Original Article

DOI: 10.7860/JCDR/2026/84554.22732

Health Management and Policy Section

Validation of an Extended Technology Acceptance Model Framework Incorporating Organisational Culture and Trust in AI usage within Hospitals: A Cross-sectional Study

JIGYASA RATHORE[1], AKANKSHA SINGH[2], UJJWAL RAO[3]

(cc) BY-NC-ND

ABSTRACT

Introduction: The hospital landscape is rapidly evolving, with Artificial Intelligence (AI) emerging as a central component of both administrative and clinical workflows. The classic Technology Acceptance Model (TAM), however, does not adequately account for the dynamic and complex nature of hospital workflows.

Aim: To empirically validate an extended TAM that incorporates Organisational Culture (OC) and Trust in AI (TAI), and to examine how these factors influence healthcare professionals' perceptions of usefulness, Ease of Use (EOU), behavioural intention, and actual AI usage in hospital settings.

Materials and Methods: The present cross-sectional survey was conducted across 5 hospitals in India's National Capital Region using a 27-item instrument. Data were collected via Google Forms between November 2024 and January 2025 from tertiary and quaternary care hospitals known to have adopted or piloted AI applications, including robotic process automation, virtual assistants, and diagnostic imaging systems. Partial Least Squares-Structural Equation Modelling (PLS-SEM) was employed to assess reliability, validity, model fit, path significance, and mediation effects.

Results: The results validated the core TAM along with the proposed extended constructs. Key findings indicated that perceived EOU strongly predicted trust, while TAI directly predicted Actual Use (AU), exerting a stronger effect than behavioural intention. Organisational culture indirectly influenced AI adoption by shaping EOU and trust, fully mediating its effect on behavioural intention.

Conclusion: AI adoption follows a mediated pathway in which OC indirectly influences intention to use through EOU, trust, and perceived usefulness, with trust emerging as a critical direct antecedent of actual usage. These findings underscore the practical imperative for healthcare administrators to implement robust AI governance mechanisms to enhance trustworthiness and to foster an innovative organisational culture.

Keywords: Artificial Intelligence, Hospital administration, Structural equation modelling, Trust

INTRODUCTION

Hospitals worldwide are undergoing rapid digitisation, with AI increasingly embedded in both clinical pathways and administrative workflows. The integration of AI into hospital administration promises to transform healthcare delivery by improving the accuracy, efficiency, and cost-effectiveness of critical operations such as patient triage, scheduling, and resource allocation [1,2]. However, the realisation of these benefits is not guaranteed by technological capability alone. Historically, the failure of health information systems has often been attributed not to technical deficiencies, but to their non-adoption or abandonment by end-users [3]. Therefore, understanding the factors that determine healthcare professionals' acceptance of these technologies is a critical prerequisite for their successful implementation.

The Technology Acceptance Model (TAM) remains one of the most influential frameworks for explaining how users come to accept and use technology [4]. TAM posits that Perceived Usefulness (PU) and Perceived Ease of Use (EOU), shape Behavioural Intention to Use (BIU), which subsequently drives Actual Use (AU) [4]. TAM and its extensions, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), are among the most extensively validated theories of individual information technology acceptance, including within healthcare contexts [5]. Nevertheless, the model's emphasis on individual perceptions has been criticised for overlooking broader contextual factors that shape these perceptions, particularly in complex organisational environments such as healthcare [6].

The deployment of AI in hospitals introduces challenges that extend beyond those of conventional information systems, including concerns related to patient safety, explainability, accountability, and governance. These challenges highlight the necessity of incorporating trust and organisational context into technology acceptance models [7,8]. Prior research suggests that systems perceived as simpler and more predictable foster greater trust, which in turn enhances perceived usefulness-an especially critical consideration when AI outputs influence clinical and administrative decision-making [9].

Furthermore, technology adoption does not occur in isolation but is deeply embedded within the social and structural fabric of an organisation [3]. In healthcare settings, organisational culture is characterised by strong leadership, formal hierarchies, stringent regulatory frameworks, and varying climates for innovation. Norms that support learning, psychological safety, and experimentation can directly influence professionals' trust in new systems and their perceptions of utility. Consequently, organisational culture can act as a powerful upstream facilitator of technology acceptance [10]. This perspective aligns with broader ethical and governance frameworks for AI in healthcare, which emphasise that trustworthiness and successful deployment depend on robust organisational safeguards and a supportive institutional environment [7,11].

The present study builds upon the original TAM proposed by Davis FD (1989), which identified perceived usefulness and perceived ease of use as key predictors of behavioural intention, ultimately leading to actual technology use [4]. Given the complexity of AI adoption within healthcare organisations, the present extended model incorporates two context-critical antecedents: Trust in AI (TAI) and Organisational Culture (OC). The proposed directional relationships reflect usability-driven trust formation in high-stakes environments, as well as the enabling or constraining role of organisational culture.

Although relationships among trust, ease of use, and perceived usefulness have been explored in other contexts [8,9], their interaction with organisational culture in healthcare remains insufficiently understood, particularly with respect to AI adoption. There is a notable lack of empirical studies that quantitatively model how organisational culture functions as an external catalyst within this acceptance pathway. This study seeks to address this gap.

The purpose of the present study is to empirically validate an extended TAM to examine the influence of OC on hospital administrators' and clinicians' TAI, their perceptions of usefulness and EOU, and their subsequent behavioural intentions and AU of AI systems. By doing so, the present research provides evidence-based insights for healthcare leaders aiming to cultivate organisational conditions conducive to the responsible and effective adoption of AI technologies.

MATERIALS AND METHODS

The present cross-sectional study was conducted using a structured questionnaire to assess AI acceptance among healthcare professionals. Data were collected via Google Forms between November 2024 and January 2025 from tertiary and quaternary care hospitals across India's National Capital Region that had adopted or piloted AI applications, including robotic process automation, virtual assistants, and diagnostic imaging systems. Of the 600 healthcare professionals invited to participate, 387 responded, and 385 complete responses were retained for analysis, yielding a response rate of 64.5%.

The study was survey based, hence the ethical committee approval was not taken. Participation was entirely voluntary and anonymous. Informed consent was obtained from all participants at the beginning of the survey. The present study design ensured that no personally identifiable information was collected, thereby safeguarding participant confidentiality.

Inclusion criteria:

- Healthcare professionals, including management personnel, clinicians (doctors and nurses), and technical staff, ensuring representation across both administrative and clinical domains
- Employment in hospitals with at least one implemented AI technology
- A minimum of six months of professional experience.

Exclusion criteria:

- Interns
- Non-clinical support staff
- Incomplete survey responses.

Sample size calculation: The final sample met the recommended criteria for Partial Least Squares-Structural Equation Modelling (PLS-SEM). Contemporary SEM guidelines by Kline RB (2023) recommend a minimum sample size of approximately 200, with 300 or more preferred for complex models [12].

In addition, a conservative minimum sample size was estimated using the inverse square root method for PLS-SEM proposed by Kock N and Hadaya P (2018), defined as:

$N_{min} \geq (Z\alpha/\beta^{min})^2$,

Using a stringent significance level of α=0.01 ($Z\alpha$=2.58) and a minimum relevant standardised path coefficient of βmin=0.15 [13], the calculation yielded:

$N_{min} \geq (2.58 / 0.15)^2 = (17.20) \approx 295.84$,

This indicates a conservative minimum requirement of approximately 296-300 cases. The final retained sample of 385 respondents exceeded all calculated thresholds and conforms to general survey sampling adequacy guidelines proposed by Cochran WG (1977), thereby providing sufficient statistical power and stability for parameter estimation in the structural model [14].

Study Procedure

A structured questionnaire was developed based on the proposed extended TAM framework. The instrument consisted of 27 items measured on a 7-point Likert scale (1=Strongly Disagree, 7=Strongly Agree). The constructs included PU, perceived EOU, BIU, AU, TAI, and OC. Questionnaire items were adapted from previously validated instruments and contextualised for healthcare AI applications [4,8,9].

A pilot study was conducted with 50 healthcare professionals to assess the clarity, reliability, and validity of the questionnaire. Feedback from the pilot resulted in minor wording refinements. Preliminary SEM analysis of the pilot data confirmed strong construct reliability (outer loadings>0.70) and validity.

STATISTICAL ANALYSIS

Data analysis followed the established two-stage analytical procedure for SEM [15]:

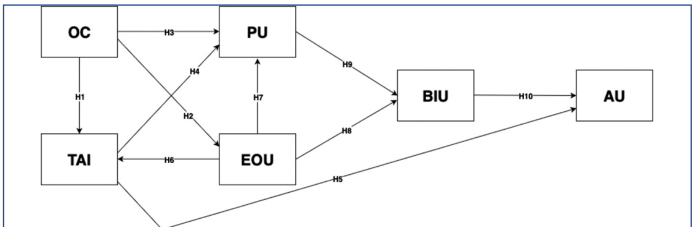
1. **Measurement model assessment:** Reliability, convergent validity, and discriminant validity were evaluated using Cronbach's alpha (α), Composite Reliability (CR), Average Variance Extracted (AVE), and the Fornell-Larcker criterion, in accordance with Fornell and Larcker (1981) and Henseler et al., (2015) [16,17].
2. **Structural model testing:** Path significance was assessed using bootstrapping with 5,000 resamples to evaluate direct, indirect, and total effects. Model fit was examined using the Standardised Root Mean Square Residual (SRMR).

Descriptive statistics were computed using Statistical Package for the Social Sciences (SPSS) version 28, while PLS-SEM analysis was conducted using SmartPLS (Partial Least Squares Structural Equation Modeling) version 4.0. A significance level of $p<0.05$ was applied for all analyses.

Hypothesis: The following hypotheses were proposed in the extended TAM model:

1. H1: OC has a significant positive effect on TAI.
2. H2: OC has a significant positive effect on perceived EOU.
3. H3: OC has a significant positive effect on PU.
4. H4: TAI has a significant positive effect on PU.
5. H5: TAI has a significant positive effect on AU.
6. H6: Perceived EOU has a significant positive effect on TAI.
7. H7: Perceived EOU has a significant positive effect on PU.
8. H8: Perceived EOU has a significant positive effect on BIU.
9. H9: PU has a significant positive effect on BIU.
10. H10: BIU has a significant positive effect on AU.
11. H11: The effect of OC on BIU is fully mediated by TAI, perceived EOU, and PU.

Structural equations: Structural equations were derived directly from the hypothesised relationships specified in the extended TAM framework [Table/Fig-1], consistent with established SEM methodology [4,15].



[Table/Fig-1]: Proposed extended TAM with OC & TAI [4,15].

1. $TAI=\beta_{11}\ EOU+\beta_{12}\ OC+e_1$
2. $PU=\beta_{21}\ EOU+\beta_{22}\ TAI+\beta_{23}\ OC+e_2$
3. $EOU=\beta_{31}\ OC+e_3$
4. $BIU=\beta_{41}\ PU+\beta_{42}\ EOU+e_4$
5. $AU=\beta_{51}\ BIU+\beta_{52}\ TAI+e_5$

RESULTS

Demographic profiles of respondents: The 385 respondents were drawn from tertiary and quaternary hospitals in India's National Capital Region (NCR). The sample was predominantly under 40 years of age 76.1%, female (54.5%), and postgraduate educated (52.9%). Participants represented managerial staff 46.7, clinical staff (37.4%), and technical personnel (15.5%), with varied levels of professional experience [Table/Fig-2].

Variables	Categories	Frequency	Percentage
Age (years)	20-29	163	42.2
	30-39	130	33.7
	40-49	67	17.4
	>50	25	6.49
Gender	Male	165	42.82
	Female	210	54.54
	LGBTQ+	10	2.6
Level of education	Diploma	10	2.6
	Undergraduate	153	39.7
	Postgraduate	204	52.9
	Ph.D.	18	4.7
Current role in the healthcare industry	Top management	43	11.1
	Mid management	90	23.3
	Lower management	47	12.2
	Doctor	60	15.5
	Nurse	85	22.07
	Technician	60	15.5
Years of experience	01-05	152	39.48
	06-10	95	24.6
	11-15	83	21.5
	>16	55	14.2

[Table/Fig-2]: Demographic profiles of the respondents.

Measurement model assessment: Prior to testing the structural relationships, the reliability and validity of the measurement model were assessed using PLS-SEM. As shown in [Table/Fig-3], all constructs demonstrated excellent internal consistency, with CR values exceeding the recommended threshold of 0.70 [15]. Convergent validity was established, as all AVE values exceeded 0.50 and all outer loadings were above 0.70, indicating strong indicator reliability [15].

Construct	Code	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Actual Use	AU	0.969	0.969	0.976	0.911
Behavioural Intention	BI	0.969	0.969	0.979	0.938
Perceived Ease of Use	EOU	0.956	0.957	0.967	0.879
Organisational Culture	OC	0.913	0.914	0.953	0.911
Perceived Usefulness	PU	0.92	0.921	0.942	0.804
Trust in AI	TAI	0.941	0.942	0.96	0.888

[Table/Fig-3]: Construct reliability and validity.

Discriminant validity was assessed using the Fornell-Larcker criterion, as recommended by Hair JF et al., (2019) [15]. The square roots of the AVE values were greater than the corresponding inter-construct correlations, confirming adequate construct distinctiveness, as shown in [Table/Fig-4]. Collectively, these results demonstrate that the measurement model possesses robust psychometric properties and is suitable for subsequent structural analysis.

Variables	AU	BI	EOU	OC	PU	TAI
AU	**0.933**					
BI	0.841	**0.961**				
EOU	0.880	0.854	**0.936**			
OC	0.771	0.718	0.739	**0.955**		
PU	0.839	0.862	0.884	0.744	**0.910**	
TAI	0.862	0.760	0.820	0.824	0.810	**0.940**

[Table/Fig-4]: Fornell-Larcker criterion for discriminant validity (Diagonal elements (in bold) are the square root of the AVE.)

Structural model and hypothesis testing: The structural relationships among the constructs were examined using a bootstrapping procedure to assess path significance. Model fit indices indicated excellent adequacy, with SRMR values of 0.036 for the saturated model and 0.042 for the estimated model. Both values are well below the recommended threshold of 0.08 [Table/Fig-5], indicating a good fit of the proposed model, in line with established guidelines [15-17].

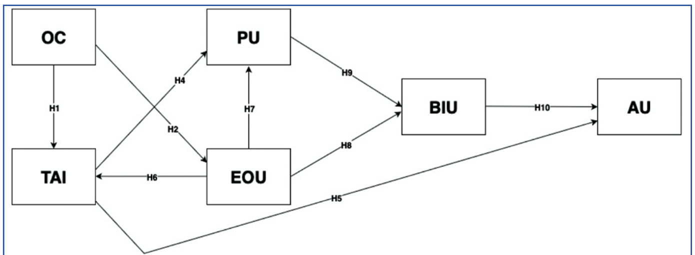
Variables	Saturated model	Estimated model
SRMR	0.036	0.042
d_ULS	0.272	0.366
d_G	0.521	0.549
NFI	0.886	0.883

[Table/Fig-5]: Model Fit (Structural Model) [15-17].

Hypothesis testing results: The results of the path coefficient analysis are presented in [Table/Fig-6,7]. Ten of the eleven proposed direct hypotheses were supported.

Hypothesis	Path	β	p-value	Supported or Not
H1	OC → TAI	0.481	<0.001	Yes
H2	OC → EOU	0.739	<0.001	Yes
H3	OC → PU	0.111	0.022	No
H4	TAI → PU	0.186	<0.001	Yes
H5	TAI → AU	0.527	<0.001	Yes
H6	EOU → TAI	0.465	<0.001	Yes
H7	EOU → PU	0.65	<0.001	Yes
H8	EOU → BI	0.42	<0.001	Yes
H9	PU → BI	0.49	<0.001	Yes
H10	BI → AU	0.44	0.001	Yes

[Table/Fig-6]: Hypothesis testing (direct effects).



[Table/Fig-7]: Extended TAM with accepted pathways.

Mediation Analysis (H11): Hypothesis H11 proposed that the relationship between OC and BI is fully mediated by TAI, perceived EOU, and PU. Specific indirect effects were examined using bootstrapping.

The results revealed a significant total indirect effect of OC on BI (β=0.675, p<0.001). The key mediating pathways were:

- OC → EOU → BI (β=0.311, p<0.001)
- OC → EOU → PU → BI (β=0.235, p<0.001)
- OC → TAI → PU → BI (β=0.044, p<0.05)

As the direct effect of OC on BI was not estimated in the model and the total indirect effect was statistically significant, H11 was supported. These findings indicate that the influence of OC on BI is fully mediated through the sequential effects of TAI, perceived EOU, and PU.

Coefficient of determination (R^2): The model demonstrated substantial explanatory power. The R^2 values for the endogenous constructs were as follows: AU=0.731, behavioural intention (BI)=0.675, perceived EOU=0.546, PU=0.744, and TAI=0.824. According to Chin WW (1998) [18], these values range from moderate (0.33) to substantial (0.67), indicating that the model explains a high proportion of variance in the dependent constructs.

Predictive relevance (Q^2): Predictive relevance was assessed using the blindfolding procedure to calculate Stone-Geisser's Q^2 values. All Q^2 values were greater than zero (AU=0.588, BI=0.512, EOU=0.412, PU=0.542, TAI=0.632), confirming strong predictive relevance of the model for all endogenous constructs.

DISCUSSION

By extending the Technology Acceptance Model (TAM) to incorporate OC and TAI, the present study demonstrates that AI adoption in hospitals follows a mediated socio-technical pathway. Rather than being driven solely by technological attributes, adoption emerges from the alignment of organisational context, users' TAI systems, and individual cognitive evaluations of PU and EOU.

The findings confirm that OC functions as a critical upstream determinant, influencing AI acceptance indirectly through perceived ease of use and trust. Strong structural paths from OC to TAI (β=0.481, p<0.001) and from OC to EOU (β=0.739, p<0.001) indicate that innovation-oriented and psychologically safe environments enhance usability perceptions and trust. The absence of a significant direct effect of OC on perceived usefulness or BI suggests that OC shapes adoption primarily through perceptual and affective mechanisms rather than direct cognitive evaluations.

These results corroborate earlier work by Greenhalgh T et al., (2017) and Nilsen P et al., (2020), who describe organisational climate as the "hidden architecture" underpinning technology assimilation [3,10]. Hospitals characterised by supportive leadership, collaborative norms, and learning-oriented practices are more likely to facilitate experimentation with emerging technologies, whereas rigid hierarchies and fear-driven cultures may inhibit adoption even when perceived utility is high. The present findings empirically operationalise the proposition by Venkatesh V and Bala H (2008) that social and normative environments act as key antecedents to individual technology appraisals [19].

Among all constructs, TAI emerged as the strongest direct predictor of Actual Use (AU) (β=0.527, p<0.001), surpassing even the traditional BI → actual use relationship (β=0.44). This shift in explanatory power indicates that in high-stakes hospital environments-where decisions directly affect patient safety-healthcare professionals' willingness to rely on AI systems is governed more by trust than by intention alone. In this context, trust is not a one-time cognitive stance but a dynamic evaluation of system reliability, transparency, and ethical adequacy.

These findings were consistent with the TrAAIT framework proposed by Stevens AF and Stetson PD (2023) and with the work of Ratta et al., (2025), both of which argue that trust functions as a behavioural gatekeeper in health-AI adoption [20,21]. Additionally, the significant relationship between perceived EOU and trust (EOU → TAI; β=0.465, p<0.001) supports longstanding evidence from Hoff KA and Bashir M (2015) that usability enhances predictability and perceived reliability, thereby strengthening trust [9]. From a practical standpoint, these results underscore that "designing for usability is designing for trust" and highlight the necessity for hospitals to institutionalise mechanisms such as explainable AI dashboards, transparent audit trails, and clinician feedback loops to sustain trustworthiness over time.

The mediation results further refine the theoretical understanding of how organisational factors cascade through cognitive and affective pathways. The full mediation of OC's effect on BI through perceived EOU, TAI, and PU quantitatively substantiates what qualitative studies have long suggested: a culture → trust → use cascade, wherein organisational support translates into adoption through enhanced usability and confidence in AI systems. This finding aligns with sociotechnical systems theory, which posits that technology acceptance emerges from the interaction between organisational structures, human cognition, and technological design.

Similar findings reported by Kalayou MH et al., (2020) and Lee AT et al., (2025) support the argument that extending TAM frameworks to include organisational and social constructs explains a greater proportion of variance in behavioural intention and actual use than traditional TAM models alone [22,23].

From a managerial and policy perspective, the findings highlight four critical priorities for hospital leaders and policymakers: fostering an innovation-supportive OC; designing for trust through transparency, accountability, and explainability; prioritising usability through clinician-led design, training, and workflow integration; and aligning AI initiatives with national digital health frameworks such as the Ayushman Bharat Digital Mission (ABDM) and #AIForAll, thereby ensuring responsible and sustainable AI adoption.

Limitation(s)

The present study has certain limitations. Its cross-sectional design and focus on advanced hospitals within a single geographic region may limit the generalisability of the findings. Future longitudinal studies should examine how these relationships evolve with increased exposure and experience and should explore which specific dimensions of organisational culture are most effective in fostering trust in AI.

CONCLUSION(S)

By integrating trust and organisational culture, the current study presents a context-sensitive extension of the Technology Acceptance Model tailored to healthcare-an environment characterised by interprofessional collaboration, ethical oversight, and regulated decision-making. The extended model bridges individual-level acceptance theory with organisational behaviour and health systems perspectives, offering a more holistic understanding of AI assimilation in hospital settings.

REFERENCES

[1] Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. Future Healthc J. 2019;6(2):94-98. Doi: 10.7861/futurehosp.6-2-94.
[2] Kilanko V. The transformative potential of artificial intelligence in medical billing: A global perspective. Int J Sci Adv. 2023;4(3):345-53. Doi:10.51542/ijscia.v4i3.8.
[3] Greenhalgh T, Wherton J, Papoutsi C, Lynch J, Hughes G, A'Court C, et al. 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. J Med Internet Res. 2017;19(11):e367.
[4] Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly. 1989;13(3):319-40. Doi: 10.2307/249008.
[5] Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. MIS Quarterly. 2003;27(3):425-78. Doi: 10.2307/30036540.

[6] Holden RJ, Karsh BT. The technology acceptance model: Its past and its future in health care. J Biomed Inform. 2010;43(1):159-72.
[7] World Health Organization. Ethics and governance of artificial intelligence for health: WHO guidance. Geneva: WHO; 2021. Available from: https://www.who.int/publications/i/item/9789240029200.
[8] Gefen D, Karahanna E, Straub DW. Trust and TAM in online shopping: An integrated model. MIS Quarterly. 2003;27(1):51-90.
[9] Hoff KA, Bashir M. Trust in automation: Integrating empirical evidence on factors that influence trust. Hum Factors. 2015;57(3):407-34.
[10] Nilsen P, Seing I, Ericsson C, Birken SA, Schildmeijer K. Characteristics of successful changes in health care organizations: An interview study with physicians, registered nurses and assistant nurses. BMC Health Serv Res. 2020;20(1):147.
[11] Mesko B, Topol EJ. The imperative for regulatory oversight of large language models (or generative AI) in healthcare. NPJ Digit Med. 2023;6(1):120.
[12] Kline RB. Principles and Practice of Structural Equation Modeling. 5th ed. New York: Guilford Press; 2023. Pp.494.
[13] Kock N, Hadaya P. Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. Information Systems Journal. 2018;28(1):227-61.
[14] Cochran WG. Sampling Techniques. 3rd ed. John Wiley & Sons; 1977.
[15] Hair JF, Risher JJ, Sarstedt M, Ringle CM. When to use and how to report the results of PLS-SEM. Eur Bus Rev. 2019;31(1):02-24. Doi: 10.1108/EBR-11-2018-0203.
[16] Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. J Mark Res. 1981;18(1):39-50. Doi: 10.1177/002224378101800104.
[17] Henseler J, Ringle CM, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J Acad Mark Sci. 2015;43(1):115-35. Doi: 10.1007/s11747-014-0403-8.
[18] Chin WW. The partial least squares approach to structural equation modeling. In: Marcoulides GA, editor. Modern Methods for Business Research. Mahwah, NJ: Lawrence Erlbaum Associates; 1998: 295-336.
[19] Venkatesh V, Bala H. Technology acceptance model 3 and a research agenda on interventions. Decis Sci. 2008;39(2):273-315. Doi: 10.1111/j.1540-5915.2008.00192.x.
[20] Stevens AF, Stetson PD. Theory of trust and acceptance of artificial intelligence technology (TrAAIT): An instrument to assess clinician trust and acceptance of artificial intelligence. J Biomed Inform. 2023;148:104550. Doi: 10.1016/j.jbi.2023.104550.
[21] Ratta R, Sodhi J, Saxena U. The relevance of trust in the implementation of AI-driven clinical decision support systems by healthcare professionals: An extended UTAUT model. Electron J Knowl Manag. 2025;23(1):47-66. Doi: 10.34190/ejkm.23.1.3499.
[22] Kalayou MH, Endehabtu BF, Tilahun B. The applicability of the modified technology acceptance model (TAM) on the sustainable adoption of eHealth systems in resource-limited settings. J Multidiscip Healthc. 2020;13:1827-37. Doi: 10.2147/jmdh.s284973/
[23] Lee AT, Ramasamy RK, Subbarao A. Understanding psychosocial barriers to healthcare technology adoption: A review of TAM technology acceptance model and unified theory of acceptance and use of technology and UTAUT frameworks. Healthcare (Basel). 2025;13(3):250. Doi: 10.3390/healthcare13030250.

PARTICULARS OF CONTRIBUTORS:
1. PhD Scholar, Department of Amity Institute of Public Health and Hospital Administration, Amity University, Noida, Uttar Pradesh, India.
2. Assistant Professor (Supervisor), Department of Amity Institute of Public Health and Hospital Administration, Amity University, Noida, Uttar Pradesh, India.
3. Medical Director, Department of Rector Healthcare, Rector Healthcare, Wakad, Pune, Maharashtra, India.

NAME, ADDRESS, E-MAIL ID OF THE CORRESPONDING AUTHOR:
Akanksha Singh,
J1 Block, Amity University, Noida, Uttar Pradesh, India.
E-mail: asingh64@amity.edu

PLAGIARISM CHECKING METHODS: [Jain H et al.]
- Plagiarism X-checker: Oct 22, 2025
- Manual Googling: Dec 22, 2025
- iThenticate Software: Dec 24, 2025 (6%)

ETYMOLOGY: Author Origin

EMENDATIONS: 7

AUTHOR DECLARATION:
- Financial or Other Competing Interests: None
- Was Ethics Committee Approval obtained for this study? No
- Was informed consent obtained from the subjects involved in the study? Yes
- For any images presented appropriate consent has been obtained from the subjects. No

Date of Submission: **Sep 24, 2025**
Date of Peer Review: **Nov 26, 2025**
Date of Acceptance: **Dec 26, 2025**
Date of Publishing: **Apr 01, 2026**

QUESTIONNAIRE

Driving AI Acceptance in Hospitals: The Roles of Trust & Culture

Consent form

Dear Participant,

You are cordially invited to take part in a research aimed at exploring perceptions and acceptance of Artificial Intelligence within the realm of healthcare. Your participation in this study entails no risk whatsoever.

Your responses will be treated with utmost confidentiality and will solely be utilised for academic purposes. This questionnaire constitutes a segment of a doctoral study conducted by a PhD scholar at Amity University, Noida.

Please note the following points:

- There are no right or wrong answers to the questions provided.
- Kindly provide your initial, instinctive response to each query.
- Feel free to seek clarification if any aspect requires explanation.
- The identities of participants will remain strictly confidential.

Do you consent to participate in this study? (Yes/No)

1. Socio-Demographic Profile

   Age: Please select your age range: 20-30, 30-40, 40-50, 50+

   Gender: Select the option that best describes your gender identity: Male, Female, LGBTQ+

   Highest academic qualification: Diploma, Graduation, Post-Graduation, PhD

   Department: Select your Department within the Organisation: Patient Care, MRD, Laboratory, Radiology, Admissions, Front Office, Admin, Other

   Designation in Organisation: Top Management, Mid Management, Lower Management, Doctor, Nurse, Technician, Other

   Years of experience in Healthcare Industry: 1-5, 5-10, 10-15, 15+

   Familiarity with AI technologies: How familiar are you with AI technologies, including Generative AI and LLMs (e.g., Chat GPT, Google Gemini, etc.,): (Very familiar to Not at all familiar)

2. Perceived Usefulness (PU)

   AI can manage patient flow, reduce wait times, and optimise resource allocation. (1-7 Likert)

   AI analysis of hospital data improves operational efficiency. (1-7 Likert)

   Generative AI can assist documentation quickly and accurately. (1-7 Likert)

   LLMs can enhance communication via automated responses. (1-7 Likert)

3. Perceived Ease of Use (EOU)

   Learning basics of an AI system would be easy. (1-7 Likert)

   Adapting workflow to include AI would be comfortable. (1-7 Likert)

   Navigating and interacting with AI would be easy. (1-7 Likert)

   Using AI would be easy without extensive technical knowledge. (1-7 Likert)

4. Behavioural Intention to Use (BIU)

   I would seek opportunities to use AI for administrative tasks. (1-7 Likert)

I can integrate AI effectively to improve performance. (1-7 Likert)

I am interested in using Generative AI & RPA for automation. (1-7 Likert)

5. Actual Use (AU)

AI systems (robotic process automation (RPA), Imaging System and natural language processing (NLP)) improve patient data management and administrative efficiency. (1-7 Likert)

AI models help analyse radiological and histopathological images, improving the accuracy and speed of diagnoses (1-7 Likert)

Generative AI (GPTs) assists with medical documentation. (1-7 Likert)

Large Language Models / chatbots / GPTs are utilised for providing automated responses to common patient inquiries. (1-7 Likert)

6. Trust in AI (TAI)

I trust AI systems to provide reliable, error-free, and contextually relevant information. (1-7 Likert)

AI systems minimise errors and biases better than manual processes. (1-7 Likert)

I am confident that AI systems protect patient data privacy and are secure from manipulation. (1-7 Likert)

7. Organisational Culture (OC)

My organisation supports AI adoption and addresses concerns. (1-7 Likert)

My organisation actively seeks staff feedback, concerns and suggestions about AI implementation. (1-7 Likert)