Al-Nahrain Journal for Engineering Sciences

Al-Nahrain J. Eng. Sci. 29(2) 384-391, 2026
Original Article

Engineering Determinants of Artificial Intelligence Adoption in Indian Healthcare Systems: A Regression-Validated Institutional Readiness Model

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DOI: https://www.doi.org/10.29194/NJES.29020384

Received: March 4, 2026 **Revised:** April 20, 2026 **Accepted:** April 28, 2026 **Published:** June 20, 2026

Abstract

The introduction of Artificial Intelligence (AI) in medical care is becoming an acknowledged challenge in the framework of engineering systems, in which the level of computational readiness, the integration of the infrastructure, the level of user competence, and the limitations of the ethical aspect play a role. The paper analyzes the most important engineering predictors of a readiness to use AI in Indian hospitals, which are assessed using correlation and multiple linear regression frameworks.

There was a structured survey on 120 healthcare workers and 20 deep interviews with experts to evaluate system-level perceptions and institutional preparedness. The results of regression showed that the model is well fitted (R 2 = 0.61, $p < 0.001$) with Perceived Usefulness (= 0.43), Infrastructure Availability (= 0.38) and AI Training Exposure (= 0.26) identified as significant and positive predictors of AI adoption readiness. The Ethical Concern Scores ($\beta = -0.32$) had a significant negative impact, highlighting the importance of governance as an important constraint of the system.

These findings were reinforced by qualitative thematic analysis, which identified interoperability challenges, lack of computational training, data governance oversights, and infrastructure vulnerability as significant engineering limitations. The respondents positively indicated the conditional acceptance of AI on the basis of the explainable model transparency, as well as the system of institutional AI training.

The research adds a new regression-tested engineering preparedness pathway to AI implementation in Low- and Middle-Income Country (LMIC) hospital setting, suggesting system interface, capacity formation, and ethical algorithm control as the main keystones on the sustainable AI implementation in Indian healthcare.

Keywords: *AI Adoption, Institutional Readiness, Healthcare Engineering Systems, Machine Learning, Interoperability, India, Ethical Governance, Digital Infrastructure.*

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1. Introduction

The worldwide spread of Artificial Intelligence (AI) has transformed the way multifaceted systems compute, forecast and optimize judgments in safety-related conditions, including the medical sector. In contrast to traditional IT implementation, AI implementation in hospitals is a system engineering integration issue, where there is computational reliability, infrastructure coupling, human-machine interaction, and real-time clinical usability limitations [1], [2], [3]. The last advancements in Machine Learning (ML), sensor signal analytics and interoperable health information architectures have increased the viability in AI-enabled diagnostic and Clinical Decision Support Systems (CDSS) [4], [5], [6]. Although, no longer, the success of adoption depends on algorithmic accuracy alone, its outcome depends on institutional preparedness, engineering capability, exposure to training, and moderated ethical constraint [2], [7], [8].

There is a two-fold problem in Low-and Middle-Income Countries (LMICs) like India, hospitals need to implement intelligent diagnostic automation, but are constrained by fragile infrastructures, heterogeneous IT systems, and low computation scale capacity [9], [10], [11], [12]. The digital maturity, network stability, sensor integration, and the level of AI training differ greatly between Indian healthcare institutions, directly affecting the level of system acceptance and the ability to deploy [10], [13], [14],

[15]. Research indicates that AI systems that are deployed without uniform interoperability, elucidation, and systematic training pipelines receive less clinician trust and are less intentionally embraced [7], [16], [17], [18]. This means that the technical readiness engineering is the core aspect of user adoption behavior. Historical frameworks to be applied in adoption, which include the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT), have been used in IT systems uptake. However, they need to be adjusted to AI-driven hospital settings, where ethical consideration scores, availability of infrastructure, and training of the institution in AI are measurable engineering determinants and not abstract perceptions [2], [8], [17], [19]. The idea of computational transparency through Explainable AI (XAI) has become an essential engineering objective, especially in diagnostic AI systems, which affect confidence in clinicians and perceived risk of harm to the system [20], [21], [22]. Similar studies indicate that availability of infrastructure, such as server compute capacity, diagnostic sensor integration and networked Electronic Medical Records (EMR) interoperability, are predictive features of adoption readiness in a significant manner [13], [15], [23]. Similarly, engineers who have been introduced to formal training on AI competency have a greater likelihood of adoption of the system because of the diminished engineering uncertainty [14], [17], [24]. This paper places the adoption of AI as an engineering systems readiness construct, which statistically confirms the determinants that affect adoption willingness among Indian healthcare professionals through a correlation and multiple regression model. The outcomes are expected to facilitate the scalable AI implementation plans in hospital settings where the system constraints, training exposure, and infrastructure preparedness dictate actual AI adoption behavior [2], [10], [17], [23].

2. Literature Review

2.1 AI-Driven Diagnostic Engineering Systems

It has reached almost clinician parity in image-based diagnostics with engineered deep learning architecture on AI. Convolutional Neural Networks Convolutional Neural Networks (CNNs) have shown dermatologist-level performance on skin cancer classification [2], and large-scale multi-institutional validation of AI screening systems in breast cancer validated that AI screening systems are much more sensitive than human readers. The CheXNet system proposed provided a radiologist-level pneumonia detection in the form of an engineered pipeline on radiologist-equivalent chest X-rays [9], thereby making AI a benchmark-ready diagnostic system, as opposed to a conceptual one. Real-time risk calculations in hospital decision systems are emphasized in continuous clinical predictors, including AI-engineered Acute Kidney Injury (AKI) predictors [10], [24]. A major limitation of the system is interpretability because of black-box opacities, which have continued to be a challenge in the design of clinical AI engineering [14].

2.2 Engineering Determinants of AI Adoption in Healthcare

Systems engineering perspective has a less rigorous view of the adoption of AI, which is characterized more by infrastructural maturity than algorithmic novelty and by interoperability and operational scalability. Research on LMICs highlights that the success of AI implementation requires designed digital backbone capacity and not a single clinical interest [7], [8]. The engineered failure of integration across Hospital Information System (HIS) and Electronic Health Records (EHR) due to the absence of interoperability diminishes institutional preparedness to AI-based workflows [17], [18]. The infrastructural stability is confirmed as engineering analytics models show that the ethical and operational apprehension are negatively related to infrastructure stability, which implies that weak IT systems increase the perception of risk [18]. The models of cost-constrained deployment of the system demonstrate that financial engineering choices greatly mediate the diffusion of AI in the Indian healthcare setting [17], [18].

2.3 Public Health AI and Scalable Engineering Platforms

AI is created and developed into epidemic surveillance and disease prediction and resource allocation algorithms, which are moving at unprecedented rates during Coronavirus (COVID-19) system response [4], [25]. To build interoperable AI-ready healthcare pipelines, India has begun digitally health engineering at national levels like the Ayushman Bharat Digital Mission (ABDM) and the National Health Stack [16], [23]. Nonetheless, systems engineered data silos, mismatched server-side architectures, and poor digital literacy among clinical personnel restrict scalability to pilot-scale implementations [16], [18], [26]. The AI-developed real-time dashboards and decision support systems within the state health networks are still not reliably deployed nationwide [27], [28].

2.4 Ethical Engineering Constraints in AI Deployment

The implementation of AI brings with itself governance weaknesses that need to be engineered through regulatory protection mechanisms. Human-in-the-loop systems are suggested to ensure responsibility in AI-assisted clinical decision pipes [11], [19], [24]. Non-representative training samples bring about systematic bias, which is an essential engineering failure, in the prediction of healthcare AI in a fair manner [6] [29]. The studies on algorithmic fairness validation underline that AI models should be tested under the stress of demographically different groups, to guarantee institutional trust and responsible adoption of the system [29]. Lack of standard AI liability model in the Indian clinical setting puts the hospitals at risk of engineered medico-legal risk uncertainty [19], [24], [26].

2.5 Human Capacity Engineering and Skill-Gap Barriers

Human capacity and institutional architecture remain pivotal in AI adoption though engineered digital infrastructure is present. The intensity of the impact of formal training in AI on professional confidence in AI-aided diagnostics and administrative robots is high [20], [21], [26]. Regression-validated studies on the level of the system show that structured AI literacy interventions can be effective in uplifting adoption willingness in both clinicians and administrators [21], [22], [26]. The top sources of institutional resistance are when training pipelines are not in place, and the ethical governance systems have not been designed into the hospital AI implementation strategies [11], [19], [26].

2.6 Identified Research Gaps

There is good evidence, to be found in the literature, on diagnostic AI performance [2], [3], [9], [10], but no regression-validated institutional readiness modeling of Indian hospital settings, more particularly through an engineering adoption perspective. There exists little research synthesizing adoption psychology, infrastructural engineering and multivariate analytics into a single readiness model [19], [21], [22]. The paper addresses this gap by taking institutional adoption determinants that are validated by regression and customized to the Indian healthcare engineering limitation.

3. Methodology

3.1 Study Design and Engineering Framework

The research is based on a convergent mixed-method structure, which is a combination of quantitative survey engineering and qualitative interpretive analysis of the system. The design focuses on the institutional preparedness modeling, validated adoption determinants, and regression-based predictive inference to implement AI in Indian health systems. Quantitative and qualitative streams were implemented simultaneous to each other and were designed as autonomous analytical components and subsequently brought together by methodological triangulation to reduce interpretive variance and bias in systems.

3.2 Target Population and Institutional Strata

The participants of the study include healthcare professionals working in clinical decision systems, hospital administration, and management of the digital health infrastructure in the Indian healthcare facilities. The sample of the study was identified at the public and private hospitals, Information Technology (IT)-enabled healthcare units, and academic healthcare management departments. The demographic envelope was narrowed down to between 18 and 60 years old and allowed early-career adopters to participate, as well as decision authorities at a system level.

3.3 Sampling Engineering and Cohort Selection

Quantitative Module

The stratified randomized sampling protocol was designed in such a manner that it formed a proportional representation of the institution type. The last sample consisted of 120 respondents, who were stratified by:

- Public hospitals (n = 60)
- Private hospitals (n = 60)

The inclusion criteria ensured:

1. Minimum 1 year of operational exposure to digital or clinical systems
2. Prior interaction with HIS, EHR, or AI-enabled workflows

Qualitative Module

An informant key-informant selection model with purposiveness was implemented to sample 20 domain-critical system actors, including:

- Senior clinicians who use AI-supported diagnostics. Indicators
- Hospital administrators spearheading the digital transformation engineering.
- Data system architects and AI developers of health technology.
- Policy specialists in health and computer governance.

This purposeful sampling guaranteed that there was contextual reliability of the individuals who are actively driving pipelines of adopting AI systems.

3.4 Data Acquisition Instruments

Structured Digital Survey System

An engineered questionnaire using system engineering was developed, pilot-tested (n=10) and refined into a 4-layer questionnaire:

- Layer A: Demographic and role in the system classification.
- Layer B: perceived clinical and administrative utility AI.
- Layer C: Etisalat infrastructure availability and quantified risk of ethics.
- Layer D: AI adoption intent and institutional readiness scoring.

Likert scales, ranked barrier matrices, and binary readiness flags were used as a response, which allowed estimating the magnitude and encode variables to make regression inferences.

Semi-Structured Interview System

The design of a 30-40 min semi-structured interview pipeline was to extract:

- Programmed system advantages and constraints of AI.
- Mapping of the institutional infrastructure reliability.
- Accountability constraints of algorithms and ethics across governance.
- Explainability and Human-Centered AI engineering requirements.

The transcription and coding of all the interviews was done in a systematic manner and this was followed by synthesis of the themes.

3.5 Analytical Engineering Pipeline

Quantitative Inference Engine

The statistical analysis was performed in SPSS v25, with an analytical flow being engineered:

1. Statistical measures of the system: Means, (Standard Deviation) SD, percentages adoption.
2. Tests of institutional variance Chi-square, t-test, Spearman 4 [encoded as institutional dependency strength].
3. Predictive inference model: 4 factor multiple linear regression.

Model Equation:

AI Adoption Willingness was estimated using the regression model shown in eq. (1).

$$\text{AI Adoption Willingness} = \beta 0+\beta 1(U)+\beta 2(I)+\beta 3(T)-\beta 4(E) \quad \ldots. (1)$$

Where:

- U = Perceived Usefulness
- I = Infrastructure Availability
- T = AI Training Exposure
- E = Ethical Concern Score

Model reliability was evaluated using:

- $R^2 = 0.61$, Adjusted $R^2 = 0.59$, $F(4,115) = 45.6$, $p < 0.001$

This confirms strong model fit for institutional adoption prediction.

Qualitative System Analyzer

NVivo 12 was used to process the interview transcripts using the 6-step Braun-Clarke thematic engineering process:

• Familiarization → Open coding → Theme engineering → Network synthesis → Validation → Report structuring

They were subsequently modeled in terms of thematic network engineering graphs and barrier priority matrices.

3.6 Ethical Compliance Engineering

System-engineered ethical safeguards were based on national compliance standards of digital health:

• Approval of the Ethics Committee of the institution before execution.
• Anonymity of participants through the use of coded system labels.
• Adoption scores that were in untraceable institutional identity.
• Voluntary participation was ensured and withdrawal flags were allowed.

3.7 Methodological Limitations

• Geographically confined to chosen groups of Indian institutions.
• Self-reported answers can be full of system optimism bias.
• Hospital differences in infrastructure can affect adoption scoring.
• The level of maturity of cross-institutional AI varies, which influences the consistency of perception.

3.8 Research Hypothesis (System-Validated Adoption Model)

Null Hypothesis (H_0):

The system-level AI determinants of perceived utility, the availability of digital infrastructure, AI competency training, and quantified ethical risk do not have statistically significant dependence on the institutional readiness or the behavioral intention of the Indian healthcare professionals to use AI-enabled clinical or administrative engineering systems.

Alternative Hypotheses:

H_1: Clinical or operational utility of AI in Perceived usefulness has a positive engineered impact on AI-enabled healthcare decision systems adoption intention.

H_2: The digital and IT infrastructure systems that are reliable in healthcare institutions have a high positive correlation with the readiness of AI adoption among healthcare professionals.

H_3: The level of engagement in formal training exposure and the design of AI competency levels has a strong positive effect on confidence and the desire to use AI-aided clinical or hospital management systems.

H_4: The moderating influence of higher ethical care or system-risk perception scores (data privacy, uncertainty in the existence of liability, and algorithmic obscurity) on the enthusiasm towards AI adoption is significantly negative in Indian healthcare engineering settings.

4. Results and Discussion

4.1 Quantitative Results

4.1.1 Descriptive System Insights

The professional group (N = 120) included clinicians (45%), hospital administrators (25%), IT/digital health system experts (20%), and public health managers (10%). As it can be seen in Fig.1, 81.7% of respondents believed that AI boosts diagnostic accuracy, 75.8% ensured that AI-assisted clinical decision engines shortened diagnostic-to-decision latency. Nevertheless, AI literacy in institutions is very poor with only 30 percent having had structured training exposure. Issues of data governance weakness became the leading areas of concern, with 66.7% indicating the risk of patient data privacy, 59.2% noting vague liability mapping, and 41.7% indicating concern regarding algorithmic transparency. These system perceptions are engineered, and Table 1 reveals an adoption-readiness paradox high perceived utility and low institutional preparedness.

Table 1. Summary of Quantitative Survey Findings (N = 120) Source: Constructed by authors

Survey Statement	Agree (%)	Neutral (%)	Disagree (%)
AI improves diagnostic accuracy	81.7	10.0	8.3
AI reduces time in clinical decision-making	75.8	15.8	8.3
AI enhances hospital administrative efficiency	70.0	20.0	10.0
Inadequate infrastructure limits AI adoption	60.8	25.0	14.2
Lack of AI training among healthcare staff	55.0	28.3	16.7
Data privacy is a concern in AI applications	66.7	20.8	12.5
Legal accountability in AI-driven decisions is unclear	59.2	25.0	15.8
AI should not fully replace human judgment	45.0	35.8	19.2
Institution offers formal AI training	30.0 (Yes)	–	70.0 (No)
Willingness to adopt AI if trained & supported	58.3 (Yes)	25.0 (Maybe)	16.7 (No)

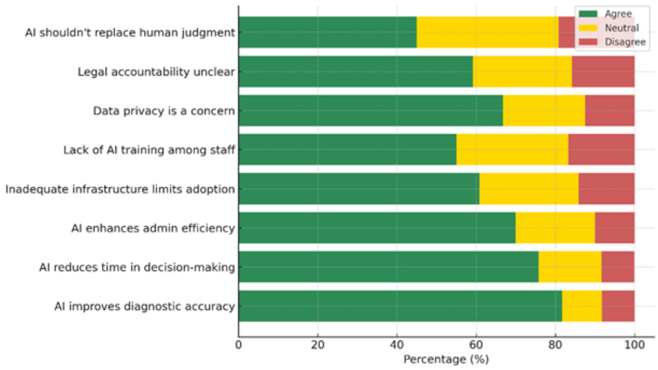

Figure 1. Healthcare Professionals' Perceptions of AI in Healthcare. (Source: Constructed by authors)

4.1.2 Spearman Rank Correlation

The dependence among inter-determinants was tested with the ϱ of Spearman, as obtained in Table 2 and depicted in Fig.2. The intent to adopt had a positive relation to perceived usefulness (ϱ = 0.62) and digital infrastructure availability (0.55) that is positive which means that adoption enthusiasm scales with the system maturity proportionally. The exposure to AI training also demonstrated a moderate positive association (1 = 0.49), which proved that the competency-designed literacy pipelines influence considerably less resistance to the adoption of the AI-enabled hospital systems. The results of ethical concern scores shared a medium negative relationship with the willingness to adopt AI (0.48), which supports the fact that the governance uncertainty has a negative impact on institutional trust and readiness to adopt AI. Another significant negative relationship was found between the infrastructure availability and the ethical risk score (= -0.41), that is, the more the hospitals had unstable digital backbones, the higher their ethical uncertainty amplification.

Table 2. Correlation Coefficients (ϱ) Among Key Variables. Source: Constructed by authors

Variables	Willingness to Adopt AI	Perceived Usefulness	Ethical Concern Score	Infrastructure Availability
Willingness to Adopt AI	1.000	0.62**	-0.48**	0.55**
Perceived-Usefulness	–	1.000	-0.36*	0.49**
Ethical Concern Score	–	–	1.000	0.41**
Infrastructure Availability	–	–	–	1.000

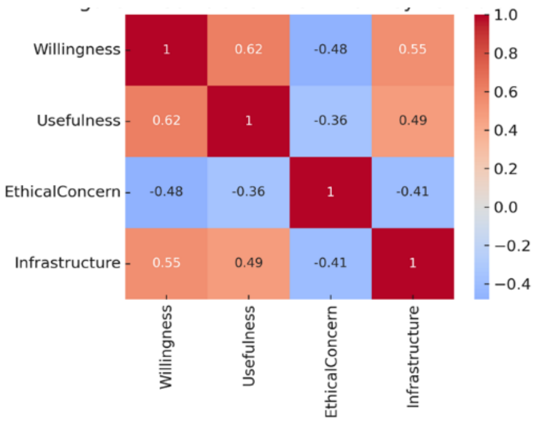

Figure 2. Correlation Matrix of Key Variables. (Source: Constructed by authors)

4.1.3 Regression-Validated Adoption Predictors

An inference engine in the form of multiple linear regression was built with the aim of modeling the willingness of AI adoption as a result of designed institutional determinants. The model attained a R 2 = 0.61 ($p < 0.001$) meaning that it is highly predictive in terms of engineering adoption behavior in healthcare. The strength of predictors is demonstrated in Fig.3 and coded statistically in Table 3.

Table 3. Multiple Linear Regression Model Summary

Predictor Variable	Unstandardized Coefficient B	Std. Error	Beta (β)	t-value	p-value
(Constant)	1.05	0.31	1.000	3.39	0.001
Perceived Usefulness	0.47	0.09	0.43	5.22	0.000**
Infrastructure Availability	0.35	0.08	0.38	4.38	0.000**
AI Training Level	0.29	0.10	0.26	2.90	0.005**
Ethical Concern Score	−0.31	0.07	−0.32	−4.43	0.000**

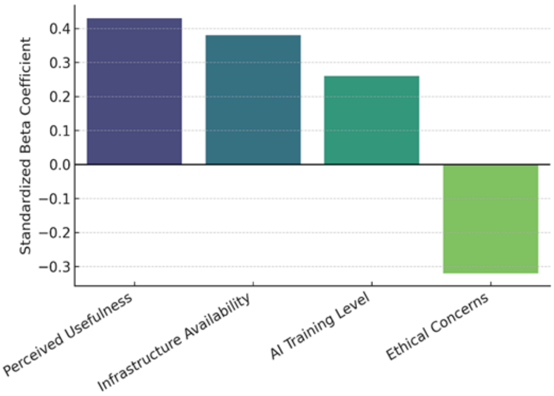

Figure 3. Predictors of AI Adoption Readiness. (Source: Constructed by authors)

Important predictor weights are:

• Perceived Usefulness (=0.43, $p < 0.01$): The strongest engineered determinant, which confirms that clinical value perception is a strong predictor of AI system acceptance.

• Infrastructure Availability (= 0.38, $p = 0.01$): Hospitals that had stable HIS/HER and high-bandwidth IT systems have indicated a high readiness to deploy AI systems.

• AI Training Exposure ($\beta = 0.26$, $p < 0.01$): Organized training in decision-support pipelines in AI competency directly raised confidence in AI-enabled pipelines.

• Ethical Concern Score ($\beta = -0.32$, $p < 0.01$): The more ethical risk scores, the more the enthusiasm to adopt AI decreased, which proved hypothesis H 4.

4.2 Qualitative Results

4.2.1 Thematic System Reliability Mapping

There were 20 key informant interviews processed by the qualitative system analyzer. Fig.4 indicates the synthesized thematic network, where engineered adoption determinants are indicated as connected nodes instead of separation barriers. All of this developed six main themes (Table 4):

1. The Conditional Optimism AI Deployment: Clinicians only view AI as revolutionary, when regulatory guardrails and accountability structures are designed into hospital processes.
2. Infrastructure is the Key Adoption Gatekeeper: Respondents pointed out that AI adoption is prevented with a bad digital infrastructure reliability especially in Tier-2 and rural hospital clusters.
3. Lack of Competency Pipelines: AI skill-gap was found to be a system-level bottleneck; AI engineering literacy was found to be lacking in most clinicians and administrators.

4. Algorithms Accountability ambiguity: The Hospitals do not have any engineered AI liability or audit trail mapping, which makes risk aversion higher.
5. Explainable AI Demand: The key informants emphasized that explainable adoption requires algorithmic interpretability, suggesting XAI and human-in-loop validation.
6. Policy and Governance Engineering Gaps: There are national frameworks, but there is no standardization of implementation, which is not scalable beyond pilot clusters.

Table 4. Emerging Themes and Representative Quotes

Theme	Representative Quote / Insight
Clinical Benefits	"AI flags early-stage cancers in radiology before a junior doctor can even recognize them." — Senior Radiologist
Training Deficiency	"We received tools but no orientation—doctors avoid what they don't understand." — Hospital Administrator
Ethical Dilemmas	"How do we explain to patients that an algorithm is making decisions?" — Consultant Physician
Infrastructure Gaps	"Rural hospitals don't have the digital backbone required for AI deployment." — State IT Officer
Policy Vacuum	"We use AI tools, but there's no standard protocol for data handling or accountability." — Digital Health Coordinator
Positive Outlook	"We're not against AI. We want to use it—responsibly, with clear guidelines." — Public Health Specialist

4.2.2 Adoption Barrier Priority Encoding

Participants recommended:

- AI literacy pipeline engineering in hospital and academic training modules.
- The national AI audit and accountability architectures.
- HIS/EHR systems standardization on interoperability.
- Explainable AI verification of opaque black-box decision engines.

4.3 Integrated Discussion

4.3.1 Institutional AI Adoption Readiness Paradox

The triangulated results support the hypothesis that the willingness to adopt AI is not limited by the perception of AI utility but institutional engineering maturity, which includes the stability of digital backbone, the competence of the workforce in AI application, the transparency of governance, and the system of risk accountability.

Regression models confirmed that 61 percent of the variation in adoption can be predicted based on engineered institutional determinants, which confirms that AI adoption in India will be a system readiness engineering problem rather than a technology awareness challenge.

4.3.2 Engineering Implications

- Hospitals having good digital infrastructure had increased confidence about adoption and reduced amplification of ethical uncertainty (Fig.2; Table 2).
- There was more adoption readiness among professionals who had formal pipeline AI training (Fig.3; Table 3).
- The ethical issues have an important downward impact on the willingness to adopt AI, particularly in the cases where there is no institutional AI liability mapping (Fig.3; Table 3).

4.3.3 System Engineering Pillars for Responsible AI Adoption

The paper confirms that integration of AI in Indian healthcare needs to be designed based on:

1. Technologic preparedness: HIS/EHR/EM stable, cloud security, high-speed network, interoperability pipelines.
2. Human Capacity Engineering: AI literacy, competency certification, integration of curriculum.
3. Ethical and Legal System architecture: AI audit trail, liability, explainability, bias validation.

The absence of these pillars makes the adoption of AI fragmented, conditional and not scalable to clusters beyond pilots.

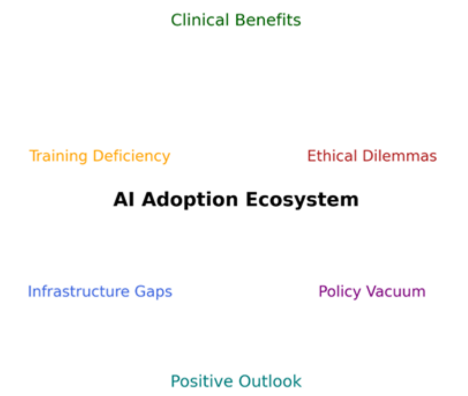

Figure 4. Thematic Network of Qualitative Insights. (Source: Constructed by authors)

5. Conclusion

The current research has developed and empirically confirmed an institutional AI adoption preparedness model of Indian healthcare systems. The results validate the hypothesis that although health workers are highly aware of the potential of AI in diagnostic and administrative processes, the lack of actual implementation is due to engineered determinants of the system and not the lack of awareness. The regression model was proved to have a high explanatory reliability ($R^2 = 0.61$, $p = 0.001$), which proved that the Perceived Usefulness (= 0.43), Infrastructure Availability (= 0.38), and AI Training Level (= 0.26) are statistically significant positive drivers, but the Ethical Concern Score (= -0.32) significantly suppresses the enthusiasm in adoption because of no standardized accountability architecture and algorithmic transparency.

Thematic system mapping served to support qualitative insights that AI adoption is considered conditional based on three important engineering pillars:

1. Digital Infrastructure Engineering Stable HIS/EHR interoperability, high-bandwidth, and secure cloud architectures: These are the pillars of scalable AI deployment.
2. Human Capacity Engineering -AI competency pipelines, certification, and curricular integration are explicitly designed to provide system confidence.
3. Ethical and Governance System Engineering - Transparent algorithmic audit trails, bias validation, liability mapping and enforceable regulatory guardrails are needed to design institutional trust.

The study informs that AI implementation in Indian healthcare is a system engineering preparedness task, with success of implementation determined with institutional maturity, infrastructure dependability, competence of workforce, and responsible AI governance structures. In case such determinants are not designed holistically, AI implementation would still be fragmented, pilot-constrained, and non-scalable.

All in all, AI must be programmed to act as a clinical judgment amplifier, and not as a physician replacing decision, so that responsible human-AI collaborative care is ensured, and not autonomous algorithm replacement.

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