

Acceptance of Artificial Intelligence in Healthcare Services: The Role of Trust, Risk, and Human Oversight among Healthcare Professionals and Service Recipients

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ABSTRACT

Introduction: The rapid development of artificial intelligence (AI) in healthcare highlights not only issues of functional acceptance but also fundamental aspects of trust, perceived risk, and human oversight. The ‘acceptance’ of AI is not limited to intention to use or technological familiarity; rather, it constitutes a multidimensional phenomenon shaped through evaluations of reliability, assessments of potential risks, and perceptions regarding its ethical implementation. Understanding these parameters is a prerequisite for the responsible and human-centered integration of AI systems into healthcare services.

Aim: The study explores the attitudes, intention, and determining factors that influence AI acceptance in healthcare, using the theoretical framework of the Technology Acceptance Model (TAM), enriched with variables of trust, perceived risk, human oversight, openness to change, and conceptual understanding of AI.

Material and Methods: A quantitative study was conducted using a structured six-point Likert-scale questionnaire in a sample of 240 participants, consisting of 120 healthcare professionals and 120 healthcare service recipients, with a response rate of approximately 84%. Data collection took place during October–November 2025. Statistical analysis was performed using SPSS software (version 29) and included reliability testing, descriptive and inferential statistics, with the aim of investigating relationships and differences among key variables and groups.

Results: The results show that AI acceptance is not formed uniformly. Among healthcare professionals, intention to use was significantly strengthened by perceived ease of use, whereas among healthcare service recipients, openness to change played a decisive role. In both groups, conceptual understanding of AI was a strong positive predictor, while perceived risk emerged as the most important negative factor in adoption intention.

Conclusions: The findings suggest that AI acceptance is closely linked to users level of understanding and to their concerns regarding the safety and reliability of AI applications. Attitudes toward the use of AI in healthcare are shaped through a continuous negotiation between technological capabilities and human values. Trust, transparency, and adequate information are not merely prerequisites, but fundamental conditions for human-centered and ethically sustainable integration, as also foregrounded in the framework of the Artificial Intelligence Act (AI Act).

Keywords: Artificial intelligence, technology acceptance, healthcare professionals, healthcare service recipients, Artificial Intelligence Act (AI Act).

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INTRODUCTION

Artificial intelligence uniquely combines strong elements of interest and concern, making it one of the most widely discussed phenomena of our time. From a science-fiction tool in the 1950s, it has evolved into an everyday reality, with influences now comparable to those of electricity or the internet. Artificial intelligence, however, is not simply another technological innovation; it is a transformative force that is reorganizing fundamental aspects of social and economic life, from the way we work and communicate to the way we understand knowledge itself (Xu et al., 2021).

Its importance is reflected in international forecasts, as global organizations converge on the estimate that AI will have a catalytic effect on innovation, productivity, and the reconfiguration of services. Studies by major international consulting organizations estimate that its contribution to the global economy could reach 15.7 trillion dollars by 2030, making it one of the most important drivers of growth in the coming decade (PwC, 2017).

Among its fields of application, healthcare holds a special place, as a field of high social sensitivity and strict regulatory requirements, while also emerging as an area with impressive potential for AI utilization. In clinical practice and research, AI contributes to improved diagnostic accuracy through imaging algorithms, prediction of clinical outcomes, and the development of new drugs and therapeutic approaches. It also strengthens personalized medicine, is used in robotic surgery, and, through biosensors and telemedicine, expands the possibilities for monitoring and managing chronic diseases (Alowais et al., 2023).

At the level of healthcare system administration and management, AI is applied to optimize workflows and resource management, to support the electronic and digital organization of individual health portfolios, and through chatbots that support communication with healthcare service recipients (Holden & Karsh, 2010). It is also used to monitor and supervise healthcare systems, enhancing transparency, effectiveness, and reliability in administrative procedures. The contemporary scientific literature shows that AI has the potential to transform clinical practice, research innovation, and organizational functioning in healthcare simultaneously (Jiang et al., 2021).

Although the integration of AI applications in healthcare is accompanied by high expectations for improving efficiency and quality of care, it raises important concerns. Issues of interpretability, transparency, and accountability limit trust, while concerns are recorded regarding the loss of the human dimension of care and the ethical consequences of algorithmic decisions (Jobin et al., 2019). Maintaining human oversight and understanding the limits of technology are critical prerequisites for strengthening

trust, while the energy footprint of AI systems adds an additional sustainability dimension that requires attention (Morley et al., 2020).

At the European level, the Artificial Intelligence Act (AI Act, 2024) seeks to create a framework of trust for the development and use of AI systems, setting requirements for transparency, data quality, human oversight, and accountability, with particular emphasis on high-risk systems. In combination with the General Data Protection Regulation (GDPR, EU 2016/679, 2018) and the regulatory framework for medical devices (MDR EU 2017/745, IVDR EU 2017/746), it forms an institutional environment that defines the conditions for safe and responsible adoption (European Parliament and Council, 2024; Edwards, 2023; Floridi, 2023). The successful implementation of these regulations, however, depends on the degree of acceptance and trust among healthcare professionals and healthcare service recipients, making it necessary to investigate the organizational and social factors that shape it.

The development of an expanded model of artificial intelligence acceptance in healthcare requires reference to the classic theoretical frameworks of technology acceptance. The Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) have served as the main interpretive tools for studying the relationship among perceived usefulness, ease of use, and adoption intention. Despite their importance, the complexity and social sensitivity of the healthcare field make it necessary to enrich them with additional dimensions that reflect the organizational, ethical, and psychosocial aspects of technological acceptance.

In this context, trust (Trust) emerges as a decisive factor, as users are asked to trust not only the technology itself, but also the institutional framework, the professionals who use it, and the organizations that provide it (Sagona et al., 2025). Similarly, perceived risk (Perceived Risk), which is associated with possible diagnostic errors, leakage of personal data, or excessive dependence on algorithmic systems, acts as an inhibitory factor in the formation of positive intention (Cocosila & Trabelsi, 2016).

Openness or resistance to change (Openness/Resistance to Change) reflects the degree of receptiveness of an organization and its members toward innovations, directly influencing the dynamics of adoption. It does not simply refer to refusal, but to a multidimensional attitude that combines cognitive, emotional, and behavioral elements (Armenakis & Bedeian, 1999; Piderit, 2000), while organizational readiness for change has been found to strengthen the acceptance of technologies such as AI (Boyaci & Soyuk, 2025).

In addition, conceptual understanding of artificial intelligence (Artificial Intelligence Literacy) is becoming increasingly important, as understanding how the

technology works, as well as its capabilities and limitations, contributes to strengthening trust and reducing skepticism (Gille et al., 2020). Information and education regarding the basic principles of AI can act as catalysts for the smooth integration of the technology into clinical and administrative practice.

Despite the continuous expansion of the literature, empirical studies that systematically examine the acceptance of artificial intelligence in healthcare remain limited, especially when attempting to capture simultaneously the attitudes of healthcare professionals and service recipients through a single analytical

framework. The present study seeks to address this gap by using an expanded theoretical model based on TAM and its extensions and by incorporating critical parameters related to understanding, oversight, and the safe implementation of AI systems, in line with the principles of the AI Act. In this way, the study aims to generate findings that can support evidence-based policies and practical strategies for implementation in healthcare. Adopting the above theoretical framework and seeking to empirically investigate the relationships among the individual factors, the present study formulates the research hypotheses shown in Table 1.

Table 1. Study Hypotheses

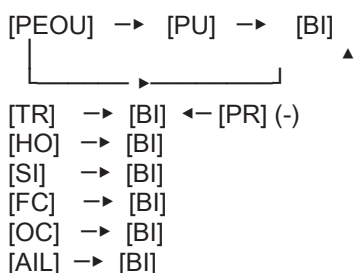
Code	Hypothesis Description	Expected Relationship
H1	Perceived Usefulness (PU) positively influences intention to adopt artificial intelligence (Behavioural Intention - BI).	+
H2	Perceived Ease of Use (PEOU) positively influences intention to adopt artificial intelligence (BI).	+
H3	Perceived Ease of Use (PEOU) positively influences Perceived Usefulness (PU).	+
H4	Trust (TR) positively influences intention to adopt artificial intelligence (BI).	+
H5	Perceived Risk (PR) negatively influences intention to adopt artificial intelligence (BI).	-
H6	Human Oversight (HO) positively influences intention to adopt artificial intelligence (BI).	+
H7	Openness to Change (OC) positively influences intention to adopt artificial intelligence (BI).	+
H8	Social Influence (SI) positively influences intention to adopt artificial intelligence (BI).	+
H9	Facilitating Conditions (FC) positively influence intention to adopt artificial intelligence (BI).	+

According to the model, perceived usefulness (PU) and perceived ease of use (PEOU) are expected to directly influence adoption intention (BI), with PEOU also exerting an indirect effect through PU. At the same time, trust (TR) and human oversight (HO) are considered to strengthen positive attitudes toward AI, while perceived risk (PR) acts as an inhibitor. In addition, social influence (SI) and

facilitating conditions (FC) function as external catalysts that shape the degree of acceptance, while openness to change (OC) expresses the capacity to adapt to innovation within the environment.

Figure 1 depicts the proposed relationships among the key factors of the theoretical model, which are empirically examined in the context of the study.

Figure 1. Conceptual Model of Variables



The proposed model aims at a systemic understanding of the cognitive, emotional, and organizational parameters that influence the acceptance of artificial intelligence in healthcare, in order to highlight both the technological and human factors that determine its successful integration.

METHODOLOGY

Design

The study adopted a quantitative, cross-sectional design, with the aim of empirically investigating the factors that influence the intention to adopt artificial intelligence (AI) in healthcare. The proposed conceptual model, based on the

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METHODOLOGY

Design

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Study sample

Sampling was carried out using convenience sampling. The sample included two distinct groups of participants:

1. Healthcare professionals, such as physicians, nurses, psychologists, physiotherapists, occupational therapists, and administrative staff, working in public or private healthcare structures.
2. Healthcare service recipients, namely individuals with recent experience of contact with healthcare services or providers.

Data collection

Data collection took place in healthcare settings in Attica, including one public healthcare service, one private healthcare provider, eight private medical practices, and four pharmacies. Two structured closed-ended questionnaires were used for data collection, one for healthcare service recipients and one for healthcare professionals, both based on the same conceptual framework and the same theoretical variables. The reliability of the subscales was assessed using Cronbach's alpha, with 0.70 as the acceptable threshold (Hair et al., 2021). As part of the reliability testing, corrected item-total correlations and the means of the composite scores were also examined in order to confirm the internal consistency of the measurements.

The questionnaires were based on established and validated scales (Davis, 1989; Venkatesh et al., 2003), with adaptations from contemporary studies (Pan et al., 2019), and included two sections:

1. Demographic and professional data (gender, age, education, and role for healthcare professionals).
2. A main body of 35 statements, organized according to the variables of the conceptual model and evaluated on a 6-point Likert scale (1 = Strongly disagree

to 5 = Strongly agree, 6 = Do not know / Not applicable). The DK/NA option was added to reduce bias and was excluded from the analyses, while the reversed (REV) items were pre-coded.

It should be noted that the two questionnaires retain a common factor structure but are not completely identical in all items, as certain statements were adapted to the context and role of each group. Therefore, comparisons between groups are conducted at the factor/scale level and not at the level of fully identical questions. The comparison concerns the variation of the conceptual constructs and not item-by-item correspondence.

Ethical considerations

The questionnaire was distributed in printed form during October-November 2025 in settings related to the healthcare sector. Participation was anonymous and voluntary, and all participants were informed in advance about the purpose of the study, the use of the data, and the right to withdraw, in accordance with the principles of the General Data Protection Regulation (GDPR, EU 2016/679). The study was conducted in compliance with the Declaration of Helsinki (World Medical Association, 2013) and the Code of Ethics for Research of the University of Patras, and approval for distributing the questionnaire was obtained from the competent bodies.

Statistical Analysis

Before the main data collection phase, a pilot application was conducted with 40 participants (20 healthcare professionals and 20 healthcare service recipients), aiming to test the clarity of wording and the appropriateness of the measurement scale.

Data collection was completed when the predetermined target of 120 valid questionnaires per group was reached. The sample size is considered sufficient for applying parametric statistical techniques, such as correlation analyses and multiple regression (Green, 1991; Hair et al., 2021). Based on the relevant guideline ($N \geq 50 + 8m$), the final sample size meets the minimum criteria for statistical power.

The following were excluded from the analysis: (a) four questionnaires with >30% DK/NA responses, and (b) three cases with an incorrect response to the attention-check item. These exclusions were applied to ensure data quality and strengthen the validity of the inferential analyses.

Data analysis was performed using IBM SPSS Statistics 29 and included: (a) reliability testing and descriptive statistics, (b) Exploratory Factor Analysis (EFA) using Principal Axis Factoring (PAF) with Promax rotation, and (c) hypothesis testing through correlations and multiple regressions. This methodology was considered appropriate for investigating the relationships among the theoretical dimensions, as well as for the comparative analysis between healthcare service recipients and

healthcare professionals.

The reliability of the scales was tested using Cronbach's alpha. In addition, to test for possible multicollinearity, Tolerance and VIF indicators, as well as Collinearity Diagnostics, were examined in accordance with the guidelines of Hair et al. (2021). All theoretical dimensions of the model were included as independent variables in the regression models, with adoption intention (BI) as the dependent variable.

Finally, the theoretically predicted relationship between perceived ease of use (PEOU) and perceived usefulness (PU), as described in the TAM model, was also examined. For this purpose, Pearson correlations were calculated between the corresponding composite indicators, separately for each group of participants, allowing assessment of the degree to which the predicted relationship between PEOU and PU is reflected in the empirical data of the study.

RESULTS

The sample consisted of 240 participants (120 healthcare professionals and 120 healthcare service recipients). The

majority of participants were women (~62%) and belonged to the 35-54 age group (~49%). A large proportion (~76%) had post-secondary or higher education (values 3 and 4 in the education variable), indicating a relatively high educational level in the total sample. The healthcare professionals group included representatives of all main professional roles in the healthcare system, according to the categorization used in the 'work role' variable, with a relatively balanced distribution. The detailed demographic characteristics of the sample are presented in Table 2.

The main descriptive indicators, reliability values (Cronbach's alpha), and correlations among the variables are summarized in Table 3. The reliability indicators of all factors ranged within acceptable levels (alpha $\approx$.79-.90) for both participant groups, confirming the high internal consistency and stability of the individual scales. Most variables showed correlations in the expected direction (positive among supportive dimensions and negative between perceived risk and intention), confirming the theoretical coherence of the proposed model and justifying continuation of the inferential analysis.

Table 2. Demographic characteristics of the sample by participant group

Variable	Category	Healthcare service recipients (N=120)	Healthcare professionals (N=120)
Gender	Male	40 (33.3%)	47 (39.2%)
	Female	78 (65.0%)	70 (58.3%)
	Other	2 (1.7%)	3 (2.5%)
Age	18-34	38 (31.7%)	22 (18.3%)
	35-54	52 (43.3%)	67 (55.8%)
	55+	30 (25.0%)	31 (25.8%)
Education	Compulsory	8 (6.7%)	0 (0.0%)
	Secondary	38 (31.7%)	12 (10.0%)
	Post-secondary / Tertiary	55 (45.8%)	64 (53.3%)
	Postgraduate/Doctoral	19 (15.8%)	44 (36.7%)
Role	Medical staff	-	28 (23.3%)
	Nursing staff	-	22 (18.3%)
	Paramedical staff	-	23 (19.3%)
	Mental health professionals	-	25 (20.8%)
	Administrative staff	-	22 (18.3%)

Table 3. Descriptive statistics, reliability, and correlations among variables (N = 240)

Factor	Mean (M)	SD	Alpha	r(BI)	p
Perceived usefulness (PU)	3.84	0.71	0.88	0.62	< .001
Perceived ease of use (PEOU)	3.91	0.69	0.86	0.58	< .001
Trust (TR)	3.76	0.73	0.89	0.65	< .001
Perceived risk (PR)	3.12	0.82	0.83	-0.56	< .001
Human oversight (HO)	3.58	0.77	0.80	0.41	< .01
Social influence (SI)	3.47	0.81	0.84	0.12	> .05 (.214)

Facilitating conditions (FC)	3.55	0.74	0.79	0.10	> .05 (.168)
Openness to change (OC)	3.64	0.69	0.85	0.38	< .01
Conceptual understanding (AIL)	3.71	0.67	0.82	0.43	< .001
Adoption intention (BI)	3.88	0.72	0.90	—	—

Note: All variables were measured on a 6-point Likert scale (1 = Strongly disagree to 5 = Strongly agree, 6 = Do not know/Not applicable; ignored in the analysis). Pearson correlations with adoption intention (BI) are statistically significant at the $p < .01$ level and in the expected direction (positive for the supportive factors and negative for perceived risk - PR), with the exception of SI and FC ($p > .05$).

In order to confirm the structural validity of the scales before the inferential analysis, an Exploratory Factor Analysis (EFA) was conducted, which showed that, in both the healthcare service recipient sample and the healthcare professional sample, the items loaded satisfactorily on the expected theoretical dimensions of the model (TAM/UTAUT). The KMO index was .736 for recipients and .625 for professionals, values considered good to acceptable for the social sciences. Bartlett's test was statistically significant ($p < .001$) in both samples, confirming the suitability of the data for factor analysis. Total explained variance ranged between 72% and 73%, indicating satisfactory convergent validity.

Mean values showed differences between the two groups. Healthcare professionals displayed higher levels of perceived usefulness (PU, $M = 4.09$) and openness to change (OC, $M = 3.74$), while healthcare service recipients showed higher perceived risk (PR, $M = 3.41$) and greater emphasis on human oversight (HO, $M = 3.97$). Mean intention to adopt AI (Behavioral Intention - BI) was moderate for both groups ($M \approx 3.0$), indicating a neutral to moderately positive attitude toward the use of artificial intelligence in healthcare.

Pearson correlations among the main factors showed distinct patterns of relationships by group. For healthcare service recipients, perceived risk (PR) was strongly and negatively correlated with adoption intention (BI) ($r = -.83$, $p < .001$), while positive correlations were identified between openness to change (OC) and intention ($r = .55$, $p < .001$), as well as between conceptual understanding of AI (AIL) and intention ($r = .65$, $p < .001$). The remaining factors (PU, PEOU, TR, HO, FC, SI) did not show statistically significant relationships with BI ($p > .05$).

For healthcare professionals, the correlations were milder but followed a similar direction: perceived risk (PR) was negatively related to intention ($r = -.65$, $p < .001$), while conceptual understanding (AIL) was strongly and positively correlated with intention ($r = .75$, $p < .001$). In addition, a positive correlation was observed between perceived ease of use (PEOU) and perceived usefulness (PU) ($r = .45$, $p < .001$), a finding that aligns with the theoretical basis of

TAM.

To investigate the factors that influence intention to adopt artificial intelligence (BI), multiple linear regression analyses were performed, with BI as the dependent variable and all theoretical factors (PU, PEOU, TR, PR, HO, SI, FC, OC, AIL) as independent variables.

Among healthcare service recipients, the model was statistically significant ($F(9,110) = 41.89$, $p < .001$) and explained 77.4% of the variance in intention ($R^2 = .774$). As shown in Table 4, perceived risk (PR) exhibited the strongest negative effect on intention ($\beta = -.618$, $p < .001$), while openness to change (OC) ($\beta = .150$, $p = .006$) and conceptual understanding of AI (AIL) ($\beta = .255$, $p < .001$) showed positive and statistically significant effects. The remaining factors (PU, PEOU, TR, HO, FC, SI) were not statistically significant ($p > .05$).

Among healthcare professionals, the corresponding model was also significant ($F(9,110) = 32.23$, $p < .001$) and explained 72.5% of the variance in intention ($R^2 = .725$). Conceptual understanding (AIL) ($\beta = .596$, $p < .001$) emerged as the strongest positive factor, followed by perceived ease of use (PEOU) ($\beta = .120$, $p = .038$). In contrast, perceived risk (PR) ($\beta = -.335$, $p < .001$) and facilitating conditions (FC) ($\beta = -.191$, $p < .001$) had a negative effect on adoption intention. The remaining variables (PU, TR, HO, SI, OC) were not statistically significant ($p > .05$).

In the unified model ($N = 240$), the results showed very good fit ($R^2 = .673$, $F(9,230) = 52.50$, $p < .001$). The factors found to be statistically significant were perceived risk (PR) ($\beta = -.556$, $p < .001$), conceptual understanding (AIL) ($\beta = .336$, $p < .001$), and human oversight (HO) ($\beta = .103$, $p = .009$). Perceived usefulness (PU) showed a small but statistically significant negative contribution ($\beta = -.115$, $p = .006$). The negative contribution of PU in the unified model is likely due to suppression effects resulting from partial overlap with PEOU and AIL and should not be interpreted as a substantive reduction in the importance of usefulness. Social influence (SI) and facilitating conditions (FC) did not show a statistically significant effect in the unified model ($\beta \approx .02$ and $\beta \approx .00$, respectively, $p > .60$).

In addition, two specific factors that differ by participant group were examined. For healthcare professionals, the work security index (WRK) had a mean value of $M = 3.62$ ($SD = 0.87$), indicating moderate concern regarding the limitation of the professional role or the possibility of job loss due to AI. Its correlation with adoption intention (BI) was not statistically significant ($r \approx -.14$, $p > .10$; $\beta \approx -.07$, $p > .25$). Correspondingly, among healthcare service

recipients, the social impact perception index (SYS) recorded a mean value of $M = 3.58$ ($SD = 0.91$), indicating relative agreement with the view that AI may imply a 'perception' of job losses. However, the variable did not show a statistically significant relationship with acceptance intention (BI) ($r \approx -.11$, $p > .20$). These findings suggest that concerns about the possible social and professional impact of AI do exist, but they do not directly influence individual attitudes toward the adoption of AI systems. Beyond these specific indicators (WRK / SYS), the overall comparisons between professionals and recipients regarding the main

factors of the model are presented in Table 5.

The multicollinearity test did not reveal issues that would affect the estimation of coefficients. Tolerance values ranged from .66 to .89, while the corresponding VIF values ranged between 1.12 and 1.52, substantially below established thresholds. The maximum Condition Index was 16.91, well below the threshold of 30, without clustering of high variance proportions in the same dimension (Table 6). These findings confirm that there is no substantive multicollinearity among the independent variables and that the model is estimated stably and reliably.

Table 4. Multiple regression results for intention to adopt AI (BI) and model-fit indicators

Factor	Unified model (N = 240)	Healthcare professionals (N = 120)	Healthcare service recipients (N = 120)
Perceived usefulness (PU)	-0.115 ($p = .006$)	-0.047 ($p = .435$)	0.000 ($p = .998$)
Perceived ease of use (PEOU)	-0.024 ($p = .553$)	0.120 ($p = .038$)	0.014 ($p = .760$)
Trust (TR)	0.055 ($p = .155$)	0.050 ($p = .364$)	0.055 ($p = .241$)
Perceived risk (PR)	-0.556 ($p < .001$)	-0.335 ($p < .001$)	-0.618 ($p < .001$)
Human oversight (HO)	0.103 ($p = .009$)	-0.013 ($p = .799$)	0.068 ($p = .150$)
Facilitating conditions (FC)	0.002 ($p = .965$)	-0.191 ($p < .001$)	-0.008 ($p = .866$)
Social influence (SI)	0.019 ($p = .628$)	0.055 ($p = .319$)	-0.013 ($p = .776$)
Openness to change (OC)	0.075 ($p = .074$)	0.015 ($p = .779$)	0.150 ($p = .006$)
Conceptual understanding of AI (AIL)	0.336 ($p < .001$)	0.596 ($p < .001$)	0.255 ($p < .001$)
Fit index R^2	0.673	0.725	0.774

Note: beta values represent standardised regression coefficients. p values $< .05$ indicate statistically significant effects.

Table 5. Mean differences between healthcare professionals and healthcare service recipients (t-test)

Factor	M(HCPs)	SD(HCPs)	M(Rec.)	SD(Rec.)	t(238)	p
Perceived usefulness (PU)	4.09	0.70	3.77	0.72	1.96	.052
Perceived ease of use (PEOU)	3.88	0.68	3.94	0.71	-0.72	.472
Trust (TR)	3.82	0.74	3.70	0.72	1.13	.261
Perceived risk (PR)	3.28	0.81	3.41	0.83	3.21	.001
Human oversight (HO)	3.44	0.76	3.97	0.78	-2.58	.011
Social influence (SI)	3.49	0.82	3.45	0.80	0.36	.719
Facilitating conditions (FC)	3.56	0.74	3.54	0.75	0.15	.883
Openness to change (OC)	3.74	0.69	3.50	0.68	2.86	.005
Conceptual understanding (AIL)	3.68	0.67	3.74	0.66	-0.71	.478
Adoption intention (BI)	3.09	0.71	3.03	0.73	0.67	.504

Note: Values of $p < .05$ indicate statistically significant differences.

Table 6. Multicollinearity indicators (Tolerance, VIF) for the unified regression model (N = 240)

Variable	Tolerance	VIF
Perceived usefulness (PU)	.89	1.12
Perceived ease of use (PEOU)	.87	1.15
Trust (TR)	.72	1.39
Perceived risk (PR)	.66	1.52
Human oversight (HO)	.82	1.22
Facilitating conditions (FC)	.74	1.35

Variable	Tolerance	VIF
Social influence (SI)	.74	1.35
Openness to change (OC)	.78	1.28
Conceptual understanding of AI (AIL)	.79	1.26

Note: No Tolerance value was $< .20$ and no VIF value was > 5 . The maximum Condition Index was 16.91, confirming the absence of multicollinearity.

In examining the theoretical relationship between PEOU and PU, Pearson correlations showed differentiated patterns between the two groups. Among healthcare service recipients, the relationship between perceived ease of use and perceived usefulness was not statistically significant ($r = .053$, $p = .568$), indicating that ease of use was not associated with the degree of perceived benefit of AI applications. In contrast, among healthcare professionals, a significant and positive correlation was observed between PEOU and PU ($r = .451$, $p < .001$), a finding consistent with the core mechanism of the TAM model.

The above results outline the main mechanisms associated with the intention to adopt artificial intelligence. Overall, the theoretical framework was partially supported, revealing a mixture of expected and unexpected relationships, which reflects the complex nature of AI acceptance in healthcare services.

DISCUSSION

The findings of the study demonstrate that the intention to adopt artificial intelligence in healthcare is a multidimensional and differentiated phenomenon, influenced by cognitive, functional, and psychological factors, while also differing significantly between healthcare professionals and healthcare service recipients. This differentiation reflects the specific needs and experiences of the two groups, confirming that AI acceptance is not a uniform process (Venkatesh et al., 2003).

Among healthcare professionals, perceived ease of use (PEOU) emerged as a significant positive factor, in line with the theoretical basis of TAM, according to which functional simplicity strengthens adoption intention (Davis, 1989). The effect of conceptual understanding of artificial intelligence (AIL) was equally strong, a finding consistent with contemporary studies indicating that understanding how AI systems work and what their limits are reduces uncertainty and strengthens intention to use (Longoni et al., 2019). In contrast, perceived risk (PR) acted as an inhibitor of adoption intention, due to concerns regarding the safety and reliability of AI applications, aligning with the literature on the risks of opaque use of algorithmic systems (Cabitza et al., 2017).

The negative effect of facilitating conditions (FC), although not consistent with predictions of models such as UTAUT, may reflect the 'critical-user effect', whereby professionals with higher familiarity evaluate deficiencies in infrastructure and resources more strictly

(van der Vaart et al., 2022). This finding suggests that the recording of functional limitations does not necessarily reflect technophobia, but may instead indicate increased expectations among users with high technological readiness.

Among healthcare service recipients, perceived risk (PR) was the strongest inhibitory factor, confirming that concerns about errors, loss of control, protection of personal data, and restriction of human judgement strongly influence acceptance (Lee & See, 2004). In contrast, conceptual understanding (AIL) strengthened adoption intention, a finding consistent with evidence suggesting that understanding and transparency improve citizens' attitudes toward AI (Wang et al., 2020). Openness to change (OC) also contributed positively, confirming that general attitudes toward innovation influence behavioral intention (Rogers, 2003).

The comparison of the two groups highlighted two stable and critical dimensions: conceptual understanding (AIL) consistently strengthens intention, while perceived risk (PR) limits it in both groups. This bipolarity forms the core of the dynamics of AI acceptance and reflects contemporary perspectives according to which the successful integration of AI requires a combination of understanding and effective risk management (Amann et al., 2020). At the same time, the findings suggest the existence of two distinct acceptance mechanisms: one that is more functional for professionals and one that is more psychological/value-based for recipients.

The interpretation of the unified model requires caution, as perceived usefulness (PU) appeared with a negative sign, possibly as a result of statistical suppression due to high overlap among cognitive variables (Cohen & Cohen, 1983). The PU-PEOU-AIL interaction may lead to artificial sign reversals; therefore, interpretation of the effects is safer when based on the separate models by group.

It is worth noting that human oversight (HO) showed a mild but statistically significant effect on intention (BI) in the unified model, without emerging as an independent predictor in the separate models by group. This suggests that its role is mainly supportive and operates in combination with other cognitive evaluations.

Social influence (SI) was not found to significantly influence intention (BI), suggesting that in healthcare settings, adoption decisions are shaped less by social norms and more by endogenous evaluations of the technology. In the same context, trust (TR), although strongly correlated with intention (BI), did not show an

independent effect in the final model, suggesting that its contribution may be embedded in broader judgements of reliability and safety.

Overall, the study highlights knowledge, understanding, and safety as fundamental axes for strengthening the acceptance of artificial intelligence in healthcare. The effect of perceived risk is consistent with the requirements of the Artificial Intelligence Act (AI Act), which emphasizes transparency, accountability, and human oversight in high-risk systems. The differentiation between professionals and recipients underscores the need for targeted information, education, and support strategies so that AI can be integrated responsibly and in a socially acceptable manner.

Study limitations

The present study was based on a cross-sectional design, which limits the ability to draw causal conclusions and captures only one temporal 'snapshot' of attitudes toward artificial intelligence. In addition, convenience sampling and the geographical concentration of the sample in the Attica region may have led to selection bias, while overrepresentation of participants with post-secondary or higher education was also observed. Although the size and characteristics of the sample are adequate for the statistical analyses applied, they limit the generalizability of the findings. Therefore, the results cannot be extended to the general population or to all healthcare professionals, but concern the specific sample and the conditions under which the data were collected.

Furthermore, data collection was carried out exclusively through a self-reported Likert questionnaire, which constitutes a single-method approach and may increase common method variance. Self-reporting may also have been affected by socially desirable responses or participants' subjective evaluations. Finally, the exclusively quantitative design does not allow in-depth exploration of complex concepts, such as organizational culture, ethical concerns, or workload conditions, which may substantially influence the acceptance of artificial intelligence.

CONCLUSIONS

The findings of the study show that the acceptance of artificial intelligence in healthcare services is shaped by different priorities among professionals and recipients, but rests on two stable pillars: knowledge and safety. The importance of these factors reflects the increased requirements of the healthcare field for transparency, accountability, and human oversight, in line with the high-risk approach also adopted in the regulatory framework of the AI Act.

At the theoretical level, the study findings show that traditional technology acceptance models (TAM/UTAUT) are not sufficient to fully explain the dynamics of adopting AI systems in healthcare. Acceptance of AI

applications appears to be shaped less by functional or social facilitators and more by deeper cognitive and psychological mechanisms, such as understanding of how the technology works, openness to change, and the management of perceived risks.

At the practical level, the results indicate the need for healthcare organizations to invest in targeted information strategies with emphasis on the AI Act regulatory framework, the strengthening of transparency, and the promotion of conceptual understanding of AI among both healthcare professionals and service recipients. Similarly, the existence of human oversight mechanisms can strengthen recipients' trust, while strengthening organizational readiness and training in user-friendly environments can support the smooth integration of AI into everyday practice. The differentiation between the two groups indicates that interventions should be tailored to their specific needs and concerns, as professionals appear to approach AI through functional and technocratic assessments, whereas recipients rely mainly on psychological and value-based evaluations.

Future research could use larger and more diverse samples, as well as longitudinal designs that capture the evolution of attitudes toward AI over time. The application of advanced multivariate models, such as PLS-SEM, could strengthen understanding of the relationships among variables and allow testing of more complex theoretical structures. In addition, the use of mixed-method approaches would facilitate an in-depth understanding of motivations, perceptions, and inhibitions that are not always evident in quantitative measurements. It would also be useful for future analyses to examine more targeted AI use scenarios (e.g., diagnostic imaging, clinical decision-support tools, chatbots), as acceptance may vary substantially depending on the application context. Overall, further research in the field will allow a more comprehensive understanding of the factors that shape AI acceptance in healthcare.

Concluding remarks and practical recommendations:

- Strengthening understanding / information about AI and the regulatory framework (AI Act).
- Transparency actions and documentation of the operation of AI systems, aiming to reduce perceived risk among all users.
- A safeguarding mechanism for the operational implementation of the expected human oversight, so that it functions as a guarantee of appropriate and controlled AI use.
- Support for organizational readiness for responsible and smooth AI integration.

Researchers' contribution:

A.S.: study design, data collection and analysis, as well as the drafting of the article. I.S.: supervision, methodological review, provision of guidance and revision suggestions.

REFERENCES

- Alowais, S.A., Alghamdi, S.S., Alsuhebany, N., Alqahtani, T., Alshaya, A.I., Alghamdi, A.A., Alabdulkarim, A., Alqahtani, S.M. and Alqahtani, M.S. (2023) Revolutionizing healthcare: the role of artificial intelligence in clinical practice, *BMC Medical Education*, 23, Article 689.
<https://doi.org/10.1186/s12909-023-04698-z>
- Alshahrani, A., Stewart, D. and MacLure, K. (2022). Barriers and facilitators to the adoption of artificial intelligence in healthcare: A qualitative systematic review, *BMC Health Services Research*, 22, p. 1320. doi: 10.1186/s12913-022-08746-1.
- Amann, J., Blasimme, A., Vayena, E. and Frey, D. (2020). Explainability for artificial intelligence in healthcare: A multidisciplinary perspective, *BMC Medical Informatics and Decision Making*, 20(310). doi: 10.1186/s12911-020-01332-6.
- Armenakis, A.A. and Bedeian, A.G. (1999). Organizational change: A review of theory and research in the 1990s, *Journal of Management*, 25(3), pp. 293-315.
- Boyacı, H. and Söyük, S. (2025) Healthcare workers' readiness for artificial intelligence and organizational change: a quantitative study in a university hospital, *BMC Health Services Research*, 25, Article 813. <https://doi.org/10.1186/s12913-025-12846-y>
- Cabitza, F., Rasoini, R. and Gensini, G.F. (2017). Unintended consequences of machine learning in medicine, *JAMA*, 318(6), pp. 517-518.
- Cheng, M., Li, X. and Xu, J. (2022). Promoting healthcare workers' adoption intention of artificial-intelligence-assisted diagnosis and treatment: The chain mediation of social influence and human-computer trust, *International Journal of Environmental Research and Public Health*, 19(20), p. 13311.
- Cocosila, M. and Trabelsi, H. (2016). An integrated model of trust in health information technology, *International Journal of Healthcare Information Systems and Informatics*, 11(4), pp. 44-62. doi: 10.4018/IJHISI.2016100104.
- Cohen, J. and Cohen, P. (1983). *Applied multiple regression/correlation analysis for the behavioral sciences*. 2nd edn. Hillsdale, NJ: Lawrence Erlbaum Associates.
- Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology, *MIS Quarterly*, 13(3), pp. 319-340. doi: 10.2307/249008.
- Edwards, L. (2023). Regulating AI: Intersections with data protection and medical device law in the European Union, *European Journal of Risk Regulation*, 14(2), pp. 356-373. doi: 10.1017/err.2023.15.
- European Parliament and Council (2024). Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Official Journal of the European Union, L 233, 12 July 2024, pp. 1-187.
- Floridi, L. (2023). The European approach to artificial intelligence: A regulatory perspective, *Philosophy & Technology*, 36(1), pp. 1-15. doi: 10.1007/s13347-022-00612-4.
- Gille, F., Jobin, A. and Vayena, E. (2020) Theory of trust for artificial intelligence in healthcare, *Intelligence-Based Medicine*, 1-2, Article 100001.
- Green, S.B. (1991). How many subjects does it take to do a regression analysis?, *Multivariate Behavioral Research*, 26(3), pp. 499-510. doi: 10.1207/s15327906mbr2603_7.
- Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. 3rd edn. Thousand Oaks, CA: Sage Publications.
- Henseler, J., Ringle, C.M. and Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based SEM, *Journal of the Academy of Marketing Science*, 43(1), pp. 115-135.
- Henseler, J., Ringle, C.M. and Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares, *International Marketing Review*, 33(3), pp. 405-431.
- Holden, R.J. and Karsh, B.T. (2010). The technology acceptance model: Its past and its future in health care, *Journal of Biomedical Informatics*, 43(1), pp. 159-172. doi: 10.1016/j.jbi.2009.07.002.
- Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H. and Wang, Y. (2021). Artificial intelligence in healthcare: Past, present and future, *Stroke and Vascular Neurology*, 6(3), pp. 230-243. doi: 10.1136/svn-2019-000366.
- Jobin, A., Ienca, M. and Vayena, E. (2019). The global landscape of AI ethics guidelines, *Nature Machine Intelligence*, 1(9), pp. 389-399. doi: 10.1038/s42256-019-0088-2.
- Lee, J.D. and See, K.A. (2004) Trust in automation: Designing for appropriate reliance, *Human Factors*, 46(1), pp. 50-80.
- Longoni, C., Bonezzi, A. and Morewedge, C.K. (2019). Resistance to medical artificial intelligence, *Journal of Consumer Research*, 46(4), pp. 629-650. doi: 10.1093/jcr/ucz013.
- Morley, J., Floridi, L., Kinsey, L. and Elhalal, A. (2020). From what to how: An initial review of publicly available AI ethics tools, methods and research to translate principles into practices, *Science and Engineering Ethics*, 26(4), pp. 2141-2168. doi: 10.1007/s11948-019-00165-5.
- Pan, Y., Zhang, J., Zhou, H. et al. (2019). Understanding the determinants of healthcare professionals' adoption of mobile health services: An integration of perceived risk and trust into the technology acceptance model, *Frontiers in Psychology*, 10, Article 1273. doi: 10.3389/fpsyg.2019.01273.
- Piderit, S.K. (2000). Rethinking resistance and recognizing ambivalence: A multidimensional view of attitudes toward an organizational change, *Academy of Management Review*, 25(4), pp. 783-794.
- PwC (2017). *Sizing the prize: What's the real value of AI for your business and how can you capitalise?* [online] PwC. Available at: <https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf> (Accessed: 10 September 2025).
- Rahimi, B., Nadri, H., Lotfnezhad Afshar, H. and Timpka, T. (2018). A systematic review of the technology acceptance model in health

- informatics, *Applied Clinical Informatics*, 9(3), pp. 604-634.
- Rogers, E.M. (2003) *Diffusion of innovations*. 5th edn. New York: Free Press.
- Sagona, M., Dai, T., Macis, M. and Darden, M. (2025). Trust in AI-assisted health systems and AI's trust in humans, *npj Health Systems*, 2, Article 10. doi: 10.1038/s44401-025-00016-5.
- Tabachnick, B.G. and Fidell, L.S. (2013). *Using multivariate statistics*. 6th edn. Boston, MA: Pearson.
- Van der Vaart, R., Drossaert, C.H.C., Taal, E. and van Gemert-Pijnen, J.E.W.C. (2022). User perspectives in eHealth development: A scoping review, *International Journal of Medical Informatics*, 162, 104753.
- Venkatesh, V. and Davis, F.D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies, *Management Science*, 46(2), pp. 186-204.
- Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003). User acceptance of information technology: Toward a unified view, *MIS Quarterly*, 27(3), pp. 425-478.
- Wang, W., Liang, C., Xu, L. and Wang, S. (2020). Understanding consumers' willingness to adopt AI medical diagnosis: An empirical study, *Information & Management*, 57(5), 103265.
- World Medical Association (2013). World Medical Association Declaration of Helsinki: Ethical principles for medical research involving human subjects, *JAMA*, 310(20), pp. 2191-2194. doi: 10.1001/jama.2013.281053.
- Xu, Y., Sun, Q., Liu, J., Zhang, L. and Wang, H. (2021). The development and challenges of artificial intelligence in recent years, *Journal of Physics: Conference Series*, 1827, 012063. doi: 10.1088/1742-6596/1827/1/012063.
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