Human TECHNOLOGY

ISSN: 1795-6889

https://ht.csr-pub.eu Volume 22(1), September 2026, 451–468

HOW PATIENTS UNDERSTAND AND TRUST HEALTHCARE TECHNOLOGIES: THE ROLE OF PERCEIVED EXPLAINABILITY IN ICT ACCEPTANCE

Katarzyna Krot
Bialystok University of Technology
Poland
ORCID 0000-0002-7404-1724

Iga Rudawska
University of Szczecin
Poland
ORCID 0000-0002-2173-931X

Abstract: *The study empirically examines how patients' perceptions of information and communication technologies (ICT) in healthcare shape their attitudes towards using them, a question of growing importance as new technologies increasingly support medical decision-making and daily patient care. The theoretical background is based on technology acceptance models, such as the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology, and on research on trust in healthcare, with particular attention to explainability, reliability, fairness, and patient safety. Data were collected through a computer-assisted web interviewing (CAWI) survey of 1,074 adult residents of Poland. A structural equation model with nine hypotheses was estimated using maximum likelihood and showed a satisfactory fit. The findings reveal that explainability is the central driver of trust: it interrelates with perceived reliability, fairness, and safety of ICT, and it also directly associated with attitudes towards using ICT. Reliability and fairness, in turn, correlate with perceived patient safety, which fosters positive attitudes. Contrary to expectations, safe ICT, understood as data and system security, can be associated neither perceived patient safety nor attitudes towards using ICT. Objective safeguards therefore appear to be a necessary prerequisite for ICT application rather than a factor shaping patients' perceptions. The study extends technology acceptance research in healthcare by showing that patients' knowledge and understanding of ICT, rather than its formal security, build trust and acceptance.*

Keywords: *health system, technology acceptance models, explainability, trust, information and communication technologies, structural equation modelling.*

©2026 Krot, & Rudawska, and the Centre of Sociological Research, Poland
DOI: https://doi.org/10.14254/1795-6889.2026.22-2.11


This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

INTRODUCTION

Technology is present everywhere. It changes the way people live, work, and even stay healthy (Chute, French, 2019; Lăzăroiu Szpilko, Gedeon, Halicka & Rzepka, 2025; Kuzior, Marszałek-Kotzur, Sansyzbayeva & Lukács 2025; Golubtsov, Kedziora, Kozhakhmetova & Kedziora, 2025; Bilan, Oliinyk, Mishchuk, & Skare, 2023). Information and Communication Technology (ICT) in healthcare are can be understood as any advanced tool or solution that revolutionises diagnosis, treatment and medical data management. Ti aims to improve the quality of healthcare services, increase the efficiency of health systems and tailor treatments to individual patients' needs (Waqas, Yu, Khan, Tanveer & Ahmad, 2023).

ICTs in healthcare are the foundation not only of modern medicine, but also of healthcare management. They offer innovative, often disruptive developments that improve not only the quality of life of patients, but also streamline the work of medical personnel, affecting organisational efficiency at the micro level. At the macro level, on the other hand, they improve the availability and the capacity of health system and its overall efficiency (Nisha, Iqbal, Rifat & Idrish 2015).

Furthermore, Information and communication technologies play a key role in healthcare innovation, improving the precision of diagnosis and treatment and supporting proactive health management and prevention strategies (Yu Wu, Yu & Xiao 2006; Duarthe & Pinho, 2019).

Today, there is a growing interest among researchers from different disciplines exploring the broad applications of new technologies in the context of healthcare (Gupta & Paiva, 2020). The scientific literature identifies key areas in which these technologies play an important role from telemedicine, medical robotics, E-health and digitisation of medical records, to the Internet of Things and artificial intelligence.

Previous research has delivered several advantages of ICT as well as barriers (Haluza & Jungwirth, 2018; Spann & Stewart, 2018). The implementation of ICT has numerous benefits, such as increasing the precision of diagnosis, personalising treatment and improving the efficiency of healthcare systems. However, at the same time, there are challenges related to data protection, ethics and the integration of new solutions into existing organisational and structures. From a system management perspective, it is crucial to plan strategically and invest in training to maximise the benefits of implementing modern technology solutions in healthcare. Equally important is the patients' perspective and their attitude towards ICT.

While prior literature features mainly on the models of technology acceptance in healthcare (AlQudah, Al-Emran & Shaalan 2021; Ammenwerth, 2019) with our study we strive to present a new insight into the accidents of patient's attitude towards using the ICT and the relation among the identified variables. In doing so, we answer the following research questions:

RQ1. How can we understand the patient's explainability of ICT and how it impacts his/her attitude towards using the ICT?

RQ2. What is the role of perceived patient safety in shaping the attitude towards using the ICT

RQ3. What are the relations among the antecedent variables of patient's attitude towards using the ICT?

In the paper ICT are understood as any health-related solution that is new to the patient and based on information, telecommunications, and communication technologies. So they cover broad spectrum of new technologies such as virtual consultations, interactions with virtual consultants, and modern medical devices used remotely for diagnostics, therapy, and rehabilitation. The term also encompasses online platforms for patient-physician communication, as well as applications designed for managing patient care and facilitating patient self-care.

Our paper is structured as follows. In the background section, we synthetize the previous studies on technology acceptance models and the phenomenon of trust in healthcare context. Then, we present the research methodology and research results. Furthermore, we discuss our findings with the state-of-the art literature. Finally, we provide some insights into the implications, study limitations and future research directions.

BACKGROUND

Technology adoption in healthcare

Technology is a polarising factor (Modahl, 1999). People either like technology or they do not. They characterise individuals with an affinity for technology as "technology optimists", and those that have an aversion to technology as "technology pessimists".

Various studies (Martínez-Caro, Cegarra-Navarro, García-Pérez & Fait 2018; Razmak & Bélanger, 2018) show that the end users' attitude towards technology is a key factor in the adoption of modern technologies. Its importance has been highlighted since the earliest research, when it was still concerned with the Internet, mobile or other technologies. Now, a new area for exploration is emerging, namely technologies entering medicine and forcing patients to use them on the daily bases.

Attitude has been a central construct in social psychology and further in management and business, applied to explain the consistencies and differences in individual behaviour. An attitude is a psychological tendency that is expressed by evaluating a particular entity with some degree of favour or disfavour. Ajzen and Fishbein (1980) understand attitude as an index of the strength of how much a person likes or dislikes something or their own behaviour concerning that thing. On the other hand Ajzen (2001) notes that there is a consensus that attitude is a kind of a complex evaluation of a psychological object in dimensions such as good–bad, harmful–beneficial, pleasant–unpleasant and likeable–dislikeable.

Attitude towards ICT is one of the central constructs in one of the most widely used models to study user acceptance of technology - the Technology Acceptance Model (TAM), introduced by F. Davis (Davis, 1989). The model is based on two important constructs: perceived usefulness and perceived ease of use, both of which influence a user's attitude towards using technology and, consequently, their behavioural intention to use it and their actual use of it.

The TAM has been modified and extended several times over the past decades to better understand the factors influencing technology acceptance. One such extension is the Unified Theory of Acceptance and Use of Technology (UTAUT), which integrates constructs from

several earlier models, including TAM, the Theory of Reasoned Action (TRA) and the Theory of Planned Behaviour (TPB) (Khechine, Lakhal & Ndjambou 2016). UTAUT takes into account additional factors such as social influence or expected performance, allowing for a more comprehensive examination of technology acceptance.

A critical analysis of the literature (Kamal, Shafiq & Kakria 2020; Sagnier, Loup-Escande, Lourdeaux, Thouvenin & Valléry 2020) indicates that modifications of TAM often focus on adapting the model to specific research contexts and including new variables such as emotional or contextual factors. Extensions that add trust and perceived risk are also common outside healthcare: in a study of e-grocery shopping in Indonesia, perceived risk lowered trust while usefulness, ease of use and social influence raised it, yet trust did not significantly affect the intention to use the service (Ryadi et al., 2021). Therefore, there are many modifications and extensions of the basic technology acceptance models, adapting them to specific healthcare sector. For example, the TAM2 and TAM3 models (Davis & Granić, 2024) incorporate additional factors, such as social influence or facilitating conditions, that may be more relevant in the health system. Another widely used in healthcare context model is TRA (Holden & Karsh, 2010), which exposes the importance of attitude towards ICT. It assumes that behavioural intentions are the main determinant of behaviour, and that these intentions are shaped by attitudes towards the behaviour and subjective social norms.

Trust in new technologies in healthcare

Trust plays a key role in the relationship between the patient and medical staff, influencing the effectiveness of treatment, adherence and overall satisfaction with healthcare (Krot & Rudawska, 2017). The research literature (Birkhäuer et al., 2017, Krot 2020) distinguishes several dimensions of trust in the context of healthcare: competence, reliability, fairness, integrity, kindness. Thus trust is a central construct describing the quality of the relationships in healthcare settings. It is responsible for shaping end-users' attitude towards medical professionals (Razmak & Bélanger, 2018).

In the context of ICT application, trust seems to be even more crucial, as technology supports decision-making process made by medical personnel that may impact human life. Some authors even state and trust is the most important quality that the system shall possess (Ali et al., 2023). Trust in this context can be understood as a cognitive and emotive element that affects how the ICT is perceived, negatively or positively (Merritt et al., 2014). It can be also referred to the patients' perception about the honesty and truthfulness of the ICT as well as the beliefs that it works as planned (Xie, Gao & Chen 2019).

According to the literature, there are many features that can promote trust in new technologies. In the face of uncertainty about how they work, good explanations how and why ICT performs can boost the trust in ICT (Calnan & Rowe, 2007). Thus, the level of trust is determined by how patients receive knowledge about the technology and how decision-making mechanisms of ICT systems are explained (Khullar, 2019). Many empirical studies focus on explainability as a feature of new technology that alleviate trustworthiness by communicating about ICT (especially AI) to end-users (Jermutus, Kneale, Thomas & Michie 2022; Asan, Bayrak & Choudhury 2020). Explainability is defined as the capacity of ICT to make its action comprehensible in human terms (Ali et al., 2023). Moreover, explainability

provides insights into the ICT application that supports doctors' ICT- driven decision in medical treatment. It is both crucial for ensuring individual trust as well as public trust (European Commission, 2020).

Many works are dedicated to AI explainability (so called explainable AI- XAI) promoting trust and ensuring that AI is making correct and non-biased decisions (Ali et al., 2023). For example, Meske & Bunde (2020) examined the theoretical influence of explainability on trust in AI and its potential applications in the medical field. They emphasized the importance of explainability and referenced previous studies in XAI for information systems, which highlighted the dangers associated with black-box AI (Meske, Bunde, Schneider & Gersch 2022). In the economics explainability is rather a strategic organizational and system capability and a key component of Human-AI interaction (Sabharwal et al., 2025). In the paper we adopt this perspective and understand explainability as the system's ability to present a rationale in a way that is understandable to patinents.

There are some studies that link explainability and trust. For example Bussone, Stumpf & O'Sullivan (2015) employed a Likert scale and a think-aloud method to gauge user trust in a clinical decision-support system. They found that providing clear explanations could reduce the adverse effects of trust loss enhance user trust. Furthermore, Stepin, Alonso-Moral, Catala, & Pereira-Fariña (2022) applied Likert scales to examine how individuals assess the trustworthiness of automated counterfactual explanations.

Previous research found that when the decision-making process based on ICT is thoroughly understood, the model becomes transparent (Ali et al., 2023). Transparency promotes trust in the new technology as it is essential for assessing the quality of decisions based on ICT (Thelisson, 2017; Larsson & Heintz, 2022). This feature is related to the other attributes of ICT which are fairness or integrity of ICT. It refers to the patient's subjective perception of whether the decisions or recommendations made by the AI system feel right and just (Dodge, Liao, Zhang, Bellamy & Dugan 2019). Some studies dedicated to the fairness of AI focus on how well patients understand the real behaviour of the AI model based on provided explanations (Laato, Tiainen, Najmul Islam & Mäntymäki 2022).

According to the literature there are many supplementary criteria that can be used to describe ICT (especially new-generation models based on AI) desired features that focus on trust enhancing, such as reliability, accuracy or robustness, responsibility, stability and interpretability (Ali et al., 2023; Nourani, Kabir, Mohseni & Ragan, 2019; Galli, Marrone, Moscato & Sansone 2021). In case of trust in ICT in medical settings reliability (or accuracy) seems to be of great importance. It can be understood as the ability to apply an explanation of a particular decision to new, unfamiliar situations (Miller, 2019). The reliability of an ICT system refers to its consistent performance and dependability in producing accurate results over time and across various conditions. It encompasses the system's ability to function correctly under expected circumstances, minimize errors, and maintain stability (Wachter, Mittelstadt & Russell 2017).

As Ali et al. (2023) note the ability of AI models to explain their internal mechanisms and decision-making processes is inherently limited when the focus is on optimizing data use and increasing predictive accuracy. However, trusting systems that lack transparency in decision-making can be difficult. Some authors add that offering explanations that are overly complex can lead to information overload for end users (Oh et al., 2018). Furthermore, as

noted by Ehsan, Tambwekar, Chan, Harrison & Riedl (2019), contextual accuracy matters more than explanation length.

Linking reliability/accuracy with trust issues Yin, Vaughan & Wallach (2019) found that over time, the first construct impacts he second one. It refers both to the declared accuracy of a model and the accuracy perceived by the user.

As the use of ICT in healthcare becomes more widespread, the role of their security is growing. It is viewed in many ways in the literature. Some researchers refer to patient safety from the perspective of system performance. For example, Sittig et al. (2020) demonstrates that ICT exerts a substantial influence on patient safety by advancing technological innovations and refining healthcare systems. Numerous researchers concur, emphasizing the critical role of ICT in modernizing the healthcare sector, thereby enhancing patient safety (Seblega, Zhang, Wan, Unruh & Miller 2015). In this sense, patient safety refers to increasing the effectiveness of diagnoses and increasing the overall healthcare quality through ICT-driven and ICT-supported decision making (Pisani, Ghataure & Merson 2018).

Moreover, patient safety can be seen in terms of secure technology or safe information systems, offering all technological safeguards, from the safety of patient data, to systemic mitigation of potential ICT risks, to issues of safeguarding by relevant legislation (Aarts, 2011; Bécue, Praça & Gama 2021; Fisher & Wenger 2021). For wearable IoT monitoring that processes physiological data, design frameworks now have to satisfy several regulatory regimes at once, including data-protection, medical-device and AI regulation (Y. Vovk et al., 2026). Safe ICT refers to the technical quality of services, but the term can also include a component of functional quality, i.e. that one perceived by end-users. Research on bank fraud likewise treats technology and employees' attitudes and compliance as joint elements of protection (Bhasin, 2016).

The above issues have been addressed in the growing body of studies on ethical and technical aspects of ICT, especially AI. Kieseberg, Weippl & Holzinger (2016) point out at the importance of patients' safety, security, transferability, transparency and privacy when it comes to decision-making process based on ICT and particularly AI. The same approach is presented by Zhang et al. (2021) recalling the need for the relevance of purpose and intended audience in data security. In his work Aarts (2011) examines the origins of risks associated with IT implementation, explores the practical measures taken to mitigate these risks, and identifies the challenges to creating safe systems. He proves that he most crucial is the IT implementation phase and identifies six barriers to ensuring safe systems. Among these, there are mandatory interoperability and incident reporting. Thus, safe information technology closes to the concept of robustness (Ali et al., 2023) perceived as the system capacity to function correctly in case of uncertainty.

Apart for the security of ICT, the issue of perceived patient safety has been raised in the literature (Samaras, Real, Curtis & Meunier 2012; Maze, Zorič, Rosi & Lobnikar 2023). Taking into account the complicated nature of many ICT applications it seems to be of great importance from the perspective of the end-users. Misunderstanding of how new technologies work can lead to patient dissatisfaction, stress and even non-compliance with medical advice (Samaras et al., 2012). Maze et al. (2023) points out that it can threaten physical, psychological, emotional and even financial safety of the patients. In this context, the role of trust building is of great importance. For instance, Cahour and Forzy (2009) proposed a trust

assessment approach that evaluates three levels a XAI presents itself to patients. Still this issue remains a challenge that we are going to address in our study.

Alraja, Farooque & Khashab (2019) define an attitude as an opinion or a feeling about something or someone, or a way of behaving that is induced by something or someone. Exploring the attitude toward Internet of Things Yesmin, Carter & Gladman (2022) concluded that patients expressed a positive attitudes towards the use of IoT. Similar conclusions have been made by Kim (2016). Moreover his study revealed that the users of IoT attributed the greater quality to the information provided. Rodić, Stevanović, Labus, Kljajić & Trajkov (2025) found that the majority of IoT users in healthcare have positive views on valuable features of ICT.

METHODOLOGY

Data collection

To gather data, an online survey was implemented utilizing the Computer-Assisted Web Interviewing (CAWI) method. The survey targeted a representative sample of 1074 adult residents of Poland. Participants were selected from individuals who had sought medical care within the six months preceding the survey. Details regarding the socio-demographic composition of the survey sample are provided in Table 1.

Table 1. Research sample structure (n=1074)

	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			

Source: own work

The demographic profile of the respondents reveals that out of the 1,074 individuals surveyed, 584 were female and 490 were male. Regarding age distribution, 11.5% of respondents were under 25 years old, 24.6% were between the ages of 25 and 34, and 23.5% fell within the 35-44 age range. Additionally, 18.8% of respondents were aged 45-54, while 21.6% were over 54 years of age. In terms of educational attainment, 40% of respondents had completed secondary education, 10.6% held a bachelor's degree, and 24.6% possessed a master's degree. Only 2.5% of respondents had primary education, while 9.8% had vocational training. The distribution of net income per capita was relatively balanced across the sample. Approximately one-third of respondents resided in rural areas, while 11.5% lived in small

towns, 21.7% in medium-sized towns, and 20.7% in large towns. Only 13.7% of the respondents lived in urban cities.

Research model

In the study modern technologies in healthcare has been defined as any health solution that is new to the patient and based on information and communications technologies, e.g.: televisions, conversations with virtual consultants, modern medical devices used remotely in diagnosis, therapy and rehabilitation. The term new technologies also encompasses online patient-physician communication platforms and applications for patient care management and patient self-care. Our study adopts a theoretical model indicating the antecedents of attitudes towards technologies used in healthcare, proposed as follow on Figure 1. All of them are aimed at enhancing trust in ICT.

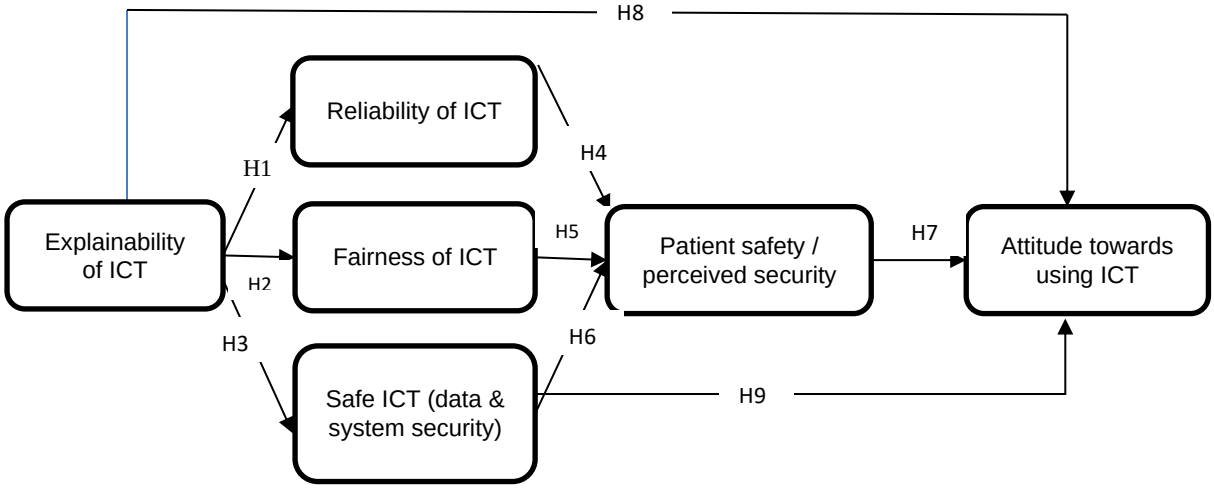

Figure 1. The Conceptual model

The following hypotheses have been proposed:
H1: Explainability of ICT perceived by patients positively influences their belief in the reliability of modern technologies
H2: Explainability of ICT perceived by patients positively influences their belief in the fairness of modern technologies
H3: Explainability of ICT perceived by patients positively influences their belief in the safe ICT
H4: Patients' belief in the reliability of ICT positively influences their belief in the patient safety
H5: Belief in fairness of ICT positively influences perceived patient safety
H6: Belief in safe ICT positively influences perceived patient safety
H7: Perceived patient safety positively influences patients' attitudes towards using ICT
H8: Explainability of ICT perceived by patients positively impacts patients' attitudes towards using ICT
H9: Safe ICT positively impacts patients' attitudes towards using ICT

Variables and scale development

The scales for measuring individual variables were formulated based on existing literature (Table 2). All constructs used in the theoretical model have an acceptable level of reliability. The Cronbach's Alpha index ranges from 0.81 to 0.91. Respondents were presented with each statement on a five-point Likert scale.

Table 2. Scale characteristics

Variable	Source	Cronbach Alpha
Explainability of ICT (2 items)	Madsen and Gregor, 2000; Garry, Harwood, 2019	0,81
Reliability of ICT (4 items)	McKnight et al., 2011; Garry, Harwood, 2019	0,91
Fairness of ICT (4 items)	McKnight et al., 2002; Garry, Harwood, 2019	0,90
Safe ICT (4 items)	Salisbury et al., 2001; Garry, Harwood, 2019	0,91
Patient safety (3 items)	(Samaras et al., 2012). Maze et al. (2023)	0,85
Attitude towards using ICT (3 items)	Liang, Xue and Byrd, 2003; Tao, Shao, Wang, Yan, Qu 2020	0,84

Source: own work

The first construct used in the study is explainability of modern technologies. It refers to patients' general knowledge of medical and high-tech-based solutions and belief in the validity of decisions regarding the use of these solutions in the treatment process. The explainability seems to be the most crucial feature of ICT systems, the starting point for any further elements shaping the attitude towards new technologies.

Another construct is reliability concerns the belief in the predictability and reproducibility of the principles of ICT solutions and the treatment outcomes based on them. Consequently, this builds trustworthiness and gives patients a sense of control over the course of treatment.

Fairness, on the other hand, is the belief in the integrity, transparency and efficiency of medical activities based on ICT. This construct is also associated with the belief that healthcare facilities use modern technology to take even better care of the interests and needs of patients. They also ensure equal treatment of patients.

Safe ICT concerns safeguards related to the use of modern technology in healthcare. It is therefore about the security of data and of the system itself. This construct also encompasses the belief that healthcare facilities are adequately prepared for the potential risks associated with modern technology and that these issues are safeguarded by appropriate legal provisions.

The use of ICT is often associated with strong fears and anxiety on the part of both patients and staff. Hence, a construct called patient safety has been incorporated into the conceptual model as a mediating variable. It refers to patients' belief that their status is protected in the context of using ICT. This construct refers, in particular, to the belief that ICT will serve to better define patients‘ health problems and increase patients’ health security.

The outcome variable in the model is attitude towards using ICT, which stresses the acceptance towards doctors' activities applying ICT-driven solutions.

RESEARCH RESULTS

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

	Reliability of ICT	Fairness of ICT	Explainability of ICT	Safe ICT	Patient safety	Attitude towards using ICT
Reliability of ICT	1,00					
Fairness of ICT	0,77	1,00				
Explainability of ICT	0,54	0,64	1,00			
Safe ICT	0,74	0,67	0,44	1,00		
Patient safety	0,77	0,73	0,50	0,72	1,00	
Attitude towards using ICT	0,69	0,72	0,56	0,54	0,68	1,00

Source: Author's own research

To verify the conceptual model structural equation modelling (SEM) was used, which is a linear cross-sectional statistical modelling technique including path analysis and regression analysis (Rodríguez Pérez & Trespalacios Gutiérrez 2007). The SEM is statistical technique used to analyse relationships between observed and latent (hidden) variables or 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 & Sorbom, 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 2). This is where the theory plays an important role in justifying the model (Rodríguez et al. 2007).

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). The following indices were used to assess the quality/fit of the model: GFI (goodness fir index), CFI (comparative fit index) i RMSEA (root mean square error of approximation).

The results revealed a $\chi 2$ of 722,8 based on 159 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

Index	Score
CMIN/DF	4,54
GFI	0,93
CFI	0,97
RMSA	0,06
Holter	302

Source: Author's own research

The theoretical model presented in Figure 1 encompassed nine research hypotheses. Seven of the proposed paths were found to be statistically significant, thus confirming these hypotheses (Table 5). Two hypotheses (H6 and H9) were not supported by the results of this study. Specifically, the findings indicate that safe ICT—understood as data and system security—is not significantly associated with higher levels of patients' perceived safety. Contrary to initial assumptions, this relationship was not empirically validated. The formal security of technological systems implemented in healthcare institutions appears to have no significant relationship with patients' subjective sense of safety. Their perception of safety seems to be independent of objective protective measures, including those mandated by relevant legal regulations. As a result, hypothesis H9 was also not confirmed. Objective safeguards associated with the implementation of ICT do not show a significant link with patients' attitudes toward the use of modern technologies. Accordingly, these safeguards can be regarded as a necessary prerequisite for the application of ICT in medical procedures, yet they do not correlate with patients' perceptions or attitudes toward modern technologies.

One of the most significant findings of this study is the central interconnection between explainability and trust. Explainability exhibits a strong, statistically significant positive association across all measured dimensions of trust—namely reliability (H1), fairness (H2), and safe ICT (H3).

Table 5. Standardized regression weights

				Estimate	Status of hypothesis
H1	Reliability of ICT	<---	Explainability of ICT	,928	support
H2	Fairness of ICT	<---	Explainability of ICT	,932	support
H3	Safe ICT	<---	Explainability of ICT	,823	support
H4	Patient safety	<---	Reliability of ICT	,510	support
H5	Patient safety	<---	Fairness of ICT	,417	support
H6	Patient safety	<---	Safe ICT	-	rejected
H7	Attitude towards using ICT	<---	Patient safety	,403	support
H8	Attitude towards using ICT	<---	Explainability of ICT	,529	support
H9	Attitude towards using ICT	<---	Safe ICT	-	rejected

Source: Author's own research

These results suggest that explainability functions as a higher-order construct that co-occurs with and relates formatively to the development of trust in modern technological solutions within healthcare contexts. Importantly, knowledge and cognitive understanding of ICT are positively linked not only to trust in these systems, but also to a more favorable attitude toward their use (H8).

The findings indicate that patients' attitudes toward using ICT are significantly correlated with their subjective sense of safety (H7). This perception of safety is, in turn, strongly associated with two key trust dimensions: reliability (H4) and fairness of ICT (H5), with reliability demonstrating a somewhat stronger positive relationship with perceived safety than fairness.

DISCUSSION

The large interest in ICT and AI in healthcare in the last decade has been mirrored by an expansion in studies on trust in patient-professional relations (Ridd, Shaw, Lewis & Salisbury 2009). They highlight many issues, our study extends. For example, Dhar, Dey, Borra & Sherratt (2023) explains the major challenges that the users of the deep learning in medical image diagnosis faces, particularly a lack of trustability among professionals and patients, and ethical problems connected to medical data. The authors study the possibilities of AI autonomy in healthcare context. Similarly Filogna et al., (2024) aim at highlighting the paramount role of co-design in bridging the gap between explainable AI, and trustworthiness of AI-based systems. Our paper differs from these works by investigating the detailed connections between the externality of ICT and reliability, fairness, and safety linking these constructs with the attitude of patients towards new technologies.

As Ali et al., (2023) argue the capacity of ICT systems to describe their inner decision-making processes is limited when striving to increase their prediction accuracy. The authors indicate that it is difficult to trust systems whose work is difficult to understand. With our work we prove that ICT explainability leads to system's reliability and further to patient's attitude towards ICT.

Our study is in the line of the work done by Eke & Shuib (2024) who provided the summary of research on transparency of AI healthcare systems by performing a systematic literature review. Our preliminary study support their findings that transparency and fairness of ICT healthcare systems play a crucial role affecting end users attitude towards them. Such features of solutions based on new technologies can forecast patients' trust. As such, we agree with the thesis of Kieseberg et al. (2016) that patients need ethical considerations while clarifying the decision clarification. There is a positive link between the explainability and fairness perceived by patients understood as integrity, privacy, portability, informativeness, and ethical decision-making when it comes to Information and Communication Technologies. The similar findings have been achieved by Upadhyay, Gradisek, Iqbal, Dhar & Syed-Abdul (2023), who call for the responsible artificial intelligence in the context of healthcare.

On the other hand we partially do not agree with Kieseberg et al. (2016). Our findings do not support their findings that safe ICT leads to the safety of patients (understood as perceived security of ICT) and finally affects the attitude of patients towards using the ICT. So our work is in the contrast to the study of Alraja et al., (2019) who applied the same method (structural equation modelling). Their study revealed that levels of security of Internet of Things (IoT) influenced trust in IoT. Furthermore, the authors showed that these levels of trust in IoT impact both users' risk perceptions and their attitudes towards using IoT. Patients' risk perceptions in part mediated the relationship between users' trust and their attitudes towards using IoT. A similar caution comes from TAM research outside healthcare, where trust shaped by perceived risk and ease of use did not by itself explain intention to use a service (Ryadi et al., 2021).

We believe that our finding make a significant contribution to human-technology research, specifically redefining how ICT in health system is evaluated by its stakeholders, especially endusers (patients). The study provides critical empirical evidence of a decoupling between objective, structural cybersecurity compliance and patients' subjective perception of

safety. As Greenhalgh *et al.* (2017) we do agree that this challenges traditional technology adoption frameworks by demonstrating that formal data security and regulatory safeguards act merely as baseline operational preconditions. Consequently, they do not automatically translate into positive patient attitudes, emphasizing that technical robustness alone cannot guarantee successful service delivery in healthcare contexts. Evidence from African economies also suggests that the benefits of digital technologies depend on institutional quality (Okoli, 2025). A comparable gap between perceived and demonstrated effectiveness of security technology is reported for public video surveillance in smart cities, where academics believed in its contribution to security more strongly than effectiveness studies justify (Markovic et al., 2021).

As a result, this research redefines the trust architecture in healthcare managment by establishing explainability as a strategic higher-order asset rather than a mere technical feature. This supports the findings by Kellogg et al. (2020) that cognitive understanding and knowledge of the system function as key drivers that allow patients to perceive reliability and fairness in ICT-supported medical processes. Moreover, we share the view of Kraus et al. (2021) that explainability, by actively reducing epistemic uncertainty, serves as the vital link between complex technology and perceived sense of safety, which directly correlates with a positive attitude toward technology use in heath systems.

CONCLUSIONS

With our work we make two main contributions to trust in ICT research. Firstly, we answer the recent calls to study the technology acceptance models in the context of healthcare more profoundly (AlQudah et al., 2021). We bridge the research gap on the field of trustworthiness of ICT from end users ‘perspective. Our work also supports the methodology approach towards investigating the core issue of the study. We introduce the new variables explaining the attitude towards using ICT.

In spite of the significant findings of our work, there are some limitations that shall be addressed in future research. Firstly, we only looked at end user attitudes while actual behaviour related to using ICT was not measured. This could be added to the model as well as some additional variables describing the outcomes of ICT usage, such as perceived value. Secondly, in this paper the sample was selected from only one country. In future research, it is recommended to extend the study to other European countries. Furthermore, the proposed model could be used in a comparative study to identify cultural differences influencing the extent of use of modern technologies in medicine. Fourthly, in this article the mediating role is embedded in the proposed model, but other variables such propensity to trust could be considered for future research. Finally, the study examined the impact of perceived safety o the attitude towards ICT without examining which other factors may influence it. Therefore, future research could investigate the main factors affecting perceived patient security.

REFERENCES

Aarts, J. (2011). Towards safe information technology in health care. *Information, Knowledge, Systems Management, 10*, 335–344.

Ajzen, I. (2001). Nature and operation of attitudes. *Annual Review of Psychology, 52*, 27–58. https://doi.org/10.1146/annurev.psych.52.1.27

Ajzen, I., & Fishbein, M. (1980). *Understanding and predicting social behavior*. Englewood Cliffs, NJ, USA: Prentice Hall.

Ali, S., Abuhmed, T., El-Sappagh, S., Muhammad, K., Alonso-Moral, J. M., Confalonieri, R., Guidotti, R., Del Ser, J., Díaz-Rodríguez, N., & Herrera, F. (2023). Explainable artificial intelligence (XAI): What we know and what is left to attain trustworthy artificial intelligence. *Information Fusion, 99*, 101805. https://doi.org/10.1016/j.inffus.2023.101805

AlQudah, A. A., Al-Emran, M., & Shaalan, K. (2021). Technology acceptance in healthcare: A systematic review. *Applied Sciences, 11*(22), 10537. https://doi.org/10.3390/app112210537

Alraja, M. N., Farooque, M. M. J., & Khashab, B. (2019). The effect of security, privacy, familiarity, and trust on users' attitudes toward the use of IoT-based healthcare: The mediation role of risk perception. *IEEE Access, 7*, 111341–111354. https://doi.org/10.1109/ACCESS.2019.2929298

Ammenwerth, E. (2019). Technology acceptance models in health informatics: TAM and UTAUT. *Studies in Health Technology and Informatics, 263*, 64–71. https://doi.org/10.3233/shti190111

Asan, O., Bayrak, A. E., & Choudhury, A. (2020). Artificial intelligence and human trust in healthcare: Focus on clinicians. *Journal of Medical Internet Research, 22*(6), e15154. https://doi.org/10.2196/15154

Bécue, A., Praça, I., & Gama, J. (2021). Artificial intelligence, cyber-threats and Industry 4.0: Challenges and opportunities. *Artificial Intelligence Review, 54*, 3849–3886. https://doi.org/10.1007/s10462-020-09900-1

Bhasin, M. L. (2016). Challenge of mitigating bank frauds by judicious mix of technology: Experience of a developing country. *Economics, Management and Sustainability, 1*(1), 23–41. https://doi.org/10.14254/jems.2016.1-1.3

Bilan, Y., Oliinyk, O., Mishchuk, H., & Skare, M. (2023). Impact of information and communications technology on the development and use of knowledge. *Technological Forecasting and Social Change, 191*, 122519.

Birkhäuer, J., Gaab, J., Kossowsky, J., Hasler, S., Krummenacher, P., Werner, C., & Gerger, H. (2017). Trust in the health care professional and health outcome: A meta-analysis. *PLoS ONE, 12*(2), e0170988. https://doi.org/10.1371/journal.pone.0170988

Bussone, A., Stumpf, S., & O'Sullivan, D. (2015). The role of explanations on trust and reliance in clinical decision support systems. In *2015 International Conference on Healthcare Informatics* (pp. 160–169). Piscataway, NJ, USA: IEEE.

Cahour, B., & Forzy, J.-F. (2009). Does projection into use improve trust and exploration? An example with a cruise control system. *Safety Science, 47*(9), 1260–1270.

Calnan, M., & Rowe, R. (2007). Trust and health care. *Sociology Compass, 1*(1), 283–308. https://doi.org/10.1111/j.1751-9020.2007.00024.x

Chute, C., & French, T. (2019). Introducing Care 4.0: An integrated care paradigm built on Industry 4.0 capabilities. *International Journal of Environmental Research and Public Health, 16*(12), 2247. https://doi.org/10.3390/ijerph16122247

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Davis, F. D., & Granić, A. (2024). Evolution of TAM. In *The technology acceptance model: 30 years of TAM* (pp. 19–57). Cham, Switzerland: Springer.

Dhar, T., Dey, N., Borra, S., & Sherratt, R. S. (2023). Challenges of deep learning in medical image analysis—Improving explainability and trust. *IEEE Transactions on Technology and Society, 4*(1), 68–75. https://doi.org/10.1109/TTS.2023.3234203

Dodge, J., Liao, Q. V., Zhang, Y., Bellamy, R. K. E., & Dugan, C. (2019). Explaining models: An empirical study of how explanations impact fairness judgment. In *Proceedings of the 24th International Conference on Intelligent User Interfaces* (pp. 275–285). New York, NY, USA: ACM. https://doi.org/10.1145/3301275.3302310

Duarte, P., & Pinho, J. C. (2019). A mixed methods UTAUT2-based approach to assess mobile health adoption. *Journal of Business Research, 102*, 140–150. https://doi.org/10.1016/j.jbusres.2019.05.022

Ehsan, U., Tambwekar, P., Chan, L., Harrison, B., & Riedl, M. O. (2019). Automated rationale generation: A technique for explainable AI and its effects on human perceptions. In *Proceedings of the 24th International Conference on Intelligent User Interfaces* (pp. 263–274). New York, NY, USA: ACM. https://doi.org/10.1145/3301275.3302316

Eke, C. I., & Shuib, L. (2024). The role of explainability and transparency in fostering trust in AI healthcare systems: A systematic literature review, open issues and potential solutions. *Neural Computing and Applications*, 1–36. https://doi.org/10.1007/s00521-024-10868-x

European Commission. (2020). *White paper on artificial intelligence: A European approach to excellence and trust* (COM(2020) 65 final). Retrieved [15 March 2025], from https://commission.europa.eu/document/download/d2ec4039-c5be-423a-81ef-b9e44e79825b_en?filename=commission-white-paper-artificial-intelligence-feb2020_en.pdf

Filogna, S., Malizia, A., Mazzei, D., Prencipe, G., Sgandurra, G., & Turchi, T. (2024). Telemedicine and AI: From co-design to explainability. In *2024 IEEE 8th Forum on Research and Technologies for Society and Industry Innovation (RTSI)* (pp. 363–368). Piscataway, NJ, USA: IEEE.

Fischer, S.-C., & Wenger, A. (2021). Artificial intelligence, forward-looking governance and the future of security. *Swiss Political Science Review, 27*, 170–179. https://doi.org/10.1111/spsr.12412

Galli, A., Marrone, S., Moscato, V., & Sansone, C. (2021). Reliability of explainable artificial intelligence in adversarial perturbation scenarios. In *International Conference on Pattern Recognition* (pp. 243–256). Cham, Switzerland: Springer.

Garry, T., & Harwood, T. (2019). Trust and its predictors within a cyber-physical system context. *Journal of Services Marketing, 33*(4), 407–428.

Golubtsov, D., Kedziora, J., Kozhakhmetova, A., & Kedziora, D. (2025). Assessing the impact of digital technologies and artificial intelligence (AI) on the efficiency of supply chain. *Economics & Sociology, 18*(1), 149–173. https://doi.org/10.14254/2071-789X.2025/18-1/8

Greenhalgh, T., Wherton, J., Papoutsi, C., Lynch, J., Hughes, G., & A'Court, C. (2017). Beyond adoption: A new framework for theorizing and evaluating nonadoption, abandonment, and challenges to the scale-up, spread, and sustainability of health and care technologies. *Journal of Medical Internet Research, 19*(11), e367. https://doi.org/10.2196/jmir.8775

Gupta, N., & Paiva, S. (Eds.). (2020). *IoT and ICT for healthcare applications*. Cham, Switzerland: Springer.

Haluza, D., & Jungwirth, D. (2018). ICT and the future of healthcare: Aspects of pervasive health monitoring. *Informatics for Health and Social Care, 43*(1), 1–11. https://doi.org/10.1080/17538157.2017.1353493

Holden, R. J., & Karsh, B. T. (2010). The technology acceptance model: Its past and its future in health care. *Journal of Biomedical Informatics, 43*(1), 159–172. https://doi.org/10.1016/j.jbi.2009.07.002

Jermutus, E., Kneale, D., Thomas, J., & Michie, S. (2022). Influences on user trust in healthcare artificial intelligence: A systematic review. *Wellcome Open Research, 7*, 65. https://doi.org/10.12688/wellcomeopenres.17663.1

Jöreskog, K. G., & Sörbom, D. (1996). *LISREL 8: User's reference guide*. Lincolnwood, IL, USA: Scientific Software International, Inc.

Kamal, S. A., Shafiq, M., & Kakria, P. (2020). Investigating acceptance of telemedicine services through an extended technology acceptance model (TAM). *Technology in Society, 60*, 101212. https://doi.org/10.1016/j.techsoc.2019.101212

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174

Khechine, H., Lakhal, S., & Ndjambou, P. (2016). A meta-analysis of the UTAUT model: Eleven years later. *Canadian Journal of Administrative Sciences, 33*(2), 138–152. https://doi.org/10.1002/cjas.1382

Khullar, D. (2019). Building trust in health care—Why, where, and how. *JAMA, 322*(6), 507–509. https://doi.org/10.1001/jama.2019.9433

Kieseberg, P., Weippl, E., & Holzinger, A. (2016). Trust for the doctor-in-the-loop. *ERCIM News, 104*, 32–33.

Kraus, S., Schiavone, F., Pluzhnikova, A., & Invernizzi, A. C. (2021). Digital transformation in healthcare: Analyzing the current state-of-the-art and charting a roadmap for future research. *Journal of Business Research, 123*, 557–567. https://doi.org/10.1016/j.jbusres.2020.10.047

Krot, K. (2020). *Zaufanie w relacji lekarz–pacjent: Implikacje dla zarządzania zakładem opieki zdrowotnej* [Trust in the doctor–patient relationship: Implications for healthcare facility management]. Warsaw, Poland: CeDeWu.

Krot, K., & Rudawska, I. (2017). Patients' trust in physicians as an antecedent of satisfaction with medical services. *Economics & Sociology, 10*(2), 207–221.

Kuzior, A., Marszałek-Kotzur, I., Sansyzbayeva, K. N., & Lukács, E. (2025). From AI vibrancy to labour market outcomes: Testing displacement across education groups. *Economics & Sociology, 18*(4), 131–159. https://doi.org/10.14254/2071-789X.2025/18-4/7

Laato, S., Tiainen, M., Najmul Islam, A. K. M., & Mäntymäki, M. (2022). How to explain AI systems to end users: A systematic literature review and research agenda. *Internet Research, 32*(7), 1–31. https://doi.org/10.1108/INTR-08-2021-0600

Larsson, S., & Heintz, F. (2020). Transparency in artificial intelligence. *Internet Policy Review, 9*(2), 1–16. https://doi.org/10.14763/2020.2.1469

Lăzăroiu, G., Szpilko, D., Gedeon, T., Halicka, K., & Rzepka, A. (2025). Digital technologies supporting predictive healthcare: Review of research trends. *Human Technology, 21*(3), 694–730. https://doi.org/10.14254/1795-6889.2025.21-3.10

Liang, H., Xue, Y., & Byrd, T. A. (2003). PDA usage in healthcare professionals: Testing an extended technology acceptance model. *International Journal of Mobile Communications, 1*(4), 372–389.

Madsen, M., & Gregor, S.D. (2000). Measuring Human-Computer Trust.

Markovic, B., Ilic, D., Milosevic, D., & Ilic, I. (2021). Academics perception of public areas video surveillance in smart cities. *Economics, Management and Sustainability, 6*(2), 21–33. https://doi.org/10.14254/jems.2021.6-2.2

Martínez-Caro, E., Cegarra-Navarro, J. G., García-Pérez, A., & Fait, M. (2018). Healthcare service evolution towards the Internet of Things: An end-user perspective. *Technological Forecasting and Social Change, 136*, 268–276. https://doi.org/10.1016/j.techfore.2017.10.013

Maze, H., Zorič, S., Rosi, B., & Lobnikar, B. (2023). Interdependence of nursing staff work engagement, quality of workplace relationships and patient safety. *Organizacija, 56*, 125–137.

McKnight, D. H., Carter, M., Thatcher, J. B., & Clay, P. F. (2011). Trust in a specific technology: An investigation of its components and measures. *ACM Transactions on Management Information Systems, 2*(2), 12. https://doi.org/10.1145/1985347.1985353

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research, 13*(3), 334–359. https://doi.org/10.1287/isre.13.3.334.81

Merritt, S. M., Heimbaugh, H., LaChapell, J., & Lee, D. (2013). I trust it, but I don't know why: Effects of implicit attitudes toward automation on trust in an automated system. *Human Factors, 55*(3), 520–534. https://doi.org/10.1177/0018720812465081

Meske, C., & Bunde, E. (2020). Transparency and trust in human-AI interaction: The role of model-agnostic explanations in computer vision-based decision support. In *International Conference on Human-Computer Interaction* (pp. 54–69). Cham, Switzerland: Springer.

Meske, C., Bunde, E., Schneider, J., & Gersch, M. (2022). Explainable artificial intelligence: Objectives, stakeholders, and future research opportunities. *Information Systems Management, 39*(1), 53–63. https://doi.org/10.1080/10580530.2021.1993046

Miller, T. (2019). Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence, 267*, 1–38. https://doi.org/10.1016/j.artint.2018.07.007

Modahl, M. (1999). *Now or never: How companies must change today to win the battle for internet consumers*. New York, NY, USA: HarperBusiness.

Nisha, N., Iqbal, M., Rifat, A., & Idrish, S. (2015). Mobile health services: A new paradigm for health care systems. *International Journal of Asian Business and Information Management, 6*(1), 1–17. https://doi.org/10.4018/IJABIM.2015010101

Nourani, M., Kabir, S., Mohseni, S., & Ragan, E. D. (2019). The effects of meaningful and meaningless explanations on trust and perceived system accuracy in intelligent systems. In *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing* (Vol. 7, pp. 97–105). Palo Alto, CA, USA: AAAI Press. https://doi.org/10.1609/hcomp.v7i1.5284

Oh, C., Song, J., Choi, J., Kim, S., Lee, S., & Suh, B. (2018). I lead, you help, but only with enough details: Understanding user experience of co-creation with artificial intelligence. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. New York, NY, USA: ACM. https://doi.org/10.1145/3173574.3174223

Okoli, T. T. (2025). The relevance of institutional quality as a transmission channel for digital financial inclusion: Evidence from African economies and implications for sustainable development. *Economics, Management and Sustainability, 10*(1), 74–81. https://doi.org/10.14254/jems.2025.10-1.5

Pisani, E., Ghataure, A., & Merson, L. (2018). *Data sharing in public health emergencies: A study of current policies, practices, and infrastructure supporting the sharing of data to prevent and respond to epidemic and pandemic threats*. Figshare. https://doi.org/10.6084/m9.figshare.5897608.v1

Razmak, J., & Bélanger, C. (2018). Using the technology acceptance model to predict patient attitude toward personal health records in regional communities. *Information Technology & People, 31*(2), 306–326. https://doi.org/10.1108/ITP-08-2016-0199

Ridd, M., Shaw, A., Lewis, G., & Salisbury, C. (2009). The patient–doctor relationship: A synthesis of the qualitative literature on patients' perspectives. *British Journal of General Practice, 59*(561), e116–e133. https://doi.org/10.3399/bjgp09X420248

Rodić, B., Stevanović, V., Labus, A., Kljajić, D., & Trajkov, M. (2024). Adoption intention of an IoT based healthcare technologies in rehabilitation process. *International Journal of Human–Computer Interaction, 40*(11), 2873–2886. https://doi.org/10.1080/10447318.2023.2175160

Rodríguez, N. G., Pérez, M. J. S., & Trespalacios Gutiérrez, J. A. (2007). Interfunctional trust as a determining factor of a new product performance. *European Journal of Marketing, 41*(5/6), 678–702.

Ryadi, W. T., Kurniasari, F., & Sudiyono, K. A. (2021). Factors influencing consumer's intention towards e-grocery shopping: An extended technology acceptance model approach. *Economics, Management and Sustainability, 6*(2), 146–159. https://doi.org/10.14254/jems.2021.6-2.11

Sabharwal, R., Miah, S. J., Wamba, S. F., & Cook, P. (2025). Extending application of explainable artificial intelligence for managers in financial organizations. *Annals of Operations Research, 354*, 309–339. https://doi.org/10.1007/s10479-024-05825-9

Sagnier, C., Loup-Escande, E., Lourdeaux, D., Thouvenin, I., & Valléry, G. (2020). User acceptance of virtual reality: An extended technology acceptance model. *International Journal of Human–Computer Interaction, 36*(11), 993–1007. https://doi.org/10.1080/10447318.2019.1694922

Samaras, E. A., Real, S. D., Curtis, A. M., & Meunier, T. S. (2012). Recognizing nurse stakeholder dissonance as a critical determinant of patient safety in new healthcare information technologies. *Work, 41*, 1904–1910.

Seblega, B. K., Zhang, N. J., Wan, T. T., Unruh, L. Y., & Miller, A. (2015). Health information technology adoption: Effects on patient safety and quality of care. *International Journal of Healthcare Technology and Management, 15*(1), 31–48.

Sittig, D. F., Wright, A., Coiera, E., Magrabi, F., Ratwani, R., Bates, D. W., & Singh, H. (2020). Current challenges in health information technology–related patient safety. *Health Informatics Journal, 26*(1), 181–189. https://doi.org/10.1177/1460458219837847

Stepin, I., Alonso-Moral, J. M., Catala, A., & Pereira-Fariña, M. (2022). An empirical study on how humans appreciate automated counterfactual explanations which embrace imprecise information. *Information Sciences, 618*, 379–399. https://doi.org/10.1016/j.ins.2022.10.098

Tao, D., Shao, F., Wang, H., Yan, M., & Qu, X. (2020). Integrating usability and social cognitive theories with the technology acceptance model to understand young users' acceptance of a health information portal. *Health Informatics Journal, 26*(2), 1347–1362.

Thelisson, E. (2017). Towards trust, transparency and liability in AI/AS systems. In *Proceedings of the 26th International Joint Conference on Artificial Intelligence (IJCAI-17)* (pp. 5215–5216). https://doi.org/10.24963/ijcai.2017/767

Upadhyay, U., Gradisek, A., Iqbal, U., Dhar, E., Li, Y. C., & Syed-Abdul, S. (2023). Call for responsible artificial intelligence in the healthcare. *BMJ Health & Care Informatics, 30*(1), e100920. https://doi.org/10.1136/bmjhci-2023-100920

Vovk, Y., Vovk, O., Holotenko, O., Vovk, Y., & Pientak, M. (2026). Wearable biosensor monitoring of driver fatigue in intelligent transport systems: A systematic review and IoT framework. *Journal of Sustainable Development of Transport and Logistics, 11*(1), 43–82. https://doi.org/10.14254/jsdtl.2026.11-1.03

Wachter, S., Mittelstadt, B., & Russell, C. (2017). Counterfactual explanations without opening the black box: Automated decisions and the GDPR. *Harvard Journal of Law & Technology, 31*(2), 841–887.

Waqas, M., Yu, Z., Khan, S. A. R., Tanveer, M., & Ahmad, A. (2023). Promoting healthcare technologies through sustainable supply chain operations: An empirical analysis of key success factors using the ISM-MICMAC approach. *LogForum, 19*(1), 91–126. https://doi.org/10.17270/J.LOG.2023.722

Xie, Y., Gao, G., & Chen, X. A. (2019). Outlining the design space of explainable intelligent systems for medical diagnosis. In *Joint Proceedings of the ACM IUI 2019 Workshops*. https://doi.org/10.48550/arXiv.1902.06019

Yesmin, T., Carter, M. W., & Gladman, A. S. (2022). Internet of things in healthcare for patient safety: An empirical study. *BMC Health Services Research, 22*(1), 278. https://doi.org/10.1186/s12913-022-07620-3

Yin, M., Wortman Vaughan, J., & Wallach, H. (2019). Understanding the effect of accuracy on trust in machine learning models. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. New York, NY, USA: ACM. https://doi.org/10.1145/3290605.3300509

Yu, P., Wu, M. X., Yu, H., & Xiao, G. C. (2006). The challenges for the adoption of m-health. In *IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI 2006)* (pp. 181–186). Piscataway, NJ, USA: IEEE. https://doi.org/10.1109/SOLI.2006.329059

Zhang, Z., Ning, H., Shi, F., Farha, F., Xu, Y., Xu, J., Zhang, F., & Choo, K.-K. R. (2021). Artificial intelligence in cyber security: Research advances, challenges, and opportunities. *Artificial Intelligence Review*, 1–25. https://doi.org/10.1007/s10462-021-09969-9

Authors' Note

Iga Rudawska
University of Szczecin
Mickiewicza 64, 71-101 Szczecin, Poland
iga.rudawska@usz.edu.pl

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