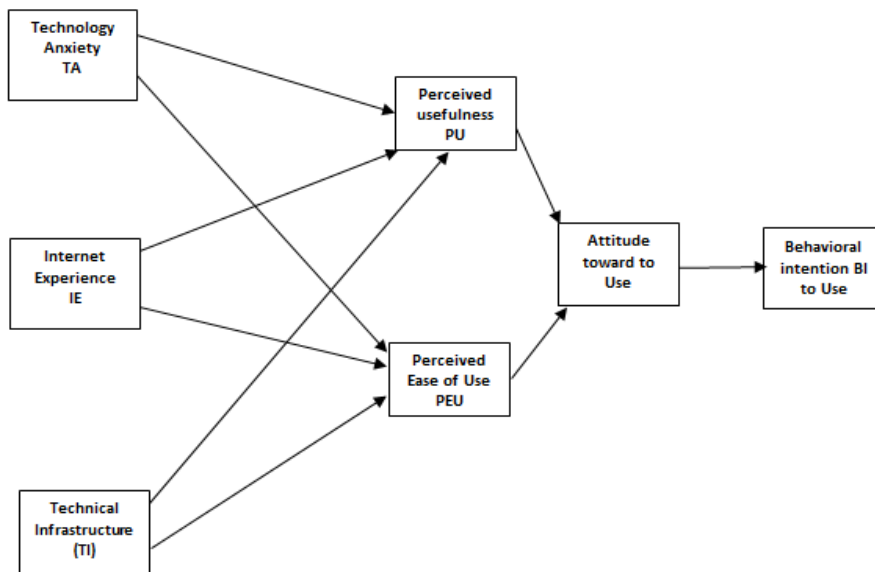


Fig. 1 research model

Numerous theories have arisen to elucidate and elucidate the potential factors that impact individuals' willingness to embrace or reject technological usage. The principal theories utilized for gauging technology acceptance encompass:

- 1 .The Technology Acceptance Model (TAM)
- 2 .The Theory of Reasoned Action (TRA)
- 3 .The Theory of Planned Behavior (TPB)
- 4 .The Decomposed Theory of Planned Behavior (DTPB)
- 5 .The amalgamation of TAM and TPB.

Originally conceived by Fred Davis in 1989, the Technology Acceptance Model (TAM) serves as an information system theory that delineates users' adoption of novel technology (Davis, 1989). In essence, TAM evolved from TRA and established a foundation for establishing connections between critical beliefs, such as perceived usefulness, perceived ease of use, attitude toward use, and behavioral intention to use (Davis, 1989).

In scholarly circles, the Theory of Reasoned Action (TRA) was initially integrated into psychological research to scrutinize behavioral intentions toward information technology (IT), later being adapted for IT contexts. As TRA underwent refinements, it culminated in the formulation of the Technology Acceptance Model (TAM) (Davis, 1989). TRA typically investigates human behavioral intention (Ajzen & Fishbein, 1980). Leveraging the TRA framework, Davis (1989) crafted the Technology Acceptance Model to assess end users' acceptance of IT. Over the preceding decade, TAM has been wielded by experts to explore IT acceptance, predicated on the anticipation of user perceptions regarding perceived usefulness and perceived ease of use, which serve as pivotal factors within the TAM model (Davis, 1989; Venkatesh et al., 2002).

2.1. Behavioral Intention to Use

The intention to engage in a behavior, known as Behavioral Intention to Use (BI), is regarded as a direct precursor to actual usage and provides an indication of an individual's inclination to carry out a specific action. As succinctly put, "the greater the intention to partake in a behavior, the higher the likelihood of its execution" (Ajzen & Fishbein, 1980).

2.2. Attitude toward Use

Attitude toward usage (ATU) refers to an individual's belief that engaging in a particular action will yield favorable outcomes (Ajzen & Fishbein, 1980). Within the TAM framework, attitude toward usage plays a pivotal role in shaping the intention to utilize a system (Davis, 1989). Moreover, numerous studies have demonstrated the constructive influence of attitude toward usage on intention (Ajzen & Fishbein, 1980; Davis, 1989; Venkatesh et al., 2003).

Hypothesis 1 (H1): The favorable attitude toward utilizing a health data center as a service will exert a positive impact on the intention to use the eHealth system as a service.

2.3. Perceived Usefulness

Perceived Usefulness (PU) refers to "the extent to which an individual believes that employing a specific system would improve their job performance" (Davis, 1989). Multiple research endeavors have been conducted to highlight the substantial impact of PU in predicting Behavioral Intention (BI) (Davis, 1989; Ajzen & Fishbein, 1980; Venkatesh et al., 2003; Liu et al., 2010).

Hypothesis 2 (H2): The perception of usefulness will positively influence the attitude toward utilizing the eHealth system as a service.

2.4. Perceived Ease of Use

Perceived Ease of Use (PEOU) is the measure of an individual's belief regarding the level of effortlessness associated with employing a particular framework or system (Davis, 1989). Numerous investigations have underscored the impact of PEOU on shaping the attitude toward system usage (Davis, 1989; Ajzen & Fishbein, 1980). Additionally, research has indicated that PEOU positively affects Perceived Usefulness (PU) (Davis, 1989).

Hypothesis 3 (H3): The perceived ease of use will positively impact the attitude toward utilizing the eHealth system as a service.

2.5. Technology Anxiety

Anxiety is a natural physiological response to stress; it can be described as a form of apprehension or unease about what lies ahead (Magid Igbaria & Parasuraman, 1989). In the realm of technology acceptance, various forms of anxiety have been delineated in recent times, such as technology anxiety, computer anxiety, online shopping anxiety, and mobile anxiety. These emotions, which can be strong and negative, often manifest during interactions with technology (Raafat George Saadé & Galloway, 2005). The sense of unease stemming from interactions with computer-based systems has been found to have an adverse connection with individuals' attitudes and behaviors toward using technological devices or systems (Venkatesh et al., 2003). A study involving elderly users who exhibited anxiety towards technology explored a healthcare service system in China. The findings indicated that technology anxiety negatively impacts perceived ease of use and perceived usefulness (Xitong Guo et al., 2013).

Hypothesis 4 (H4): Technology Anxiety will positively influence the perceived ease of use of the eHealth system as a service.

Hypothesis 5 (H5): Technology Anxiety will positively influence the perceived usefulness of the eHealth system as a service.

2.6. Technical Infrastructure (TI)

TI refers to a collection of information technology (IT) elements forming the fundamental framework of an IT service within an organization (Venkatesh et al., 2003). This encompasses the technological backbone of the organization, encompassing aspects such as the availability of computers for utilizing eHealth systems, the preexisting infrastructure of the hospital, and the ongoing system responsible for maintaining the hospital's established infrastructure. While the technical infrastructure isn't classified as one of the constructs within the Technology Acceptance Model (TAM), a number of studies consistently demonstrate that favorable conditions play a crucial role in shaping users' attitudes and intentions toward technology adoption (Venkatesh et al., 2003; Ajzen & Fishbein, 1980). Consequently, it is anticipated that the technical infrastructure will emerge as a key predictor for the sustainable integration of eHealth solutions.

Hypothesis 6 (H6): The Technical Infrastructure is expected to exert a positive influence on the perceived usefulness of the eHealth system as a service.

Hypothesis 7 (H7): The Technical Infrastructure is expected to exert a positive influence on the perceived ease of use of the eHealth system as a service.

2.7. IT Experience

IT experience pertains to the familiarity health professionals possess regarding information technology, encompassing their grasp of the fundamental advantages of technology, exposure to it, and participation in training related to it (Abebe, 2013). Healthcare practitioners who possess a solid foundation of IT experience have been observed to actively engage with various contemporary eHealth applications, including medical information systems, electronic health records, telehealth solutions, and other advanced digital health tools (Delone & McLean, 2003).

Hypothesis 8 (H8): IT Experience is expected to yield a positive impact on the perceived usefulness of the eHealth system as a service.

Hypothesis 9 (H9): IT Experience is expected to yield a positive impact on the perceived ease of use of the eHealth system as a service.

3. Methodology

3.1. Sample and Data Collection

The research adopted a quantitative methodology, employing an online survey as the data collection instrument. The survey was bifurcated into two distinct sections: the initial segment encompassed demographic variables, while the subsequent portion comprised questionnaires probing the items linked to the constructs. The participant pool consisted of individuals whose primary language was not English, leading to the translation of the items into the Arabic language. A total of 150 respondents contributed to the study, with male participants constituting 63.44% and female participants comprising 36.56% of the total sample. The corresponding responses are presented in detail within Table 1.

Table1 Demographic profile

Gender	98 male	52 female		
	65.33	34.67		
Education Level	High School degree	Undergraduate	Graduate	
Job description	Administrative staff	Technical staff	Nurse	Doctor
Working years in Health sector	Less than 5 years	More than 5 years		
Place of work	Primary health service	Central Hospital	Laboratory	other
IT Experience	None	Less than 5 years	More than 5 years	
Internet Experience	None	Less than 5 years	More than 5 years	
Weekly Internet of things usage	None	Less than 5 Hours	More than 5 Hours	
Age	Min 20 years	Max 68 years		

4 Measurement development and Results

This study employed a methodology known as partial least squares (PLS) structural equation modeling (SEM) to evaluate the proposed theoretical framework. This approach allowed for the simultaneous assessment of both the measurement model and the structural model, as articulated by prior literature (Delone & McLean, 2003; Swoboda et al., 2021; Alhur, 2022). PLS, in addition to its effectiveness in handling intricate models featuring hierarchical compositions, is also particularly adept at managing models characterized by multiple relationships, indicators, and constructs, as noted in existing research (Hair et al., 2021, P.7). To put the methodology into practice, PLS Version 4.0 was utilized to scrutinize the proposed model. The initial phase of this process encompassed evaluating the reliability and validity of the measurement model, as established in prior research (Hair et al., 2021, P.7).

The study's methodology consisted of a two-step procedure. The initial step comprised the assessment of the measurement model, while the subsequent

step involved scrutinizing the structural model. In a partial least squares SEM PLS path model, two distinct analyses were conducted. In the initial phase, attention was directed toward the measurement models of the constructs, elucidating the associations between the constructs and the corresponding indicator variables. This phase also encompassed evaluating the model's validity and reliability. Subsequently, the second phase centered on the creation of a structural model, elucidating the interrelationships (paths) between the constructs within the model to systematically investigate the hypotheses posited in the research (Hair et al., 2021, P.7).

4.1. Measurement Model

To ascertain the convergent validity of the study, the analysis incorporated criteria such as Average Variance Extracted (AVE), indicator reliability, internal consistency, and discriminant validity, concepts previously introduced by other researchers (Hair Jr et al., 2021, P.69; Pallant, 2020; Nunnally & Bernstein, 1994). Composite reliability (CR) values, item loadings, Cronbach's alpha (CA), and the AVE of constructs are detailed in Table 2. The tabulated data indicates that all CA values surpassed the threshold of 0.60, a level of acceptability supported by Pallant (2020) and Nunnally and Bernstein (1994). Furthermore, CR values consistently exceeded 0.70 across all constructs, affirming robust internal consistency and the sound nature of constructs in line with the guidance of Hair et al., 2021, P.89). The findings also indicated that the items within the constructs exhibited reliabilities greater than 0.40, a value deemed sufficient for their acceptability (Hair Jr et al., 2021, P.90).

Table2. The measurement model

Construct	Measurement Items	Factor loading	Cronbach's Alpha	Composite Reliability	(AVE)
Behavioral intention (BI)	BI1	0.798	0.781	0.871	0.693
	BI2	0.860			
	BI3	0.837			
Attitude toward use (ATU)	ATU1	0.749	0.713	0.833	0.625
	ATU2	0.839			
	ATU3	0.781			
Perceived ease to use (PEOU)	PEOU1	0.857	0.801	0.882	0.715
	PEOU2	0.879			
	PEOU3	0.799			
Perceived usefulness	PU1	0.847			

(PU)	PU2	0.873	0.802	0.883	0.716
	PU3	0.818			
Technology Anxiety	TA1	0.938			
(TA)	TA2	0.908	0.928	0.947	0.856
	TA3	0.929			
Internet Experience	IE1	0.720			
(IE)	IE2	0.876	0.768	0.863	0.680
	IE3	0.868			
Technical	TI1	0.814			
Infrastructure (TI)	TI2	0.839	0.623	0.796	0.571
	TI3	0.588			

Concerning convergent validity, it is noteworthy that all Average Variance Extracted (AVE) values exceeded the threshold of 0.50, as established (Hair Jr et al., 2021, P.91). Upon analyzing the squared AVE values corresponding to the constructs, it becomes evident that the discriminant validity of these constructs surpassed the designated threshold. This conclusion can be drawn from the observation that all values exceeded the correlations between the constructs. This fact, substantiated by the values surpassing the correlations between constructs, firmly confirmed the constructs' discriminant validity, as outlined in Table 3.

Table 3. Correlation matrix and discriminant validity.

	BI	ATU	PEOU	PU	TA	IE	TI
BI	0.832						
ATU	0.455	0.791					
PEOU	0.178	0.397	0.845				
PU	0.427	0.526	0.266	0.846			
TA	0.064	0.106	0.122	0.275	0.925		
IE	0.360	0.426	0.265	0.745	0.202	0.825	
TI	0.338	0.182	0.014	0.651	0.188	0.548	0.756

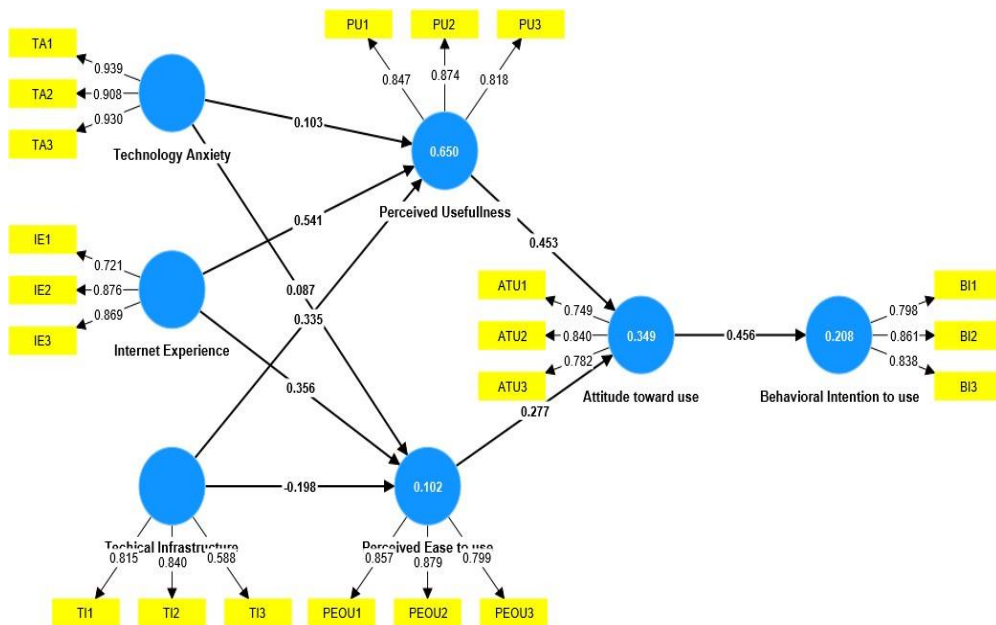


Fig 2. Research Model

4.2. Structural Model and Hypotheses testing

The assessment of the structural model encompassed the evaluation of its capacity to elucidate the variance within dependent variables, as denoted by the R^2 values, as well as the significance of path coefficients and corresponding t-statistics (Hair Jr et al., 2021, P.128). Given that the software employed in this study was SmartPLS, the examination of inter-construct relationships within the structural model involved the utilization of a bootstrap routine. This routine, in turn, computed empirical p and t values. Typically, researchers adopt critical values for significance levels, setting them at 5% for two-tailed tests (1.96) and 1.65 for one-tailed tests. Indeed, the majority of researchers employ p values to assess the significance levels. In order to establish path coefficients and appraise the significance of the study model's effects, the PLS path algorithm was employed to analyze the outcomes of the study models.

Drawing from recommendations offered in prior research (Hair Jr et al., 2021, P.129; Pallant, 2020; Nunnally & Bernstein, 1994), a total of 5000

bootstrapping resamples were executed, as depicted in Fig 2. Through this process, the significance of path coefficients for direct effects was determined, as outlined in Table 4. The findings derived from this procedure are detailed in Table 4. Consequently, the nine hypotheses that were introduced in preceding sections of this paper were systematically tested, and the path significance was confirmed.

Table 4. Direct Relationship Hypotheses

Hypothesis no	Hypothesis title	Beta β	P-value	t-Statistic	Decision
H1	Attitude toward use -> Behavioral Intention to use	0.455	0.000	5.10	Accepted
H2	Perceived Usefulness -> Attitude toward use	0.453	0.000	3.48	Accepted
H3	Perceived Ease to use -> Attitude toward use	0.276	0.000	3.88	Accepted
H4	Technology Anxiety -> Perceived Ease to use	- 0.487	0.045	1.94	Accepted
H5	Technology Anxiety -> Perceived Usefulness	- 0.303	0.042	1.98	Accepted
H6	Technical Infrastructure -> Perceived Usefulness	0.334	0.018	2.36	Accepted
H7	Technical Infrastructure -> Perceived Ease to use	0.197	0.043	1.78	Accepted
H8	Internet Experience -> Perceived Usefulness	0.540	0.000	4.461	Accepted
H9	Internet Experience -> Perceived Ease to use	0.356	0.002	3.02	Accepted

Aligned with the hypotheses of the study, the outcomes presented in the aforementioned table illustrate a substantial and favorable influence of individuals' Attitude toward use on their Behavioral intention to use eHealth services ($\beta = 0.455$, $t = 5.10$, $p = 0.000$), thereby corroborating H1. Similarly, in the context of Perceived Usefulness, a noteworthy and affirmative impact was observed on individuals' Attitude toward the use of eHealth services ($\beta = 0.453$, $t = 3.48$, $p = 0.000$), thereby providing support for H2. Additionally, the study identified that the perception of ease of use significantly impacted individuals' Attitude toward using eHealth services ($\beta = 0.276$, $t = 3.88$, $p = 0.000$), thus substantiating the validity of H3.

Furthermore, the results lend credence to H6, wherein Technical Infrastructure exhibited a positive association with Perceived Usefulness ($\beta = 0.334$, $t = 2.36$, $p = 0.018$) and also demonstrated a constructive effect on Perceived Ease of use ($\beta = 0.197$, $t = 1.78$, $p = 0.043$). Expanding upon this, the mainstream of findings corroborated H8 and H9, illuminating that Internet Experience had a positive impact on Perceived Ease of use ($\beta = 0.356$, $t = 3.02$, $p = 0.002$) and Perceived Usefulness ($\beta = 0.540$, $t = 4.61$, $p = 0.000$).

Conversely, the investigation ascertained a direct and adverse correlation between Technology Anxiety and both Perceived Ease of use ($\beta = 0.487$, $t = 1.94$, $p = 0.045$) and Perceived Usefulness ($\beta = -0.303$, $t = 1.98$, $p = 0.042$).

Table 5 Indirect effects

Hypothesis	Beta β	T statistics	P values	Decision
Internet Experience -> Behavioral Intention to use	0.157	2.125	0.034	Accepted
Perceived Ease to use -> Behavioral Intention to use	0.126	2.788	0.005	Accepted
Perceived Usefulness -> Behavioral Intention to use	0.206	2.447	0.014	Accepted
Technical Infrastructure -> Behavioral Intention to use	0.044	0.918	0.035	Accepted
Technology Anxiety -> Behavioral Intention to use	- 0.032	1.779	0.045	Accepted

The findings presented in Table 5 validate that Perceived Ease of use, Perceived Usefulness, Internet Experience, and Technical Infrastructure collectively exert a positive indirect impact on the Behavioral Intention to engage with the eHealth system in Misurata City. Moreover, the outcomes also highlight a detrimental indirect influence of Technology Anxiety on the Behavioral Intention to utilize the eHealth system in Misurata City.

5. Discussion

This research provides validation for the accuracy of the Technology Acceptance Model (TAM) in forecasting the utilization of eHealth services by clients. This validation is achieved through the incorporation of supplementary external variables that reinforce the assumptions of the model, thereby augmenting its predictive capacity. The outcomes of this study lend support to the substantial correlation between perceived usefulness and clients' inclination to adopt eHealth, as evidenced by a p-value below 0.05. This outcome is consistent with previous investigations into the adoption of eHealth, such as the works of Alsyouf et al. (2021, 2022), as well as the adoption of Personal Health Records (PHRs), including Abdekhoda et al. (2019) and Liu (2013). It is apparent that clients' favorable attitudes towards eHealth technologies exert a positive impact on their propensity to engage with eHealth systems. Likewise, healthcare professionals, recognizing eHealth technologies as instruments for enhancing service quality, exhibit an increased intention to adopt eHealth.

The findings of this study align with analogous research (Tilahun & Fritz, 2015; Kipturgo et al., 2014), which underscores the role of perceived usefulness in steering users' intent to embrace eHealth systems. In essence, if clients perceive that eHealth systems offer advantages, they are more likely to adopt them to augment healthcare services. Moreover, a significant correlation is discerned between perceived ease of use and perceived usefulness, as substantiated by a p-value lower than 0.01. This observation echoes prior literature on eHealth adoption, exemplified by the works of Alsyouf et al. (2021, 2022), Abdekhoda et al. (2019), Liu (2022), and Noblin et al. (2013). It is evident that clients who find eHealth systems user-friendly are predisposed to frequent usage, reinforcing their perception of the systems' value and significance.

This study further highlights the influential role of clients' IT experience in shaping their perception of usefulness and ease of use regarding eHealth systems. A statistically significant relationship is established, denoted by a p-value below 0.05. As individuals acquire IT proficiency and familiarity with IT systems, their appreciation of the utility of novel systems and their proclivity to adopt eHealth are heightened. This conclusion echoes findings from analogous research (Aslani et al., 2019; Alsyof et al., 2021, 2022). Additionally, the study's results underscore the potency of technical infrastructure in shaping clients' intent to adopt eHealth technologies. This trend is substantiated by congruent investigations (Tao et al., 2016; Marangunić & Granić, 2015; Wang et al., 2016; Sharifian et al., 2014). Plausibly, the availability of a robust infrastructure, coupled with systems in place to uphold existing hospital infrastructure, amplifies staff attitudes and intentions toward adopting eHealth technologies in the same direction. Consequently, in resource-constrained hospital settings, guaranteeing uninterrupted power supply, computer accessibility, and budget allocation emerges as pivotal factors for nurturing positive attitudes and intentions towards eHealth technology adoption.

6. Conclusion

This study demonstrated the applicability of the Technology Acceptance Model (TAM) in evaluating the inclination to utilize eHealth for the sustainable integration of eHealth technologies. Among the determinants, attitude towards eHealth emerged as the most influential factor shaping the intention to adopt eHealth. Furthermore, perceived usefulness and perceived ease of use emerged as pivotal factors influencing both attitude towards eHealth usage and the intention to adopt eHealth.

Furthermore, the study revealed that Technical Infrastructure holds predictive significance concerning both attitude and intention to embrace eHealth, particularly in settings with limited resources. In light of these findings, providers of eHealth services within the health sector of Misurata Municipality are advised to prioritize enhancements to hospital technical infrastructure and communication networks. Accomplishing this could involve delivering consistent fundamental ICT training to healthcare professionals and meticulously considering the implementation of new

systems. By doing so, these initiatives are poised to heighten clients' perceived usefulness and foster more positive attitudes towards eHealth.

7. Strength and Limitation of the Study

This study is poised to make a substantial contribution to the future implementation of eHealth systems in resource-constrained environments. Furthermore, the findings discussed herein have been derived from a multicenter study involving diverse eHealth systems within the country, thereby allowing for potential generalization to other populations and emerging platforms. In addition, forthcoming research endeavors could explore alternative data collection methods beyond the conventional survey questionnaire. Such methods could facilitate comparative analyses or evaluations of behaviors before and after the adoption of eHealth systems, a particularly valuable pursuit for health-related applications. Embracing a qualitative approach would also enable the capture and observation of lived experiences, a crucial aspect for situational analysis. This could be achieved through narrative analysis or by delving into explanatory accounts of the phenomenon.

In addition, future studies have the potential to expand upon the Technology Acceptance Model (TAM) by considering additional external variables not explored in the current study. For instance, elements such as technological self-efficacy, quality factors (comprising service, system, and information quality), and user satisfaction with the technologies could be incorporated. These factors collectively contribute to a more comprehensive understanding of the adoption process and its implications.

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