



Examining Patient Acceptance of Emerging Healthcare Technologies: The Mediating Role of Trust and Perceived Value

Shubham Naresh Bhoir

Assistant Manager Volo Health Services, RH No.9, Villa Delphine, Opp Infant Jesus School, Mahada Colony Ambarnath East 421501,

Article Received: 08/09/2026, Article Accepted: 14/09/2026, Article Published: 30/09/2026

Abstract

The fast digital revolution in healthcare brought new technologies such as artificial intelligence (AI), telemedicine, mobile health applications, wearables, and remote monitoring devices that can potentially enhance the quality of healthcare delivery through higher efficiency and personalization of services. However, their success will be contingent upon patient acceptance, which will be influenced by psychological and technological factors. This research takes a look at how eHealth literacy, trust, and perceived value affect attitudes towards healthcare technologies that are based on artificial intelligence. It sees the use of trust and perceived value as mediators in this relationship. The number of participants in the quantitative cross-sectional study was 300 and statistical analyses conducted included ANOVA, regression and correlation. The most significant determinant of a positive attitude toward the use of artificial intelligence (AI) healthcare technologies is eHealth literacy, with trust and perceived value acting as important intermediaries. It demonstrates that trust, perceived value, and usability are the three defining characteristics of AI technology acceptance. These findings have important implications for the philosophy and practice of technology acceptance research as well as for patients' attitudes toward digital healthcare aids.

Keywords: Health literacy, technology trust, perceived value, patient acceptance, AI in healthcare, digital health adoption, mediation analysis.

Introduction

The healthcare sector is facing a significant digital transformation with the introduction of new technologies that are gaining ground in diagnosis, treatment, monitoring, communication and healthcare administration[1]. Improved accessibility, efficiency, personalization, and continuity of care are becoming possible thanks to new technological developments such as AI, robotics, telemedicine, mobile health apps, wearable devices, electronic health platforms, and AI-enabled decision-support systems. Adoption success is dependent on more than just having the technology available. The benefit of health innovation is highly dependent on patient willingness to accept, use and follow the use of these technologies [2].

Technology acceptance has thus emerged as a matter of research relevance in healthcare [3]. Previous studies have shown that frameworks like the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and variations on these models

are commonly used to examine the adoption of healthcare technology. A systematic review of 142 empirical studies identified TAM and UTAUT as two of the most frequently used theory models to explain the acceptance of healthcare technologies in various users, technologies and settings [4].

Patient acceptance is especially critical in relation to healthcare technologies, which are associated with sensitive personal information, health-related decisions and perceived risks [5]. If patients have questions about data privacy, system reliability, accuracy, security, or the involvement of healthcare professionals, they may be hesitant to use an AI-powered healthcare app or service. The study found that among 416 healthcare users in New Delhi, the most important criteria impacting patients' adoption of healthcare technology were perceived utility, perceived ease of use, trust, and privacy concerns. Trust is thus an essential part of healthcare technology adoption [6]. Healthcare technologies have the potential to impact patients' health and wellbeing, unlike most other digital

services [7][8][9]. Patients need to believe that the technology will be reliable, that their information will be safe and secure, that it will give them accurate information and that it will work in their best interests. Recent studies on digital healthcare have shown that trust plays a role in how people utilize, accept, and interpret digital healthcare. Factors like quantity of human engagement, data accuracy, digital literacy, perceived danger, privacy, and perceived risk all play a role in determining trust [10][11].

Perceived value is another key factor underlying technology adoption other than trust. The perceived benefits of the technology are a greater influence on the acceptance of emerging healthcare technologies than perceived effort, financial costs, privacy concerns, inconvenience, or perceived risks of using the technology [12][13]. Perceived value can therefore be the patient's general judgment of the benefits of a technology compared to what they have to sacrifice to use it. Empirical evidence in recent years also validates the importance of trust and perceived value. A research study conducted in 2025 found that there is a correlation between eHealth literacy and views towards the use of artificial intelligence in nursing. The study also found that trust in technology and perceived value play a role in these relationships [14].

A. Problem Statement

- Healthcare technologies in development provide potential in the areas of accessibility, efficiency, customization, monitoring, and patient participation.
- Technology adoption is based on perceptions of usability, reliability, safety, intrusiveness, and usefulness by patients.
- The adoption of healthcare technology is more sensitive and riskier than general consumer technology.
- The literature highlights the significance of practicality, use, reliability, and confidentiality in the adoption process.
- However, there is a knowledge gap regarding how these perceptions lead to adoption through psychological constructs such as trust and value.

B. Research Question

- RQ1: How does eHealth Literacy affect patients' perceptions of healthcare devices powered by artificial intelligence?
- RQ2: How does Technology Trust influence consumers' perceptions of healthcare devices that utilize artificial intelligence?
- RQ3: When it comes to artificial intelligence (AI) healthcare solutions, how does perceived value factor into patients' opinions?
- RQ4: Which of the following factors influences patients' views on AI-powered medical devices: eHealth

Literacy, Technology Trust, and Perceived Value?

- RQ5: How do patients' opinions about AI-based healthcare technology relate to their level of eHealth Literacy? Are trust and perceived value mediators in this relationship?

C. Objective of the study

- Review the influence of perceived utility, simplicity of use, privacy and security, and technology innovativeness on the acceptance of healthcare technology by patients.
- Evaluate the effects of technology-related perceptions on patients' trust.
- Analyze the impact of technology-related perceptions on perceived value.
- Determine the impact of patients' trust and perceived worth on their acceptance.
- Examine the link between patients' views of technology and their willingness to use it, and see whether trust and perceived value mediate this relationship.

II. LITERATURE REVIEW

A. Emerging Healthcare Technologies

Emerging healthcare technologies are digitally supported technologies that facilitate healthcare service provision, healthcare monitoring, diagnostics, communication, decision-making, and patient engagement. The current research concentrates specifically on AI-supported healthcare systems, telemedicine, mobile health applications, wearables, remote patient monitoring, and digital healthcare platforms. They may facilitate patients with greater access to healthcare services, continuous monitoring, fast communication, personalized recommendations, and greater engagement in healthcare decision-making. Nevertheless, their implementation necessitates patients' perception of usefulness, comprehensibility, reliability, security, and value [15].

The rapid development of mobile health technologies further emphasizes the importance of acceptance research. One recent systematic review of TAM-based research on mobile health applications indicated that TAM remains an essential tool for acceptance analysis, yet it highlighted the need to incorporate extended constructs along with healthcare technology evolution [16].

B. Technology Acceptance Model

Acceptance of technology means the extent to which a person is ready to accept a certain technology. In healthcare, it may include accepting digital health technologies, participating in teleconsultation, using wearables for monitoring, working with artificial intelligence, or other activities supported by digital means. Technology acceptability is influenced by variables such

as perceived utility and perceived simplicity of use. The degree to which an individual thinks a certain piece of technology may help them perform better is known as their perceived usefulness. An indicator of how user-friendly a technology is is its perceived ease of use [17].

The significance of these concepts has been demonstrated by several studies in the area of healthcare technology. In their analysis of healthcare technology acceptance studies, Rahimi et al. cited TAM and UTAUT as two important theoretical frameworks [18].

C. Perceived Usefulness

Usefulness is defined as patients' perception of how useful the new healthcare technology is for improving healthcare-related activities. Patients will see telemedicine as useful because it allows easy access to healthcare professionals, while wearable devices will be seen as useful because they allow constant monitoring. Artificial intelligence is also seen as useful if it makes fast information and personalized decisions possible [19].

D. Perceived Ease of Use

Perceived ease of use is an indicator of how easy patients feel using healthcare technology, from both a cognitive and physical perspective. There will be differences in the level of digital literacy of the healthcare users. An overly complex interface, difficulties in signing up, confusing directions, and too many technical requirements may hinder adoption [20].

Alternatively, simpler interfaces, intuitive navigation, easily available information, and user-friendly features may reduce hindrances.

E. Perceived Security and Privacy

Technologies used in healthcare involve handling very private and confidential personal and clinical information. Therefore, issues such as unauthorized access, breach of confidentiality, misuse of patient health records, and lack of privacy can impact acceptance. Results from studies of Indian healthcare consumers show that privacy concerns are a key factor in healthcare technology acceptance [21].

Patients who have faith that their information is being handled securely can embrace the use of health

information technologies.

F. Technological Innovativeness

Technological innovativeness describes the extent to which emerging healthcare technology is considered innovative and modern enough to solve new healthcare issues. It can lead to the adoption of the technology if patients feel that the technology will improve the healthcare services offered. Nonetheless, technological innovativeness alone might not be enough if the technology is considered unreliable or difficult for the patient to comprehend [22].

G. Trust in Emerging Healthcare Technologies

Trust refers to the level of confidence that the patient has in the technology for delivering health care services, the technology vendor, and also in the healthcare organization using this technology. This plays an important role in healthcare since the usage of technology may affect health-related decision-making processes. The patient might not be interested in adopting any AI-driven diagnostic technology or application if he or she does not have any confidence in this technology or organization. A study carried out in India proved that trust was one of the predictors of the usage of healthcare technology. Recent studies in the telemedicine field showed that trust in healthcare organizations could play an important role in adoption intentions [23].

H. Perceived Value

The concept of value is subjective and entails the patient's assessment of the perceived benefit from using the new healthcare technology against any effort, time, costs, inconveniences, privacy threats, and other potential risks incurred in using it. Telemedicine can be seen as a valuable tool by the patient as it cuts down on travel time and offers the convenience of consulting medical practitioners. Similarly, a wearable monitor can be considered valuable as it delivers continuous data for preventative care [24].

It is therefore believed that the concept of perceived value will play a role in linking the patient's perception with acceptance of the technology.

III. Conceptual Framework And Hypothesis Development

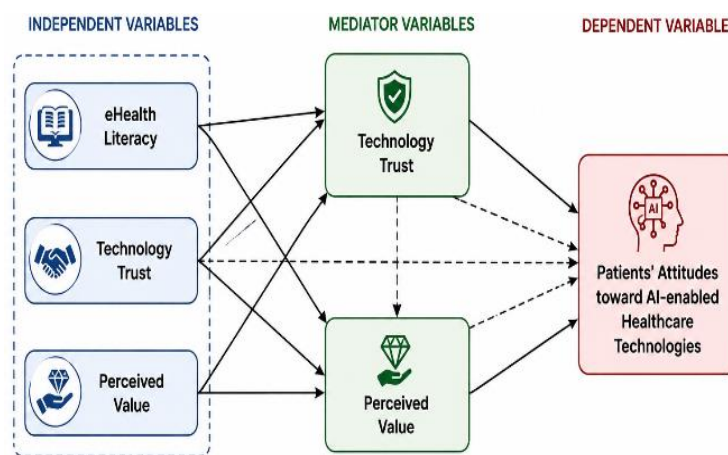


Fig. 1. Conceptual Framework

The proposed working model in Fig 1 provides insight into how attitudes towards AI-enabled healthcare technologies among patients are influenced by the interplay between psychological and technological variables [25]. Patient attitudes can be influenced by three independent variables: eHealth Literacy, Technology Trust, and Perceived Value. High levels of eHealth literacy mean that a person is better able to comprehend and assess AI-based healthcare technologies and thus feels more confident about his/her experience and acceptance. The other two variables, Trust and Perceived Value, play double roles of both independent and mediatory variables, connecting literacy and attitudes in the model. In particular, trust is related to patients' belief in the AI system's reliability, security, and effectiveness, whereas perceived value is associated with the assessment of the technology's usefulness and value. Both mediators help amplify the positive effect of literacy on patients' attitudes towards AI-based healthcare systems. Thus, this model reveals that patient attitudes towards AI-enabled healthcare technologies are determined by the interaction between different knowledge-based, trust-related, and perceived-value aspects [26].

Hypothesis Development

- H1: A patient's perspective on AI in healthcare is positively impacted by eHealth Literacy.
- H2: Patients' perceptions of AI-powered medical devices are positively impacted by technology trust.
- H3: Patients' views on artificial intelligence (AI) healthcare technology are positively impacted by perceived value.

IV. RESEARCH METHODOLOGY

- Research Design: This study will examine patients' perspectives on health technology driven by artificial intelligence (AI) using a quantitative cross-sectional research approach. Patients' perspectives on AI-driven health tech are the focus of this investigation on the relationship between eHealth Literacy, Technology Trust, and Perceived Value. Further investigation into the role of

technology trust and perceived value as mediators between these three factors and patients' perspectives will also be undertaken. Data collection involved a structured survey [27].

- Research Approach: This study employs a deductive research technique due to the interconnected nature of eHealth Literacy, faith in technology, perceived value, and patients' views. These theoretical relationships have been empirically tested using quantitative statistical analysis tools [28].

- Study Population and Sample: It comprises 300 respondents who can be considered healthcare technology users or non-users. The dataset includes information on various demographic groups, such as gender, age, education, employment, income, marital status, and geographical location. Moreover, the dataset also contains information about respondents' exposure to healthcare/technology, knowledge of AI, and their social media usage.

The data was collected using two parts of a structured questionnaire. The first part begins with demographic information about the respondents, such as their sex, age, educational level, occupation, income level, relationship status, geographic location, work experience, AI knowledge, and social network usage.

The second part consists of 8 questions related to eHealth literacy (EH1-EH8), 3 questions related to technology trust (TT1-TT3), 3 questions on perceived value (PV1-PV3), and 15 questions on patients' attitude towards artificial intelligence-based health technologies (AT1-AT15).

A. Result and Discussion

The results of the research are summarized and the results are interpreted in the following sections. The segment shows the level of validation of the hypotheses, shows the correlation between the variables, and connects the results with previous literature. The research findings and their implications are briefly discussed in this section. Here, it is discussed whether the study's hypotheses were accepted, what the relations between the variables used in the research are, and what the implications of the findings are.

TABLE I. RELIABILITY STATISTICS FOR MEASUREMENT SCALE

Reliability Statistics	
Cronbach's Alpha	N of Items
.981	4

Table I shows reliability statistics for the measurement scale based on the Cronbach's Alpha reliability coefficient, which reflects internal consistency. The reliability coefficient of 0.981 represents a very high reliability level and means that there is a very high consistency among the four items in the measurement

scale. From a practical point of view, the items in the scale are strongly interrelated and provide reliable results.

- Frequencies: It explains the frequency at which a certain value or category occurs in a set of data. The statistical result gives the count and the percentage, indicating how the response is distributed in different

variables. Frequency distribution helps in spotting trends in data such as the most frequent response, unusual

responses, and any other trend present in the data.

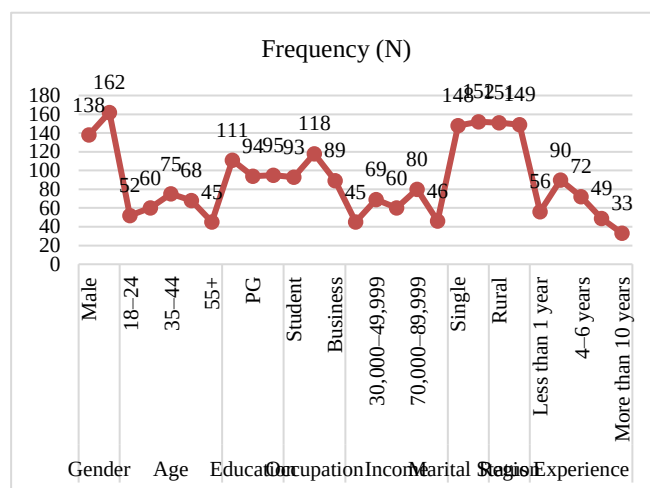


Fig. 2. Frequency Distribution of Respondents' Demographic and Socioeconomic Characteristics

From the graph in Fig 2, an elaborate analysis of the demographics and socioeconomic background of the respondents has been made to see their contribution to the whole sample pool. The gender distribution depicts a slightly higher number of female respondents (162) than male respondents (138). There is also a balanced age distribution among 35-44 years (75), 25-34 years (60), and 45-54 years (68). Thus, there is good representation of middle-aged individuals in the sample pool. The education level distribution among the participants is undergraduate (111), postgraduate (94), and PhD (95). This distribution indicates a highly educated sample pool. Occupations include employees (118), students (93), and business professionals (89). It also indicates that the sample pool has people from various professions. Income levels range widely, but the largest number of respondents falls in the 70,000-89,999 range (80), indicating a dominance of moderate incomes. In terms of marital status, the area is almost equally divided between those who are single (148) and those who are married (152); and in terms of rural (151) and urban (149). The experience level gets lower with years and the majority of respondents have 1-3 years of experience (90).

- **Descriptive Table:** It gives a brief description of the basic statistical features of the data. These are common data elements such as averages, medians, standard deviations, minimums and maximums for each variable. The Table gives II a brief summary of the distribution of the data, including any extreme values, and allows comparisons to be made between variables. It shows the main statistical features of the data and makes it easier to analyze [29].

TABLE II. DESCRIPTIVE STATISTICS OF STUDY VARIABLES

Descriptive Statistics				
Variable	Minimum	Maximum	Mean	Std. Deviation
eHealth Literacy Item	1.38	5	3.4967	1.06336
Technology Trust Item	1	5	3.43	1.10365
Perceived Value Item	1	5	3.4833	1.08266
Attitude Toward AI Item	1.53	4.93	3.4653	1.05341

The research's independent variables—eHealth Literacy, Technology Trust, Perceived Value, and Attitude Towards AI—are shown in the table with descriptive statistics. The minimum and maximum values, as well as the mean and standard deviation, are included in each variable. The range of answers, or the lowest and highest scores, represents the variability in answers, and the mean score represents the average score for each construct. For instance, the average value of eHealth Literacy is 3.49, which means that respondents' literacy is moderately high. Likewise, the mean scores for Technology Trust (3.43) and Perceived Value (3.48) illustrate moderate responses with neutral levels of trust and value perception. Attitude Toward AI is positive (mean = 3.46). In terms of the standard deviation, this is 1.05 in all situations, indicating that there is a moderate variance of opinions.

- **Correlations:** This is a measure of the association between two criteria in terms of both the strength and the direction of the association. The correlation coefficient ranges from -1 to +1, with +1 indicating a positive correlation and -1 indicating a negative correlation. A correlation table is used to measure the strength of association and how variables vary with each other during the research. These variables include things like eHealth literacy, technology trust, perceived value, and attitudes towards AI [30].

TABLE III. CORRELATION MATRIX OF STUDY VARIABLES

Correlations		eHealth Literacy Item	Technology Trust Item	Perceived Value Item	Attitude Toward AI Item
eHealth Literacy Item	Pearson Correlation	1			
Technology Trust Item	Pearson Correlation	.923**	1		
Perceived Value Item	Pearson Correlation	.915**	.902**	1	
Attitude Toward AI Item	Pearson Correlation	.965**	.942**	.935**	1

The correlation coefficients between the four variables of interest—eHL, TT, PV, and ATAI—are displayed in Table III. The two asterisks (**) indicate that these relationships are very significant and positive. For instance, a positive

attitude toward AI is associated with higher levels of eHealth literacy (.965). There is a positive correlation between ATAI and two additional variables, TT (.942) and Perceived Value (.935). The correlations among independent variables and mediating variables (between each other) are high as well, such as the one between eHL and TT (.923), as well as eHL and PV (.915). Therefore, the table indicates that increased literacy, trust, and perceived value are related to patients' positive attitudes towards AI.

- **Regression:** Regression analysis is a statistical method of investigating how independent variables affect a dependent variable. Indicators of significance for determining the presence or absence of significant effects are provided by this method, together with coefficients that show the kind and intensity of the link between the dependent and independent variables. Finding the most influential factors on the dependent variable, the amount of variation explained by the regression equation, and the presence or absence of mediating or moderating variables are all outcomes of regression analysis [31].

TABLE IV. MODEL SUMMARY OF REGRESSION ANALYSIS

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.978 ^a	.957	.956	.22060
a. Predictors: (Constant), Perceived Value Item, Technology Trust Item, eHealth Literacy Item				

The regression study that looked at how Health Literacy, Technology Trust, and Perceived Value, the independent variables, affected patients' views towards AI-enabled healthcare solutions is summarized in Table IV above. As can be seen from the data in the table, there is a significant association between the dependent variable and the predictors, as indicated by the correlation coefficient ($R = .978$). The predictors share a high amount of agreement with the dependent variable as indicated by the relatively high R Square value of .957. The Adjusted R Square (.956), which measures the strength of the model for the number of predictors included, is very telling. The Standard Error of the Estimate (.22060) demonstrates the average difference between actual and predicted scores and is a good indicator of how well the model is predicting the dependent variable.

TABLE V. ANOVA RESULTS FOR REGRESSION MODEL

Anova						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	317.391	3	105.797	2174.068	.000 ^a
	Residual	14.404	296	.049		
	Total	331.795	299			
a. Dependent Variable: Attitude Toward AI Item						
b. Predictors: (Constant), Perceived Value Item, Technology Trust Item, eHealth Literacy Item						

Table V shows the ANOVA results of the regression

model used to predict patients' attitudes towards AI healthcare technology. The comparison of the Regression Sum of Squares (317.391) against the Residual Sum of Squares (14.404) suggests that most of the variability in attitudes can be attributed to the explanatory variables: eHealth Literacy, Technology Trust, and Perceived Value. The F statistic (2174.068) is very high and the Sig. (.000) is very small, suggesting that the model is statistically significant. This means that all explanatory variables have a considerable influence on attitudes, and the probability that these outcomes occurred by chance is negligible.

TABLE VI. COEFFICIENTS OF REGRESSION MODEL

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.052	.044		1.180	.239
	eHealth Literacy Item	.508	.036	.513	14.108	.000
	Technology Trust Item	.247	.032	.259	7.625	.000
	Perceived Value Item	.226	.031	.233	7.215	.000
a. Dependent Variable: Attitude Toward AI Item						

Table VI provides the regression coefficients, which measure how much each independent variable (eHealth Literacy, Technology Trust, and Perceived Value) influences the dependent variable, which is attitude towards AI. In Unstandardized Coefficients (B), we can see the actual effect size: when the value of eHealth Literacy increases by 1, Attitude increases by 0.508. Standardized Coefficients (Beta) help us to compare the effect sizes of predictors. Thus, the most important predictor is eHealth Literacy with a coefficient of 0.513, followed by Technology Trust (0.259) and Perceived Value (0.233). t-value and significance level (Sig. = .000) prove that all predictors are significant, so there are no random influences on the dependent variable. Constant (.052) is not significant because predictors themselves influence Attitude.

V. CHALLENGES IN PATIENT ACCEPTANCE OF EMERGING HEALTHCARE TECHNOLOGIES

There are various obstacles to the implementation of novel healthcare technologies that stand in the way of their patients' adoption. Among these challenges, privacy and security concerns play an important role since patients are hesitant to share their health data because of potential breaches or misuse. Patients' lack of trust in new technology is yet another obstacle, as they may question its reliability and accuracy, as well as how ethically it is used. Moreover, lack of digital literacy is another problem when adopting technology, since patients who do not know much about technology cannot handle complex technology-based processes and thus, their chances of implementing the technology decrease. Poor usability and accessibility discourage patients from using it, whereas value perception is crucial since people tend to evaluate whether the benefits outweigh the effort. Psychological and social barriers, including the fear of reduced

interactions with other humans and the fear of AI taking away human professional judgment, can be cited, as well as cultural and contextual sensitivity, where attitudes differ by region, socioeconomic status, and culture [32].

VI. CONCLUSION

The study results clearly indicated that eHealth literacy, technology trust, and the perception of value were key factors in shaping patients' receptivity to AI in healthcare. EHealth literacy played a strong role in determining patients' attitudes toward the technology. Trust and value perception were also found to be significant intermediary variables, suggesting that in addition to usability, technology adoption requires trust and perceived value. The study determined that psychological and technological factors contributed to patients' acceptance of A.I. in health care.

VII. FUTURE SCOPE

Regarding the future prospects for this research, one may suggest expanding this model by including other psychological and contextual factors, such as cultural attitudes, ethical aspects, and patient outcomes after using technology. Cross-regional comparisons could also be considered as future research to find out the effect of socio-cultural and socio-economic peculiarities on the patients' acceptance of technology. Longitudinal studies will also be valuable to examine shifts in attitudes toward the use of technology within the healthcare system over time. Besides, qualitative data might be utilized together with quantitative models to realize patients' experiences and fears. It will also be crucial to investigate ways to increase digital literacy, improve communication, and develop technologies that benefit patients.

REFERENCES

1. P. Patel, "Revolutionizing Healthcare: Multicast Medicine Engineering for Real-Time Patient Monitoring at Scale," in 2026 2nd International Conference on Emerging and Intelligent Technologies and Systems (EITS), Valencia, Spain: IEEE, Jun. 2026, pp. 270–276. doi: 10.1109/EITS70066.2026.11609590.
2. A. I. Stoumpos, F. Kitsios, and M. A. Talias, "Digital Transformation in Healthcare: Technology Acceptance and Its Applications," *Int. J. Environ. Res. Public Health*, vol. 20, no. 4, p. 3407, Feb. 2023, doi: 10.3390/ijerph20043407.
3. M. Mittal, "Ai In Healthcare: The Next Frontier In Medical Diagnosis," *Int. J. Inf. Technol. Manag. Inf. Syst.*, vol. 16, no. 2, pp. 1448–1455, Mar. 2025, doi: 10.34218/IJITMIS_16_02_091.
4. G. Tetik, S. Türkeli, S. Pinar, and M. Tarim, "Health information systems with technology acceptance model approach: A systematic review," *Int. J. Med. Inform.*, vol. 190, p. 105556, Oct. 2024, doi: 10.1016/j.jmedinf.2024.105556.
5. S. Mahmud, K. K. Mohammed, V. R. Jain, and S. A. Shah, "Artificial Intelligence-Driven Predictive Models for Identifying Risk Factors of Chronic Diseases," in 2026 14th International Symposium on Digital Forensics and Security (ISDFS), Boston, MA, USA: IEEE, Mar. 2026, pp. 01–06. doi: 10.1109/ISDFS69419.2026.11459003.
6. N. Alhammad, M. Alajlani, A. Abd-alrazaq, G. Epiphaniou, and T. Arvanitis, "Patients' Perspectives on the Data Confidentiality, Privacy, and Security of mHealth Apps: Systematic Review," *J. Med. Internet Res.*, vol. 26, p. e50715, May 2024, doi: 10.2196/50715.
7. M. Mittal and S. Balamurugan, "Ethical Challenges In Ai-Based Healthcare: Balancing Innovation With Patient Privacy And Fairness," *Int. J. Artif. Intell. Med.*, vol. 3, no. 2, pp. 1–20, Jul. 2025, doi: 10.34218/IJAIMED_03_02_001.
8. R. Snehamrutha, "Development and In-Vitro Evaluation of a Sustained-Release Transdermal Patch for Improved Patient Adherence," *ESP Int. J. Adv. Sci. Technol.*, vol. 2, no. 4, pp. 34–43, 2024, doi: 10.56472/25839233/IJAST-V2I4P105.
9. N. K. S. Patel, "Enterprise AI Operations in Healthcare IT Infrastructure," *J. Inf. Syst. Eng. Manag.*, vol. 11, no. 3, pp. 2508–2522, September, 2026, doi: 10.5281/zenodo.22773821.
10. S. Sawesi, M. Rashrash, K. Phalakornkule, J. S. Carpenter, and J. F. Jones, "The Impact of Information Technology on Patient Engagement and Health Behavior Change: A Systematic Review of the Literature," *JMIR Med. Informatics*, vol. 4, no. 1, p. e1, Jan. 2016, doi: 10.2196/medinform.4514.
11. S. Mukherjee, "Machine Learning-Enabled Classification of Diabetes Using Clinical via Lifestyle Health Data," in 2026 IEEE 5th International Conference on AI in Cybersecurity (ICAIC), Houston, TX, USA: IEEE, Feb. 2026, pp. 1–6. doi: 10.1109/ICAIC67076.2026.11395709.
12. A. Warriar and K. Abhilash, "Autonomous Agentic AI for Clinical Workflow Orchestration: Self-Managing Healthcare Operations," in 2025 6th International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS), Bengaluru, India: IEEE, 2025, pp. 1450–1457, December. doi: 10.1109/ICICNIS66685.2025.11315712.
13. S. Murumkar and S. Sen, "A Critical Review on Ethical and Privacy Challenges of AI-Powered Healthcare Systems," *Int. J. Artif. Intell. Data Sci. Mach. Learn.*, vol. 6, no. 1, pp. 254–257, March, 2025, doi: 10.63282/3050-9262.IJAIDSML-V6I1P129.
14. T. D. N. Thanh D. Nguyen and O. H. N. Oanh H. Nguyen, "The Role of Perceived Value on Adoption and Usage of Artificial Intelligence in Business," *Glob. Bus. Financ. Rev.*, vol. 30, no. 9, pp. 183–197, Sep. 2025, doi: 10.17549/gbfr.2025.30.9.183.
15. B. Sachdeva, J. Panda, and S. Taran, "Recent

- advancements in emerging technology for healthcare management systems,” in *Artificial Intelligence*, IOP Publishing, 2024, pp. 2-1-2–26. doi: 10.1088/978-0-7503-5964-1ch2.
16. B. Rahimi, H. Nadri, H. Lotfnezhad Afshar, and T. Timpka, “A Systematic Review of the Technology Acceptance Model in Health Informatics,” *Appl. Clin. Inform.*, vol. 09, no. 03, pp. 604–634, Jul. 2018, doi: 10.1055/s-0038-1668091.
 17. M. Wang et al., “Health workers’ adoption of digital health technology in low- and middle-income countries: a systematic review and meta-analysis,” *Bull. World Health Organ.*, vol. 103, no. 2, pp. 126-135F, Feb. 2025, doi: 10.2471/BLT.24.292157.
 18. A. Shachak, C. Kuziemy, and C. Petersen, “Beyond TAM and UTAUT: Future directions for HIT implementation research,” *J. Biomed. Inform.*, vol. 100, p. 103315, Dec. 2019, doi: 10.1016/j.jbi.2019.103315.
 19. A. Haleem, M. Javaid, R. P. Singh, and R. Suman, “Telemedicine for healthcare: Capabilities, features, barriers, and applications,” *Sensors Int.*, vol. 2, p. 100117, 2021, doi: 10.1016/j.sintl.2021.100117.
 20. I. J. Borges do Nascimento et al., “Barriers and facilitators to utilizing digital health technologies by healthcare professionals,” *npj Digit. Med.*, vol. 6, no. 1, p. 161, Sep. 2023, doi: 10.1038/s41746-023-00899-4.
 21. A. K. Conduah, S. Ofoe, and D. Siaw-Marfo, “Data privacy in healthcare: Global challenges and solutions,” *Digit. Heal.*, vol. 11, May 2025, doi: 10.1177/20552076251343959.
 22. A. Yusuf, L. Olaniyan, H. S. Ayobami, A. K. H. Oluwakemi, and L. A. Igbini, “The Role of Technology in Enhancing Healthcare Administration and Service Delivery,” *CogNexus*, vol. 1, no. 02, pp. 37–50, Apr. 2025, doi: 10.63084/cognexus.v1i02.77.
 23. P. Wissawaswaengsuk, P. Kumar, B. Frank, and Y. F. Badir, “The role of trust as the facilitator and contingency factor in the adoption of digital healthcare services: A telemedicine context,” *Comput. Human Behav.*, vol. 172, p. 108722, Nov. 2025, doi: 10.1016/j.chb.2025.108722.
 24. J. M. Myszewski and M. Sinha, “A model for determining the value of patient satisfaction in healthcare,” *Bus. Process Manag. J.*, vol. 26, no. 3, pp. 798–815, Sep. 2019, doi: 10.1108/BPMJ-03-2019-0123.
 25. A. Warriar, “Real-Time Healthcare Event Processing: Stream Analytics for Clinical Decision Support,” *Int. J. Emerg. Res. Eng. Technol.*, vol. 1, no. 4, December, pp. 47–54, 2020, doi: 10.63282/3050-922X.IJERET-V1I4P106.
 26. I. Koo, U. Zaman, H. Ha, and S. Nawaz, “Assessing the interplay of trust dynamics, personalization, ethical AI practices, and tourist behavior in the adoption of AI-driven smart tourism technologies,” *J. Open Innov. Technol. Mark. Complex.*, vol. 11, no. 1, p. 100455, Mar. 2025, doi: 10.1016/j.joitmc.2024.100455.
 27. D. Hammoudi Halat, R. Shami, A. Daud, W. Sami, A. Soltani, and A. Malki, “Artificial Intelligence Readiness, Perceptions, and Educational Needs Among Dental Students: A Cross-Sectional Study,” *Clin. Exp. Dent. Res.*, vol. 10, no. 4, Aug. 2024, doi: 10.1002/cre2.925.
 28. Z. Chen et al., “The mediating effects of technology trust and perceived value in the relationship between eHealth literacy and attitude toward the usage of artificial intelligence in nursing: a cross-sectional study,” *BMC Nurs.*, vol. 24, no. 1, p. 989, Jul. 2025, doi: 10.1186/s12912-025-03577-w.
 29. R. W. Cooksey, “Descriptive Statistics for Summarising Data,” in *Illustrating Statistical Procedures: Finding Meaning in Quantitative Data*, Singapore: Springer Singapore, 2020, pp. 61–139. doi: 10.1007/978-981-15-2537-7_5.
 30. L. Zhang et al., “Deep Negative Correlation Classification,” *Mach. Learn.*, Dec. 2022, doi: 10.1007/s10994-024-06604-0.
 31. R. Hirsch, “Regression Analysis,” in *Synthesis Lectures on Mathematics and Statistics*, 2024, pp. 83–92. doi: 10.1007/978-3-031-41914-0_9.
 32. M. I. Ahmed, B. Spooner, J. Isherwood, M. Lane, E. Orrock, and A. Dennison, “A Systematic Review of the Barriers to the Implementation of Artificial Intelligence in Healthcare,” *Cureus*, Oct. 2023, doi: 10.7759/cureus.46454.