ISSN: 1795-6889

https://ht.csr-pub.eu Volume 20(1), May 2024, 114-130

UNVEILING THE NEXUS OF TECHNOLOGY ACCEPTANCE IN HEALTHCARE: EMPIRICAL EXPLORATION OF THE MULTIFACETED DRIVERS

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Abstract: *In the rapidly evolving landscape of healthcare, the integration of cutting-edge technologies has become pivotal for enhancing patient care, optimizing operational efficiency, and driving overall advancements in the field. However, the successful adoption of these technologies hinges upon the acceptance and utilization by healthcare stakeholders, particularly patients. Unraveling the complexities of technology acceptance in the healthcare domain necessitates a nuanced understanding of the underlying factors that shape individuals' attitudes and behaviors towards technology. This paper aims to provide a holistic understanding of the support factors that influence health technology acceptance. To explore these drivers (variables), 5 study hypotheses were made using the PSL-SEM model based on a developed questionnaire. The obtained results suggest that systemic support for the development of ICT in healthcare has a stronger positive impact on patients' intention to use ICT than professional support. On the other hand systemic support does not affect patients' self-efficacy unlike professional support.*

Keywords: *health sector, information technology, technology acceptance models, ICT drivers, patients' intention to use, survey, SEM*

DOI: https://doi.org/10.14254/1795-6889.2024.20-1.6

INTRODUCTION

In recent decades, the healthcare sector has witnessed an unprecedented transformation propelled by rapid advancements in Information and Communication Technology (ICT). The integration of digital technologies into healthcare practices has not only streamlined administrative processes but has also revolutionized patient care, research, and overall healthcare delivery (Nisha et al., 2015). From improving diagnostic accuracy and treatment precision to fostering proactive healthcare management and preventive strategies, ICT has become an indispensable catalyst for innovation in healthcare delivery (Yu et al., 2006; Duarthe & Pinho, 2019). The advent of electronic health records (EHRs), telemedicine, wearable devices, and data analytics has ushered in a new era, where the healthcare ecosystem is becoming increasingly interconnected and data-driven. These technological innovations have not only enhanced the accessibility and quality of healthcare services but have also presented novel challenges and ethical considerations that demand careful scrutiny (Sun & Qu, 2015).

In an era characterized by rapid technological advancements (Bilan et al., 2023; Florek & Lewicki, 2022; Remeikiene et al., 2021), the integration of innovative solutions in the healthcare sector has become pivotal for enhancing patient care, improving outcomes, and optimizing healthcare delivery systems. The emergence of health technologies, ranging from wearable devices and mobile applications to advanced medical equipment and telehealth platforms, promises to revolutionize the landscape of healthcare. However, the successful implementation of these technologies relies heavily on their acceptance by healthcare professionals, administrators and patients (Dwivedi et al., 2019; Gagnon et al., 2015; Lotfi et al., 2020). Unraveling the complexities of technology acceptance in the healthcare domain necessitates a nuanced understanding of the underlying models and the myriad factors that shape individuals' attitudes and behaviors towards technology (Mehra et al., 2020). Particularly, understanding the support factors that influence the acceptance of health technologies by patients is paramount to unlocking their full potential and ensuring widespread adoption across diverse healthcare settings.

The burgeoning field of technology acceptance models (TAMs) serves as a theoretical framework to decipher the intricate interplay between individuals and technology in the healthcare sector (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Venkatesh et al., 2012). TAMs, rooted in psychological and behavioral theories, offer a structured lens through which researchers and practitioners can scrutinize the multifaceted dynamics influencing the acceptance and utilization of health technologies. The backdrop of the study lies in the imperative to bridge the gap between technological innovation and its effective implementation in healthcare settings. While the potential benefits of technologies such as electronic health records, telemedicine, wearable devices, and artificial intelligence are vast, their successful integration requires a deep understanding of the support factors that influence the acceptance or resistance to change among diverse stakeholders, particularly patients (Tam et al., 2020).

Therefore, this paper embarks on a comprehensive exploration of health technology acceptance, delving into the intricate interplay of psychological, organizational, and systemic drivers that shape individuals' willingness to embrace and effectively utilize these innovations. The significance of understanding these factors cannot be overstated, as it directly impacts the efficacy, efficiency, and ultimately the success of health technology implementations (Wu 2018). Our study adopts an interdisciplinary approach, drawing on insights from technology acceptance models, behavioral psychology, and healthcare management. By synthesizing and analyzing existing literature and performing an empirical study, we aim to unravel the key support factors that impact the technology intention to use among patients in Poland. We construct a structural framework that elucidates the interplay of various drivers influencing ICT intention to use among patients in healthcare. This paper embarks on a comprehensive exploration of these factors, shedding light on their conceptual foundations, and applicability within the healthcare context.

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THEORETICAL APPROACHES ON TECHNOLOGY ADOPTION IN HEALTHCARE

Information and Communication Technologies (ICT) in health, often referred to as Health ICT or eHealth (electronic health), encompass a broad range of digital and analogue technologies and tools that facilitate the capturing, processing, storage, and exchange of information via electronic communication (Gagnon et al., 2009). Key components of ICT in health include: Electronic Health Records (EHRs), Telemedicine and Telehealth, Health Information Exchange (HIE), Mobile Health (mHealth), Health Information Systems (HIS), Clinical Decision Support Systems (CDSS), Health Analytics, and E-learning and Health Education (Wienstein et al., 2018; Aanestad et al., 2017). In terms of healthcare delivery and patients' relationship telemedicine and telehealth play a significant role. These technologies involve the use of electronic information and telecommunications technologies to support long-distance clinical health care, patient and professional health-related education, public health, and health administration (Richmond et al., 2017). Telemedicine can include video consultations, remote monitoring of patients, and the exchange of health information through secure communication channels (Kruse et al., 2017; Lewicki et al., 2021, Rahi et al, 2021).

From the 1960s onwards scholars have proposed many approaches to understand the attitudes, the intention to use and the behaviors towards the adoption of ICT (Lemos de Almeida et al., 2017). Exploring the influence of intentions on individual behavior has led to the development of two prominent theories: the Theory of Reasoned Action (TRA) by Fishbein and Ajzen (1975) and the Theory of Planned Behavior (TPB) by Ajzen (1985). TRA was designed to explain and predict human social behavior, especially in the context of decision-making regarding health-related behaviors, attitude change, and social influence. The central idea of TRA is that individuals are rational actors who make decisions based on a combination of their attitudes and subjective norms. Over time, Fishbein and Ajzen expanded on the TRA and developed the TPB, which includes an additional component called Perceived Behavioral Control (PBC). According to TPB, individuals are more likely to accept and use a health technology if they have a positive attitude toward it, perceive social pressure to use it, and believe they have control over its use (Ajzen, 1991).

Technology Acceptance Model (TAM) is the most popular framework, explaining the technology intention to use. It has been developed by Davis (1989) with the goal of validating measurement scales for perceived usefulness and ease of use. These constructs represent an individual's belief in a system's utility for enhancing work performance and the perceived effort required to use the system, respectively. Davis focused on user acceptance, linking perceived usefulness and ease of use to usage intention and behavior. Furthermore, Davis, Bagozzi, and Warshaw (1989) emphasized the need for a foundation to assess the impact of external drivers on beliefs, attitudes, and internal intentions in technology acceptance. They measured intentions in terms of attitudes, subjective norms, perceived usefulness, perceived ease of use, and related variables. In turn Venkatesh and Davis (2000) introduced TAM2 – an extension of the original model to account for additional factors and contextual considerations in understanding technology adoption. Their modification includes new constructs such as social influence, cognitive instrumental processes, subjective norms, voluntariness, image, job relevance perception, output quality, and demonstrability of results.

Next, Venkatesh et al. (2003) and Venkatesh, Thong, and Xu (2012) developed a unified model (Unified Theory of Acceptance and Use of Technology - UTAUT), based on TAM, incorporating four key predictors of technology acceptance: performance expectancy, effort expectancy, social influence, and facilitating conditions. It also considers moderating factors such as gender, age, and experience. In the realm of e-health, researchers such as Hoque and Sorwar. (2017), Kaium et al. (2020), and Seethamraju, Diatha, and Garg (2018) have applied this theory to investigate user behavior regarding the adoption of e-health services. Inhibiting and facilitating drivers have been also considered by Ratchford and Barnhart (2012), who addressed the propensity of use, evaluating the attitudes and beliefs of potential technology users and non-users.

Social influence is a key component of UTAUT, being understood as "the degree to which a patient believes in the recommendations of significant others regarding the adoption of telemedicine health services" (Cho 2016; Venkatesh, Thong, and Xu 2012). According to previous studies social influence has demonstrated a positive influence on patient behavior in embracing telemedicine (Cho 2016; Kaium et al. 2020; Zhou & Li 2014). Researchers such as Kaium et al. (2020), Ahmad and Khalid (2017) and Sun et al. (2012) have proved the significant effect of social influence on user behavior in sustaining the use of m-health services. It is important to stress that Ward et al. (2017) found that healthcare practitioners play an important role in stimulating the acceptance and use of technologies. This subject had gained little exploration so far, although the impact of healthcare professionals on the acceptance of health information technology have been incorporated into another model called Health Information Technology Acceptance Model – HITAM (Aggelidis &Chatzoglou, 2009; Rashid et al., 2018).

On the other hand, facilitating condition is acknowledged as "the extent to which a patient believes that organizational infrastructure enables him/her to use telemedicine health services" (Venkatesh et al., 2012). Scholars like (Deng 2013), Aggelidis and Chatzoglou (2009) and Nysveen and Pedersen (2016) have confirmed that the presence of infrastructure encourage patients and enhances their proficiency in utilizing telehealth and telemedicine. Further, various other researchers have revealed that facilitating conditions exert a significant impact on the intention and/or actual usage of technology (Mun et al. 2006; Aggelidis & Chatzoglou, 2009; Deng 2013, Alam et al., 2020).

THE MEDIATING ROLE OF SELF-EFFICACY

Investigations into the acceptance of consumer health technology have predominantly employed the TAM or its updated iterations (UTAUT) as a foundational theoretical framework (Tao et al., 2018; Tao et al., 2016). Despite their broad applicability, there exists a necessity for its modification through the incorporation of contextual and theoretically justified factors. Such factors aim to enhance the model's predictive efficacy within specific contexts (Priyansyah et al., 2023).

In the specific domain of ICT in healthcare the challenge of non-acceptance appears to be intricately linked to patients' initial interaction experiences with the applications (Tao et al., 2020). These experiences are predominantly shaped by self-efficacy. It refers to users' self-perceptions regarding their capability to effectively utilize the applications (Douneva et al., 2016). Therefore, a comprehensive understanding of acceptance issues in the context of healthcare settings necessitates the integration of the self-efficacy into the research framework.

The meaningful exploration for self-efficacy is delivered by Social Cognitive Theory - SCT (Maddux, 1993; Badura, 2004). SCT posits that self-efficacy assumes a preponderant function in directing individual conduct within the domain of technological utilization (Vancouver & Purl, 2017). If patients perceive themselves as incapable of executing prescribed tasks using a particular eHealth application, their persistence in its utilization may falter. Consequently, self-efficacy, particularly in relation healthcare settings, seems to be instrumental in fostering intention to use and delineating patient approval (Ma & Liu, 2005).

Earlier investigations have demonstrated the influence of self-efficacy particularly on the perceived utility and perceived ease of use of technology in a broad sense (Kulviwat et al., 2014), including applications in health informatics (Tsai, 2014). Moreover, it has been proposed by Compeau and Higgins (1995) that the predictive efficacy of the self-efficacy construct can be enhanced by contextualizing it through a domain-specific measure, as opposed to its generic manifestation. A substantial number of previous studies (Bilgrami et al., 2020; Tang et al., 2019; Deng & Liu, 2017) have proved that individuals possessing elevated levels of self-efficacy exhibit affirmative intentions to adopt telemedicine applications, thereby facilitating effective disease management. Kohnke et al. (2014) also prove that he cognitive constructs of self-efficacy beliefs exert a decisive influence on cognitive processes, emotional states, motivational propensities, and behavioral manifestations in individuals. This influential role extends to their proclivity to engage with information technology, thereby significantly impacting both the intention to employ such technology and the subsequent actual utilization behaviors.

RESEARCH METHODOLOGY

Research Model

In the study, modern technologies in healthcare were defined as any health solution that is new to the patient and based on information, ICT and communication technologies, e.g.: televisions, conversations with virtual consultants, modern medical devices used remotely in diagnosis, therapy and rehabilitation. The term new technologies also includes online patient-doctor communication platforms and applications for patient care management and patient self-care.

Moreover, we perceive social influence in terms of professional support (PS), provided by physicians to patients in healthcare settings. We define PS as the degree to which doctors, clinicians and caregivers support patients' use of ICT. On the other hand, facilitating condition is perceived as systemic support (SS), performed by government a various levels, enabling patients access to infrastructure and information about ICT solutions when needed. A substantial number of studies has confirmed that both social influence and facilitating conditions positively effect on patient intention to adapt telemedicine and telecare. Thus back up by earlier studies following hypotheses are proposed:

H1: Systemic support has positive influence on patient's intention to use modern technologies in healthcare

H2: Professional support has positive influence on patient's intention to use modern technologies in healthcare

As highlighted in the previous section, self-efficacy may significantly impact the behavior intention of the individuals in accepting technologies in healthcare settings. Consequently, this study delves into the assessment of patients' self-efficacy (SE). This construct is defined as an individual's evaluative judgment regarding their own proficiency in utilizing new technologies for the acquisition of health-related information and services. The present study contributes to the existing body of knowledge and elucidates computer self-efficacy's role as a mediating variable in the relationship among both systemic support and professional support and the intention of patients to adopt new technologies in health services. Thus, these relationships are hypothesized as:

H3: The systemic support has positive influence on patient's self-efficacy

H3a: The relationship between systemic support and intention to use modern technologies is positively mediated by patient's self-efficacy

H4: The professional support has positive influence on patient's self-efficacy

H4a: The relationship between professional support and intention to use modern technologies is positively mediated by patient's self-efficacy

H5: Patient's self-efficacy has positive influence on patient's intention to use modern technologies in healthcare

The proposed research model as depicted in Figure 1 presents all hypothesized relations among identified constructs. He current study advances the body of knowledge by examining the mediating impact of patient's self-efficacy between systemic and professional support and intention to use new technologies by patients in Poland. The model is based on the unified theory of acceptance, referring to the fundamental role of facilitating drivers (here: support by regulatory bodies) and social influence (here: organizational and professional support). The current study develops an integrated research model to examine patients' intention towards the adoption of new technologies in healthcare settings in Poland.

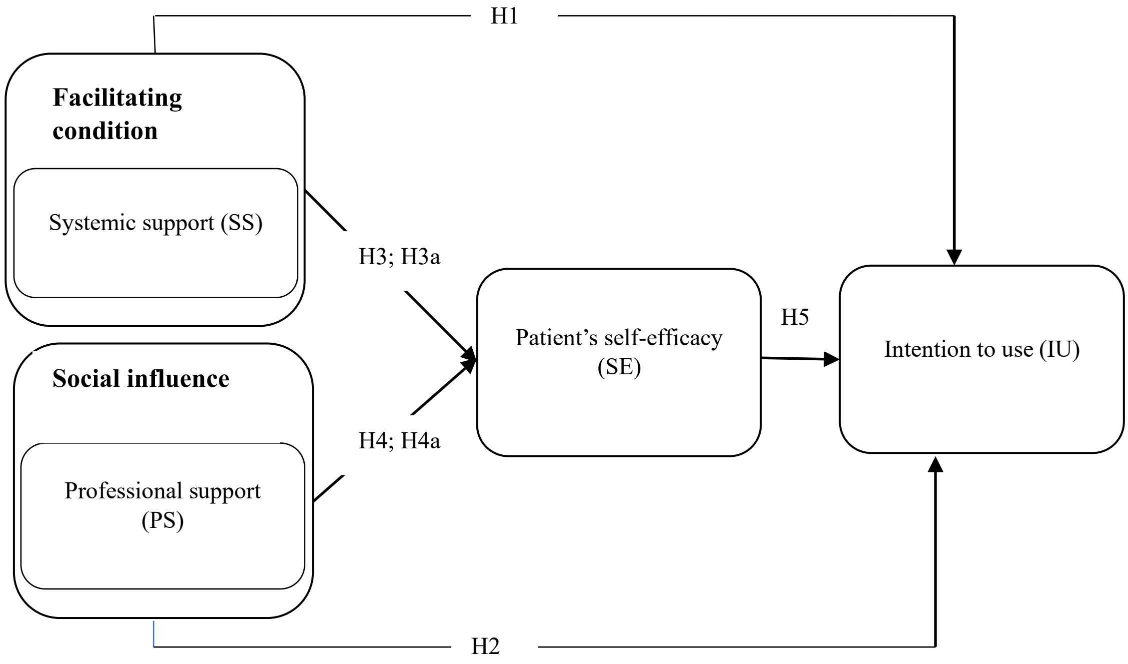

Figure 1. The proposed research model
[Source: own work]

Table 1. Scale characteristics [Source: own work]

Variable	Source	Cronbach Alpha
Systemic support (7 items)	Li & Atuahene-Gima (2001); Shu et al. (2019); Lean et al. (2009);	0,91
Professional support (10 items)	Wu (2018); Ward et al. (2007);	0,96
Intention to use (4 items)	Priyansyah et al. (2023); Shareef et al. (2014); Ahmed et al. (2023);	0,91
Self-efficacy (4 items)	Sun et al. (2013); Gao et al. (2015), Tao et al. (2020);	0,92

The study assumed that a patient who is convinced of new technologies will declare his intention to use these technologies if the need arises. This variable was measured by 4 statements depicting the willingness to use new technologies in the health area more and more in the future. The Alpha Cronbach index for this scale assumed a value of 0.91.

The construct of *systemic support* (government institutional support), on the other hand, was measured by 7 statements, which indicated that health system institutions provide patients with the information necessary to learn about new technologies, provide access to infrastructure to ensure the use of new technologies, encourage patients to use modern technologies, and are aware of the benefits that can be achieved through the use of new technologies. The Alpha Cronbach index for this scale assumed a value of 0.91.

The variable *professional support* for the development of new technologies" is a construct consisting of 10 statements, among others, emphasizing doctors' concern for the safety, convenience and comfort of patients when using new technologies and proper communication in the doctor-patient relationship regarding new technologies. The Alpha Cronbach index for this scale assumed a value of 0.96.

In addition, the *intention to use* new technologies in medicine was considered to be determined by the perception of *self-efficacy* in this regard. Therefore, this variable was entered into the model as a mediating variable, consisting of 4 assertions. These statements related to the ease of using modern technologies in daily life, even without the help of third parties. The Alpha Cronbach index for this scale assumed a value of 0.92.

DATA COLLECTION

For data collection, an online survey was carried out. The survey was conducted in January-February 2022 using the CAWI technique on a representative sample of 1,074 adult residents of Poland. Those invited to participate in the survey were those who had used medical care in the last six months before the survey. Information on the socio-demographic structure of the survey sample can be found in the Table 2.

Table 2. Research sample structure (N=1074) [Source: own work]

	Number	%		Number	%
Sex			**Place of residence**		
Female	584	54,4	Countryside	354	32,9
Male	490	45,6	Small town (up to 20 000 residents)	123	11,5
Education			Middle-size town (20 000- 99 000 residents)	233	21,7
Primary	27	2,5	Big town (100 000-500 000 residents)	222	20,7
Vocational	105	9,8	City (over 500 000 residents)	142	13,2
Secondary	433	40,3	**Net income per capita**		
Bachelor	114	10,6	Up to 1500 PLN	198	18,4
Master	395	36,8	1501-2000 PLN	200	18,6
Age			2001-2500 PLN	176	16,4
18-24	124	11,5	2501-3000 PLN	174	16,2
25-34	264	24,6	3001-3500 PLN	121	11,3
35-44	252	23,5	Over 3500 PLN	205	19,1
45-54	202	18,8			
55 and over	232	21,6			

The demographic profile of the respondents indicate that among 1074 individuals 584 were female and 490 respondents were male. Concerning with respondents age there were 11,5% less than 25 years old, 24,6% were having age 25 to 34 and 23,5% had an age range 35-44. Similarly, 18,8% of respondents were having age 45-54 and 21,6% were older than 54. As much as 40% of respondents had secondary education, while 10,6% had bachelor degree and 24,6% held master degree. Respondents with primary education were found at the lowest level only 2,5%, and those with vocational education: 9,8%. The distribution of net income per capita was quite balanced across the sample. Almost on third of the respondents live in the countryside, while 11,5% in a small town, 21,7% in a middle-size town and 20,7% in a big town. Only 13,7% of the respondents live in a city.

RESEARCH RESULTS

To verify the theoretical model, structural equation modelling (SEM) was used, which is a linear cross-sectional statistical modelling technique including path analysis and regression analysis. The SEM is used to explain the pattern of a series of interrelated dependence relationships simultaneously between a set of latent constructs. In addition, SEM is also used to estimate variance and covariance, test hypotheses, conventional linear regression, and factor analysis (Jöreskog & Sörbom, 1996). However, an SEM-tested model must be based on theoretical assumptions and it is the only theory that can stimulate and trigger the development or modification of the model. Because SEM is mostly used to determine whether a certain model is valid rather than to “find” a suitable model, it is the most applicable statistical method to validate the proposed model (Figure 1). This is where the theory plays an important role in justifying the model.

To verify the theoretical model, the maximum likelihood (ML) estimation method was applied. The ML function is a structured means model reflecting how closely the sample mean vector is reproduced by the estimated model mean vector. It is also indicated how closely the sample covariance matrix is reproduced by the estimated model covariance matrix (Bentler, 1995). Moreover, to assess the quality/fit of the model, the following indexes were used: GFI (goodness fit index), CFI (comparative fit index) and RMSEA (root mean square error of approximation).

The descriptive statistics of the variables are presented in Table 3. It is worth noting that some of the dependencies are negative.

Table 3. Descriptive statistics [Source: own work]

	Mean	SD	Systemic support	Professional support	Intention to use
Systemic support	3,10	5,82	1,00		
Professional support	3,00	9,46	0,71		
Intention to use	3,78	3,10	0,30	0,31	
Self-efficacy	3,80	3,20	0,18	0,20	0,67

The results revealed a $\chi 2$ of 1009.4 based on 270 degrees of freedom with a probability level of 0.00. As the indicators show, the goodness-of-fit measures of the model are satisfactory (Table 4).

Table 4. The goodness of fit indexes [Source: own work]

Index	Score
CMIN/DF	3,73
GFI	0.92
CFI	0.97
RMSA	0.05
Holter	348

All model paths, except one, are statistically important. Thus four out of five hypotheses have been confirmed (Table 5).

Table 5. Standardized Regression Weights [Source: own work]

					Estimate	Status of hypothesis
H1		Intention to use	<---	Systemic support	0,14	support
H2		Intention to use	<---	Professional support	0,07	support
H3		Self-efficacy	<---	Systemic support	-	rejected
H3a	Intention to use <---	Self-efficacy	<---	Systemic support	-	rejected
H4		Self-efficacy	<---	Professional support	0,21	support
H4a	Intention to use <---	Self-efficacy	<---	Professional support	0,15	support
H5		Intention to use	<---	Self-efficacy	0,70	support

Seven hypotheses have been proposed in the model based on the previous findings. Five of them (H1, H2, H4, H4a and H5) have been statistically confirmed. In turn, there are two hypotheses (H3 and H3a) that have not been confirmed. It turned out that systemic support for the development of ICT in healthcare does not increase patients' self-efficacy in the use of these technologies. Instead, this feeling is quite significantly perpetuated by the professional support of physicians (H4). Thus, it appears that physicians, as part of their direct contact with patients and their attitudes toward technology, can shape patients' beliefs about their ability to use modern technologies. Systemic support for the development of ICT in healthcare definitely has a stronger positive impact on patients' intention to use these technologies than professional/ organizational support (H1 and H2). However, according to respondents, patients' intention to use modern technologies is definitely impacted by their self-efficacy in this regard (H5).

Thus, considering the two types of drivers to use ICT in healthcare, i.e., systemic and professional / organizational support, the former more strongly influences patients' intention to use technology, but on the other hand does not affect patients' self-efficacy in this regard. Professional support, on the other hand, impacts less the intention to use, but influences patients' self-efficacy, which in turn strongly determines their intention to use technology. Therefore, it would be interesting to see what the total impact of the different types of support is on the patients' intention to use technology in healthcare settings. For this purpose, the direct and indirect influences on intention to use were examined.

Considering the two types of analyzed support (systemic versus organizational), it turned out that the support of physicians more strongly determines intention to use than systemic support (Table 6). The analysis showed that in the case of systemic support, patients' self-efficacy is not a mediating factor, i.e. it does not mediate in encouraging patients to use modern technology (H3a). A completely different situation applies to professional support. In this case, the direct effect on intention to use is small, but the introduction of the self-efficacy variable increased the strength of the effect (H4a). This means that familiarizing patients with modern technology by doctors improves their self-efficacy, which in turn significantly increases patients' willingness to use them when necessary.

Table 6. Standardised total, indirect and direct effects [Source: own work]

	Systemic support	Professional support	Self-efficacy
Standardized Total Effects			
Self-efficacy	0,00	0,21	
Intention to use	0,14	0,22	0,7
Standardized Direct Effects			
Self-efficacy	0,00	0,21	-
Intention to use	0,14	0,07	0,7
Standardized Indirect Effects			
Self-efficacy	0,00	0,00	
Intention to use	0,00	0,15	

DISCUSSION

Several researchers (Ward et al., 2007; Shareef et al., 2014; Wu, 2018; Priyansyah et al., 2023, Ahmed et al., 2023) have attempted to conceptualize and restructure the technology acceptance in healthcare. Although consumers of medical services are the most important link in the service delivery chain, their intention to use ICT and subsequently their adoption behavior has not been explored in the Polish healthcare settings comprehensively so far. Therefore, the present study sought to evaluate and theorize the adoption behavior of general consumers who engage in the health system as patients. The authors accomplished the research objective by developing a conceptual model highlighting the driving forces in adopting modern technologies in healthcare.

Our findings are in addition to the concept of UTAUT (Tao et al., 2018; Tao et al., 2016) and are justified in the perspective of e-health organizational and technological nature based on the concept of TRA (Fishbein & Ajzen, 1975) and TPB (Ajzen, 1985). The results of our study strengthen the premise that e-health adoption behavior is a final outcome shaped not only by patients' beliefs in technology but also by social and institutional beliefs (Shareef et al., 2014). Therefore, our findings are in line with the research results obtained by Zhou & Li (2014), Cho (2016), Ahmad and Khalid (2017) and Kaium et al. (2020). All these studies explored and empirically confirmed the significant effect of social influence on user behavior in sustaining the use of m-health services. Moreover, our findings are in line with those obtained by Ward et al. (2017), who found that medical doctors play a crucial role in reinforcing the acceptance and usage of ICT by patients.

Moreover, our research confirmed that institutional, systemic support is a significant driver, stimulating the intention to use of modern technologies in healthcare setting, although it does not impact the patient's self-efficacy. This result supported by some studies exploring facilitating conditions for M-health (Mun et al. 2006; Aggelidis & Chatzoglou, 2009) and some other studies discussing external, governmental issues impacting the intention to use modern technology in healthcare (Deng 2013, Alam et al., 2020). Therefore, under the institutional context of e-health, the patients' perception of reliability of the overall system contributes significantly to their adoption behavior. The similar conclusions have been drawn by Li & Atuahene-Gima (2001), Lean et al. (2009) and Shu et al. (2019).

Finally, with our study we confirmed the important role of patients' self-efficacy in shaping the intention to use of ICT in health system, although according to our research it is not stimulating by institutional support. Our empirical investigation strengthens the premise done other researchers (Deng & Liu, 2017; Tang et al., 2019; Bilgrami et al., 2020) that patients demonstrating higher levels of self-efficacy show affirmative intentions to adopt ICT in the service delivery process. Moreover, it turned out that self-efficacy strengthens doctors' actions aimed at encouraging patients to use modern technology (becoming an important mediating variable, Ma & Liu, 2005; Tao et al., 2020). However, a similar effect could not be observed in the case of systemic support.

CONCLUSIONS

Our research has been designed on a conceptual model exploring the crucial drivers stimulating adoption of modern technologies in health system. We explored two types of drivers: systemic and professional support. The findings contribute to the overall understanding of the factors underling he patients' intention to adopt and finally to use ICT in healthcare settings. The value of the study is based on the discovery of the impact of the both systemic / institutional and professional / organizational factors on patients' self-efficacy and finally their adoption of e-health.

However, although with our research we contribute significantly to the scare literature in the field of ICT adoption by end-users (patients), the study has some limitations. Frist of all our study examined only two types of drivers enhancing usage of ICT in healthcare. It would be interesting to incorporate psychological factors into the research model in the subsequent studies. Another limitation of the study is the region. Since the study was conducted in Poland whose health sector can be classified as low technology saturated, its results cannot be generalized for developed countries. Therefore, it would be recommended to replicate the research process in both types of countries in order to identify a difference in perception of drivers in ICT adoption.

Finally, it is true to state that adoption of ICT in healthcare is a complex issue. The advent of health technologies has ushered in transformative potential, promising improved patient outcomes, enhanced communication between healthcare providers and patients, and increased operational efficiency within healthcare systems. Yet, despite these promises, the widespread acceptance of health technologies remains a complex challenge. Recognizing the diverse range of factors that shape user perceptions and behaviors towards health technologies is crucial for developing strategies that promote their seamless integration into healthcare ecosystems.

IMPLICATIONS FOR THEORY, APPLICATION, AND POLICY

With this paper we provided a nuanced understanding of the systemic, organizational and psychological factors that underpin the intention to use of health technologies. Moreover, it bridges gaps in existing literature by considering the unique challenges and opportunities within the healthcare context that impact the adoption of these technologies. Such insights are of key importance for informing policy decisions, guiding the design of user-friendly technologies, and promoting effective strategies for implementing and integrating health technologies into routine healthcare practices. As we stand at the crossroads of technological innovation and healthcare delivery, this examination serves as a timely and essential contribution to the ongoing discourse surrounding the future of health technology acceptance.

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Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu