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Understanding how AI acceptance shapes Employee-AI collaboration in hospitals: Insights from a pilot study

Tang Song[1], Nor 'Ain Bt Abdullahz[2]*, Zunirah Mohd Talib[3]

[1]*Department of Human Resources, Affiliated Hospital of North Sichuan Medical College, Nanchong, China*
[2]*Faculty of Business Management and Professional Studies, Management and Science University, Shah Alam, Malaysia*
[3]*Postgraduate Centre, Management and Science University, Shah Alam, Malaysia*

Abstract

The growing integration of Artificial Intelligence (AI) into healthcare highlights the need to understand how healthcare professionals collaborate with AI systems in clinical and administrative workflows. This pilot study examines how four dimensions of AI acceptance, awareness, understanding, skills, and trust, shape employee-AI collaboration in Chinese public hospitals. Using survey data from 55 hospital employees and Partial Least Squares Structural Equation Modeling (PLS-SEM), the study finds that AI trust is the strongest predictor of collaboration, followed by AI skills and AI understanding. AI awareness, however, does not significantly influence collaborative behavior. These results suggest that collaboration with AI extends beyond basic acceptance and depends on deeper psychological readiness and technical capability. The findings advance theoretical discussions by highlighting the differentiated roles of acceptance dimensions and underscore the importance of trust and competency-building in human-AI teaming. Practically, the study recommends that hospitals prioritize transparent communication, training, and skill development to foster safe and effective AI integration. As AI technologies continue to reshape healthcare delivery, strengthening the human factors that enable collaboration will be essential for maximizing their clinical and organizational value.

Keywords: AI acceptance, Employee-AI collaboration, Healthcare technology, Trust in AI, Technology acceptance model, Human-AI interaction, PLS-SEM pilot

1.Introduction

Artificial Intelligence (AI) technologies are rapidly reshaping clinical care and hospital management by enhancing diagnostic accuracy, streamlining workflow processes, and enabling data-driven decision support. However, successful AI integration in healthcare depends not only on technical capability but also on the acceptance, readiness, and engagement of healthcare employees who must interact with these systems daily. Numerous studies indicate that AI-driven transformations can create feelings of uncertainty, job insecurity, and emotional strain among medical staff, particularly when employees perceive AI as a threat to their professional identity or employment stability (Sharma et al., 2025). These anxieties can reduce willingness to engage with AI tools and may hinder effective technology assimilation, making the human dimension of AI adoption an urgent management challenge in hospital environments.

Employee-AI Collaboration (EAC) refers to the interactive, task-oriented process through which employees and AI systems jointly contribute to organizational workflows (Sun et al., 2025). In digitalized workplaces, such collaboration has been identified as a strategic capability that can improve service quality, enhance employee proactivity, and reduce cognitive workload when implemented effectively (Al-Qerem et al., 2025; Yang et al., 2017). Within healthcare, collaborative work between clinicians and AI, such as diagnostic algorithms, decision support systems, and conversational agents, is increasingly viewed as essential for achieving high-performing, technology-enabled hospital operations (Wessel et al., 2024). Yet many healthcare institutions continue to experience low trust in AI, insufficient AI literacy, and limited staff skills to use AI tools optimally. These human-related barriers remain among the most commonly cited impediments to successful AI implementation (Li et al., 2025).

Although technology acceptance models, particularly the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) have provided substantial insights into employees' attitudes, perceived usefulness, and intentions to use digital systems, most AI-in-healthcare studies continue to focus only on intention or attitude rather than the actual collaborative

Correspondence: Nor 'Ain Bt Abdullahz, Faculty of Business Management and Professional Studies, Management and Science University, Shah Alam, Malaysia, **e-mail:** norain _abdullah@msu.edu.my, **Received:** November 1, 2025 **Accepted:** December 10, 2025

behaviors that emerge after acceptance (Dwivedi et al., 2019). This limitation is significant because the degree to which employees collaborate with AI by integrating AI recommendations, delegating tasks, or jointly interpreting clinical outputs may differ widely, even among employees with similar acceptance levels. Furthermore, although some research shows that AI awareness can elicit negative reactions such as heightened fear of job displacement (Arboh et al., 2025), there remains limited empirical evidence examining how positive acceptance-related factors facilitate constructive collaboration with AI systems.

To address this gap, the present study investigates four core dimensions of AI acceptance identified across the literature: AI awareness, AI understanding, AI skills, and AI trust. These dimensions respectively reflect employees' recognition of AI's presence and organizational role, their comprehension of AI technologies, their competence in using AI tools, and their confidence in AI system outputs. We propose that these acceptance dimensions serve as antecedents to employee-AI collaboration in healthcare contexts. Understanding this acceptance → collaboration linkage is essential for designing effective AI implementation strategies, building employee capability, and improving human-AI teaming in hospitals.

Accordingly, this study pursues three primary objectives: (a) to develop a theoretical model linking the four AI acceptance dimensions to employee-AI collaboration; (b) to empirically test this model using pilot data collected from healthcare employees; and (c) to articulate implications for technology acceptance theory and human resource management in healthcare organizations. The study deliberately focuses on antecedents of collaboration; downstream outcomes, such as workflow efficiency, quality of care, or employee performance, will be examined in the broader dissertation project.

2 Literature Review

2.1 AI acceptance in organizations

AI acceptance is a critical determinant of whether technology-enabled systems deliver value in organizational settings. Early frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) emphasize the importance of perceived usefulness, ease of use, and performance expectancy as drivers of individual adoption decisions (Dwivedi et al., 2017). Although these models have been applied extensively across information systems research, scholars increasingly note that AI differs fundamentally from earlier technologies because its autonomous and opaque nature introduces psychological, ethical, and socio-organizational considerations not fully addressed by traditional acceptance theories (Gelashvili-Luik et al., 2025). In particular, employees may evaluate AI not only in terms of usability but also in terms of its implications for professional autonomy, job roles, and identity.

Recent empirical evidence suggests that AI acceptance is shaped by both cognitive assessments and emotional responses. For instance, healthcare workers may resist AI when they fear that AI systems might displace human expertise or undermine professional judgment (Rony et al., 2024). Perceived threats to job security and concerns about algorithmic bias or errors can exacerbate negative reactions, even when the technology demonstrates clear functional benefits. Conversely, transparent communication about the goals, capabilities, and limitations of AI can strengthen acceptance by reducing uncertainty and encouraging employees to view AI as an augmentation tool rather than a replacement.

Organizational conditions further influence AI acceptance. Leaders who articulate a coherent vision of AI-enabled transformation, provide sufficient training resources, and foster a supportive climate for technological learning contribute to stronger adoption outcomes. Employees demonstrate higher acceptance when AI initiatives are accompanied by opportunities to develop competence, when work processes are redesigned collaboratively, and when psychological safety is established around learning and experimenting with new technologies (Mills & Watson, 2021). These findings underscore the multidimensional nature of AI acceptance and highlight the importance of organizational context in shaping how employees perceive and engage with AI tools.

2.2 Human-AI collaboration

Human-AI collaboration refers to the interactive

process through which human workers and AI systems jointly engage in tasks that require shared decision-making, complementary strengths, and coordinated action. Unlike traditional human-computer interaction, collaboration with AI involves reciprocal influence, as AI systems increasingly participate in tasks that require autonomy, prediction, and adaptive learning (Strielkowski et al., 2024). In healthcare, AI applications such as diagnostic support, patient risk stratification, and automated documentation require clinicians to interpret, validate, and integrate algorithmic outputs into their workflows. This relational aspect positions AI not merely as a tool but as a partner that shapes and supports clinical decision-making.

The success of human-AI collaboration hinges on employees' ability to develop calibrated trust and an accurate mental model of how AI systems function. Research indicates that collaboration improves when employees understand AI's strengths, such as processing large data sets, and its limitations, such as susceptibility to biased inputs or reduced performance in atypical cases (Romeo & Conti, 2025). Effective collaboration also requires employees to feel psychologically comfortable engaging with AI, particularly in complex or high-stakes environments such as hospitals. If employees experience anxiety, distrust, or role insecurity, the quality of collaboration may decline, resulting in underutilization of AI tools or over-reliance without appropriate scrutiny.

As AI systems become more sophisticated, organizations must support employees in developing the competencies needed to collaborate effectively. Collaboration requires more than technical interaction skills; it demands cognitive flexibility, willingness to adapt workflows, and the capacity to integrate human judgment with algorithmic insights (Magliocca et al., 2024).

In the healthcare domain, where clinical expertise and ethical sensitivity are essential, achieving productive human-AI collaboration is especially critical. However, the literature remains limited on the antecedents of such collaboration, particularly the role of employee acceptance.

2.3 Key dimensions of AI acceptance: Awareness, understanding, skills, and trust

A growing body of research highlights four acceptance-related factors, AI awareness, AI understanding, AI skills, and AI trust, that are especially relevant to employees' ability to collaborate effectively with AI systems. AI awareness refers to the extent to which employees recognize the presence, functions, and organizational role of AI technologies. Awareness is foundational because employees cannot meaningfully adopt or collaborate with technologies they do not fully perceive or understand. However, awareness may generate ambivalent reactions; while it enables informed engagement, it may also heighten concerns about job displacement or workflow disruption if the purpose of AI implementation is not clearly communicated (Rane et al., 2024).

AI understanding encompasses employees' conceptual comprehension of how AI systems operate, including their logic, data requirements, strengths, and limitations. Understanding contributes to calibrated trust and appropriate reliance, empowering employees to critically interpret AI recommendations. Studies show that employees with higher levels of understanding are less susceptible to algorithm aversion and more capable of integrating AI into complex decision-making processes (Brink et al., 2023; Jam et al., 2017). In healthcare, understanding is particularly important because clinicians must judge when AI outputs align with clinical reasoning and when human expertise should override algorithmic suggestions.

AI skills refer to employees' technical and procedural ability to use AI tools effectively. These skills include the capacity to interpret AI-generated data, navigate decision support interfaces, and integrate AI insights into work routines. Skill development is closely tied to organizational training initiatives, which have been shown to enhance employee confidence and reduce resistance to AI (Maity, 2019). Without adequate skills, employees may feel overwhelmed or incompetent, limiting their willingness to engage with AI collaboratively.

AI trust is widely recognized as a central determinant of sustained engagement with AI systems. Trust

reflects employees' perceptions of AI reliability, accuracy, transparency, and alignment with professional and organizational goals. When trust is high, employees are more likely to rely on AI recommendations and integrate AI tools into their decision-making processes; when trust is low, collaboration deteriorates (Wen et al., 2025). In clinical contexts, where decisions carry significant consequences, trust is indispensable. Employees must believe not only that AI produces accurate outputs but also that it does so consistently and fairly across different patient populations.

2.4 Linking AI acceptance to Employee-AI collaboration

Research increasingly suggests that AI acceptance serves as a precursor to effective human–AI collaboration. Employees who are aware of AI's functions, understand how AI systems operate, possess the necessary skills to use AI tools, and trust AI outputs are more likely to engage in productive collaboration. These acceptance dimensions provide the cognitive, emotional, and behavioral foundation needed for employees to integrate AI into their work processes. Collaboration demands not only a willingness to use AI but also the capability to interpret, evaluate, and coordinate actions with AI systems.

Although existing studies provide valuable insights into acceptance factors and collaboration dynamics, few have empirically examined how acceptance translates into collaborative behavior in healthcare settings. This gap is significant because collaboration involves deeper engagement than simple system use; it requires the integration of AI recommendations into clinical workflows, joint problem-solving, and coordinated decision-making. Understanding the acceptance → collaboration linkage is therefore essential for healthcare organizations seeking to maximize the value of AI-based tools. The present study contributes to this emerging field by investigating how four core acceptance dimensions influence employee-AI collaboration in hospital environments.

AI awareness, understanding, skills, and trust collectively form the core acceptance factors that shape how employees perceive and engage with AI systems. When these factors are strong, employees are more willing and able to collaborate effectively with AI in their daily tasks.

H1: AI awareness is positively associated with employee-AI collaboration.

H2: AI understanding is positively associated with employee-AI collaboration.

H3: AI skills are positively associated with employee-AI collaboration.

H4: AI trust is positively associated with employee-AI collaboration.

3 Methodology

3.1 Research design and sampling

The study employed an empirical pilot investigation using a cross-sectional survey design. The target population comprised hospital employees in China who work with or alongside AI-based systems. Chinese public hospitals were selected as the study context because they have increasingly incorporated AI technologies for applications such as medical imaging analysis, electronic medical records, patient triage, and administrative decision support. This setting is particularly relevant, as the effective implementation of AI in hospitals depends substantially on employee acceptance and collaboration, yet many institutions continue to face staff apprehension toward emerging technologies.

Data were collected through convenience and purposive sampling, yielding responses from N = 55 employees in a major public hospital in China during the pilot phase. The sample included doctors, nurses, and administrative staff working in departments where AI systems had been deployed (e.g., radiology, patient registration, hospital information management). Participation was voluntary, and anonymity was assured. Among the respondents, approximately 58% identified as female and 42% as male. Ages ranged from the early 20s to late 50s, with an estimated mean age of 35 years based on self-report. Approximately 38% reported having received formal training in the use of AI tools, while 62% indicated no prior AI-specific training, providing a diverse range of AI-related experience and competence levels.

Although modest in size, the sample is consistent with recommended thresholds for pilot studies using partial least squares structural equation modeling (PLS-SEM), particularly when the objective is to assess instrument reliability and detect large effect sizes. The pilot results, therefore, serve primarily as an initial feasibility assessment of the measurement instrument and as an exploratory test of the proposed hypotheses. Statistical analyses were conducted using established PLS-SEM procedures, described in detail in the subsequent section.

3.2 Measurement

AI Awareness (AA). AI awareness was assessed using the *Artificial Intelligence Awareness Scale (AIAS)* developed by Kaya and Bayram (2025), one of the few empirically validated instruments for measuring employees' awareness of AI technologies in organizational settings. The scale evaluates the extent to which individuals recognize the presence of AI systems in their work environment, understand AI-related developments, and perceive AI as relevant to their professional tasks. In its original validation study, the AIAS demonstrated strong psychometric properties, including satisfactory factor loadings and a Cronbach's alpha of .83, across diverse occupational groups, providing evidence of its reliability and construct validity. Its applicability to healthcare employees was additionally supported by the inclusion of hospital-sector participants in the original dataset.

For the current study, the AIAS was adapted to reflect the specific context of Chinese public hospitals where AI-supported diagnostic and administrative systems have recently been introduced. The wording of items was adjusted to ensure relevance to clinical and administrative workflows, and the instrument underwent translation–back-translation procedures to maintain conceptual equivalence in Chinese. Respondents rated each item on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree), with higher scores indicating greater awareness of AI technologies and their potential implications for daily work. Expert review by healthcare management scholars and pilot testing with hospital staff confirmed the suitability and clarity of the adapted instrument for measuring AI awareness among healthcare employees.

AI Understanding (AU). AI understanding was measured using the *AI Knowledge Scale (AIKS)* developed by Shin (2020), a validated instrument designed to assess users' comprehension of how AI systems function. The AIKS evaluates an individual's perceived understanding of algorithmic logic, familiarity with how AI systems process information, and ability to interpret AI-generated outputs. In its original validation, the scale demonstrated solid reliability and construct validity, capturing users' intellectual grasp of AI mechanisms as opposed to mere awareness or exposure. Shin's framework has since been widely recognized in studies examining human perceptions of algorithmic decision-making, particularly in contexts where employees interact with AI-supported systems.

For the present study, items from the AIKS were adapted to reflect the operational environment of Chinese public hospitals, where staff increasingly engage with AI-driven diagnostic tools, clinical decision-support systems, and administrative algorithms. The adaptation focused on maintaining the scale's emphasis on cognitive understanding while ensuring contextual relevance for healthcare tasks. A translation-back-translation procedure was employed to ensure linguistic and conceptual equivalence for Chinese-speaking respondents. Items were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), with higher scores indicating a stronger self-assessed understanding of AI principles and outputs. Expert review and pilot testing confirmed the clarity and appropriateness of the adapted instrument for assessing AI understanding in the healthcare setting.

AI skills. AI skills were measured using the Meta Artificial Intelligence Literacy Scale (MAILS) developed by Carolus, Koch, Straka, Latoschik, and Wienrich (2023). MAILS is a validated instrument designed to assess a broad set of AI-related competencies, including subdimensions such as "Use & Apply AI" and "AI Self-Efficacy/Competence," which correspond closely to the operational and practical skills required to interact effectively with AI-enabled systems. In its original validation, MAILS demonstrated satisfactory psychometric properties, including a clear factor structure and adequate internal reliability.

For adaptation to the Chinese hospital context,

relevant items from the "Use & Apply AI" and "AI Self-Efficacy" subscales were translated via a translation-back-translation procedure, then reviewed by healthcare technology experts for contextual appropriateness. Respondents rated their agreement on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), with higher scores indicating greater perceived competence in using and managing AI tools. Pilot testing confirmed that the adapted items were comprehensible and relevant to hospital workflows, supporting the use of MAILS as an operational measure of AI skills in healthcare settings.

AI Trust (AT). AI trust was measured using items adapted from the Trust in Automated Systems Scale developed by Jian et al. (2000). This scale is one of the most widely validated instruments for assessing user trust in machine- or algorithm-driven systems and has been applied across domains including healthcare, aviation, and human–computer interaction. The scale captures multiple dimensions of trust, including perceived reliability, dependability, predictability, and confidence in automated decision outputs. In its original validation, the instrument demonstrated strong psychometric properties and has since become a foundational measure in studies examining how humans evaluate and rely on automated or AI-assisted systems.

For application in the hospital context, items were adapted to reference AI-based diagnostic and administrative tools commonly used in Chinese public hospitals. Statements reflected employees perceived confidence in the accuracy of AI recommendations, willingness to rely on AI outputs, and general expectations of AI system dependability. All items were rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree), with higher scores indicating greater trust in AI systems. A translation–back-translation procedure ensured linguistic clarity and conceptual equivalence for Chinese respondents, and expert review confirmed the contextual appropriateness of the adapted items. Pilot testing further supported the clarity and relevance of the instrument for assessing trust in AI among healthcare employees.

Employee-AI Collaboration (EAC). Employee-AI collaboration was measured using the validated 5-item scale developed by Kong et al. (2023). This scale was created to assess employees' collaborative engagement with AI tools in organizational contexts and has demonstrated strong psychometric properties across two separate studies, including a multi-wave dataset of employee–supervisor dyads. The scale captures core aspects of human-AI collaboration, such as the extent to which employees integrate AI into their workflows, perceive AI as a collaborative partner, and coordinate their actions with AI-generated recommendations. Because this measure was specifically designed to operationalize employee-AI collaboration rather than general technology use, it represents the most empirically grounded instrument currently available for this construct.

For the present study, the scale items were adapted slightly to reflect the hospital environment in which employees interact with AI-based diagnostic, administrative, and decision-support systems. A translation–back-translation procedure ensured conceptual equivalence for Chinese-speaking participants, and two experts in healthcare management reviewed the adapted wording for contextual appropriateness. Respondents rated each item on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), with higher scores indicating greater perceived collaboration with AI systems. Pilot testing with hospital staff confirmed the clarity and face validity of the instrument. This approach provides a rigorous and theoretically supported measurement of employee-AI collaboration in the healthcare setting.

3.3 Data analysis

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), which is appropriate for prediction-oriented research, exploratory model testing, and studies with relatively small sample sizes. PLS-SEM was selected because the present investigation represents a pilot study designed to assess the initial validity of the proposed measurement instruments and to examine the preliminary relationships between AI acceptance factors and employee-AI collaboration. All analyses were conducted using Smarts 4.0, following established guidelines for measurement and structural model evaluation.

The analysis proceeded in two stages. First, the

measurement model was assessed by examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Indicator reliability was evaluated using standardized factor loadings, with values ≥ 0.70 considered acceptable. Internal consistency was assessed through Cronbach's alpha and composite reliability (CR), both expected to exceed 0.70. Convergent validity was evaluated using the average variance extracted (AVE), with the recommended threshold of ≥ 0.50. Discriminant validity was examined using the heterotrait–monotrait ratio (HTMT), ensuring all values were below 0.85.

After establishing adequate measurement properties, the structural model was evaluated. Collinearity diagnostics were examined using variance inflation factors (VIF). Path coefficients were estimated through bootstrapping with 5,000 resamples to obtain significance levels and confidence intervals for the hypothesized relationships. The model's predictive ability was assessed using the coefficient of determination (R^2) for the endogenous variable (Employee-AI Collaboration) and effect size estimates (f^2) for exogenous constructs. In addition, Stone–Geisser's Q^2 values were generated through blindfolding to evaluate predictive relevance. Interpretation followed conventional benchmarks for pilot behavioral research.

This structured analytical approach ensures robust preliminary validation of the measurement instruments and provides an initial empirical test of the theoretical model linking AI acceptance factors to employee-AI collaboration in a healthcare context.

4 Results

4.1 Descriptive statistics and correlations

Table 1 presents the descriptive statistics and intercorrelations for the five study constructs. Overall, respondents reported moderately positive perceptions of AI, with mean scores ranging from 3.58 to 3.89 on a 5-point scale. AI Awareness (M = 3.89, SD = 0.61) and AI Trust (M = 3.86, SD = 0.63) were rated highest, indicating that hospital employees were generally aware of and receptive to the AI tools operating within their work environment. Employee-AI Collaboration (EAC) also showed a relatively high mean (M = 3.74, SD = 0.67), suggesting that AI is becoming an increasingly integrated component of healthcare workflow.

Correlations revealed theoretically consistent patterns: EAC showed the strongest associations with AI Trust (r = .63) and AI Skills (r = .57), followed by AI Understanding (r = .45). AI Awareness displayed a comparatively weaker correlation with EAC (r = .31), indicating that recognition of AI's presence alone may not translate directly into collaborative engagement.

Table 1. Descriptive statistics and correlations (N = 55)

Construct	Mean	SD	AA	AU	ASK	AT	EAC
AA	3.89	0.61	1				
AU	3.77	0.66	0.41	1			
ASK	3.58	0.72	0.37	0.52	1		
AT	3.86	0.63	0.34	0.47	0.54	1	
EAC	3.74	0.67	0.31	0.45	0.57	0.63	1

4.2 Measurement model

The reliability and validity of the reflective measurement model were assessed before hypothesis testing. All standardized item loadings were above the recommended threshold of .70, indicating satisfactory indicator reliability. Cronbach's alpha values ranged from .84 to .90, and Composite Reliability (CR) values ranged from .89 to .94, demonstrating strong internal consistency across constructs. Average Variance Extracted (AVE) values ranged from .67 to .79, exceeding the .50 criterion and establishing convergent validity.

Discriminant validity was examined using the heterotrait–monotrait ratio (HTMT). All HTMT values fell below .85, supporting the distinctiveness of the five constructs. Collectively, these results confirm that the adapted AIAS, AIKS, MAILS, Jian et al. (2000) trust items, and the Kong et al. (2023) EAC scale are psychometrically robust in the healthcare context.

Table 2. Measurement model results

Construct	Item	Loading	Cronbach's α	CR	AVE
AA	AA1	0.81	0.84	0.89	0.67
	AA2	0.84			
	AA3	0.86			
	AA4	0.79			
AU	AU1	0.83	0.87	0.92	0.74
	AU2	0.89			
	AU3	0.85			
ASK	ASK1	0.88	0.88	0.93	0.77
	ASK2	0.9			
	ASK3	0.85			
AT	AT1	0.86	0.9	0.94	0.79
	AT2	0.91			
	AT3	0.89			
EAC	EAC1	0.84	0.89	0.93	0.73
	EAC2	0.88			
	EAC3	0.86			
	EAC4	0.82			
	EAC5	0.85			

Table 3. HTMT Matrix

	AA	AU	ASK	AT	EAC
AA	—				
AU	0.62	—			
ASK	0.54	0.67	—		
AT	0.49	0.59	0.7	—	
EAC	0.45	0.64	0.78	0.82	—

Note. All HTMT values < .85, supporting discriminant validity

4.3 Structural model

Variance inflation factors (VIFs) ranged from 1.32 to 2.11, indicating no multicollinearity concerns, and bootstrapping with 5,000 resamples was used to evaluate the hypothesized relationships. The results showed that AI Trust (AT) was the strongest predictor of Employee–AI Collaboration (EAC; β = .42, $p < .001$), highlighting the central role of employees' confidence in AI reliability. AI Skills (ASK) also had a substantial effect (β = .33, $p = .003$), suggesting that employees who feel competent using AI tools collaborate more effectively. AI Understanding (AU) contributed positively but more modestly (β = .19, $p = .041$), indicating that conceptual knowledge supports but does not drive collaboration. In contrast, AI Awareness (AA) was not significantly related to EAC (β = .07, $p = .238$), suggesting that awareness alone does not translate into collaborative behavior. Overall, the four predictors explained 57% of the variance in EAC ($R^2 = .57$), with a Stone–Geisser Q^2 value of .36, demonstrating strong predictive relevance for a pilot model.

Table 4. Structural model results

Path	β	t-value	*p*-value	f^2	Supported
AA → EAC	0.07	1.18	0.238	0.01	No
AU → EAC	0.19	2.06	0.041	0.04	Yes
ASK → EAC	0.33	3.01	0.003	0.12	Yes
AT → EAC	0.42	4.38	<.001	0.24	Yes

Table 5. Explained variance and predictive relevance

Endogenous Variable	R^2	Q^2
Employee–AI Collaboration (EAC)	0.57	0.36

The findings offer compelling preliminary evidence that trust, skills, and understanding represent core mechanisms fostering employee-AI collaboration in healthcare settings. AI Trust emerged as the most influential factor, consistent with research

highlighting trust as a prerequisite for human reliance on AI-assisted decisions. AI Skills also played a substantial role, emphasizing the importance of technical proficiency in enabling employees to leverage AI effectively. AI Understanding contributed modestly but significantly, suggesting that comprehension enhances confidence and appropriate use. Conversely, AI Awareness alone did not translate into collaborative behavior, reinforcing the idea that awareness must be accompanied by deeper engagement to motivate active collaboration.

Discussion

This study examined how four dimensions of AI acceptance, awareness, understanding, skills, and trust, influence employee-AI collaboration in Chinese public hospitals. As AI becomes increasingly embedded in clinical decision-making, diagnostic support, and administrative processes, understanding the human factors that enable effective collaboration is essential for ensuring both organizational performance and patient safety. Although previous work in healthcare technology adoption has largely emphasized clinicians' intentions to use digital systems, this study expands the focus to examine how employees move beyond mere acceptance toward meaningful collaborative engagement with AI systems. The results show that the four acceptance dimensions do not exert the same influence; instead, trust, skills, and understanding play more decisive roles, while awareness alone is insufficient to drive collaboration.

The finding that AI trust emerged as the strongest predictor of employee-AI collaboration is particularly significant in the healthcare context. Workflows in hospitals involve high-stakes decisions in which the perceived reliability and safety of AI systems directly affect whether employees incorporate AI recommendations into clinical or administrative tasks. When employees believe that AI tools are accurate, dependable, and aligned with medical standards, they are more willing to rely on AI outputs and integrate them into their practices. This aligns with longstanding research emphasizing trust as a necessary precursor to human reliance on intelligent systems. In contrast, when trust is lacking, employees may disregard AI-generated insights even when those insights have the potential to improve efficiency or diagnostic accuracy.

AI skills also played an influential role in predicting collaboration. Healthcare professionals must work in environments characterized by time sensitivity, information overload, and procedural precision. Employees with stronger AI-related competencies are better able to engage with AI tools effectively, navigate interfaces, troubleshoot routine issues, and make informed judgments about when to accept or challenge AI input. This suggests that technical competence is no longer peripheral but central to contemporary clinical and administrative work, especially in hospitals that increasingly depend on algorithmic tools to manage patient flows, resource allocation, and diagnostic imaging.

AI understanding contributed modestly yet significantly to collaboration, indicating that conceptual knowledge about how AI systems function helps employees interpret outputs more appropriately. Understanding how an AI model processes information or generates risk assessments allows staff to make calibrated decisions about when AI recommendations should be trusted or overridden. In healthcare, where overreliance on technology or misinterpretation of outputs can have serious consequences, this type of understanding supports safer and more responsible integration of AI into daily workflows. Nonetheless, the smaller effect size relative to trust and skills suggests that understanding is helpful but not sufficient without the confidence and capability to use AI tools effectively.

In contrast, AI awareness did not significantly predict collaboration. Although employees were generally aware that AI had been introduced in their departments and recognized its potential relevance to their work, this awareness did not translate into meaningful behavioral engagement. This finding highlights an important distinction between knowing about AI and being prepared to collaborate with it. In hospital environments, where workflows are complex and responsibilities are tightly coupled to patient outcomes, awareness must be supplemented by more substantive psychological and behavioral foundations. Awareness-raising initiatives, often a key component of digital transformation campaigns, may therefore be insufficient on their own to encourage deeper forms of human-AI teaming.

These findings jointly contribute to the literature by

illuminating how different facets of AI acceptance influence collaborative behavior in healthcare. They extend traditional technology acceptance frameworks by demonstrating that acceptance is not a uniform construct and that its dimensions vary substantially in their behavioral implications. The results also contribute to broader discussions on human-AI collaboration by showing that collaboration requires more than system availability or basic user buy-in; it depends on relational, cognitive, and skill-based elements that collectively support shared task performance. This reinforces perspectives that frame AI not merely as a tool but as a partner whose successful integration requires human readiness at multiple levels.

Several practical implications arise for healthcare administrators and policymakers. Building trust in AI systems should be a central priority during implementation, especially given the sensitivity of clinical tasks. Transparent communication about AI model performance, opportunities for staff to examine how AI recommendations are generated, and ongoing feedback between clinical experts and system developers may enhance employees' confidence in AI tools. Equally important is the provision of structured and continuous training that builds AI-related skills. Healthcare workers cannot be expected to collaborate effectively with AI without hands-on experience and operational fluency. Training programs should also aim to improve employees' conceptual understanding of AI mechanisms, as such understanding supports more accurate interpretation and safer use of AI outputs. Importantly, these findings caution against relying solely on awareness campaigns, which may raise interest but are unlikely to foster the level of engagement required for true collaboration.

From a human resource management perspective, the results highlight the need for hospitals to integrate AI readiness into competency frameworks, professional development pathways, and performance evaluation systems. As AI becomes more deeply woven into healthcare delivery, the ability to collaborate with AI systems may emerge as a key professional attribute alongside clinical knowledge and interpersonal skills. Organizational cultures that support learning, experimentation, and psychological safety may help staff overcome apprehension and develop stronger collaborative relationships with AI technologies.

Despite the valuable insights generated, this study has limitations. The pilot sample was relatively small and drawn from a single public hospital, which may constrain generalizability. Future research should incorporate larger, multisite samples and examine potential differences across departments or professional roles. Longitudinal approaches could illuminate how trust, skills, and collaboration evolve as AI systems mature and become more integrated into routine operations. Qualitative studies may also provide deeper insight into the contextual dynamics shaping human-AI collaboration, such as clinical hierarchies, ethical considerations, and workflow constraints. Further research could also investigate how collaboration influences downstream outcomes such as diagnostic accuracy, treatment efficiency, job satisfaction, and patient safety.

In conclusion, this study demonstrates that trust, skills, and understanding are key determinants of employee-AI collaboration in healthcare environments. Awareness alone is insufficient, underscoring the importance of fostering deeper forms of AI readiness among hospital staff. By identifying the determinants of collaborative interaction with AI, this study offers theoretical insight and practical guidance for healthcare organizations seeking to leverage AI technologies safely and effectively. As AI continues to transform hospital operations and clinical workflows, a nuanced understanding of the human dimensions of collaboration will be crucial for realizing AI's full potential in healthcare delivery.

Conclusion

This study offered a focused examination of how employees in Chinese public hospitals collaborate with AI technologies, highlighting the distinct roles of AI awareness, understanding, skills, and trust. As AI becomes increasingly embedded in healthcare, from diagnostic imaging and clinical decision support to administrative automation, understanding the human factors that shape collaboration is essential for ensuring safe, effective, and sustainable integration into hospital workflows. The findings from this pilot study demonstrate that not all dimensions of AI acceptance contribute equally to employee-AI collaboration. Instead, trust, skills, and

understanding emerge as the primary drivers of collaborative engagement, whereas awareness alone is not sufficient to motivate meaningful behavioral interaction with AI.

The central conclusion is that employee-AI collaboration is not a passive byproduct of AI adoption but the outcome of deeper psychological and competency-based readiness. AI trust proved to be the strongest determinant, underscoring that healthcare professionals must perceive AI systems as reliable and clinically sound before integrating them into their workflows. AI skills and understanding also made significant contributions, suggesting that employees are more likely to collaborate when they feel technically capable and conceptually informed. These findings reinforce the idea that collaboration with AI requires both cognitive confidence and operational fluency, particularly in high-stakes clinical and administrative environments.

The study advances theoretical discourse by illustrating that AI acceptance is multidimensional and that its subcomponents exert differentiated behavioral effects. This contributes to ongoing debates in health informatics and organizational behavior regarding how humans form working relationships with intelligent systems. Practically, the results emphasize the need for hospital administrators and policymakers to move beyond awareness campaigns and instead prioritize trust-building, competency development, and transparent communication about AI systems. Effective AI implementation in healthcare requires strategic, human-centered approaches that enhance staff readiness and cultivate an environment where AI is perceived not merely as a technological tool, but as a reliable, supportive component of clinical and operational processes.

While this study provides valuable preliminary insights, its pilot nature and limited sample size call for further research. Larger and more diverse samples, longitudinal designs, and qualitative investigations would deepen understanding of how employee-AI collaboration develops over time and across different healthcare settings. Future research should also examine downstream organizational outcomes, such as clinical accuracy, workflow efficiency, patient care quality, and staff well-being.

In sum, this study highlights the foundational roles of trust, skills, and understanding in fostering effective employee-AI collaboration in healthcare. As hospitals continue to incorporate AI technologies, prioritizing these dimensions will be essential for ensuring that AI augments, rather than disrupts, clinical and administrative work. Strengthening these human factors will not only support successful AI integration but also contribute to safer, more efficient, and more responsive healthcare delivery in the era of intelligent systems.

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