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# Integrating technology anxiety into the TPB-TAM framework to examine AI adoption intention in hospital HRM: a study of Chinese healthcare professionals

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**Abstract**

Artificial intelligence (AI) can empower healthcare professionals to make data-driven decisions and streamline administrative tasks in hospital human resource management (HRM). However, it is vital to understand their perceptions towards AI for seamless implementation in practice. Therefore, the study aimed to assess the role of technology anxiety within an integrated framework combining the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) to better understand adoption intentions in this high-stakes context. A cross-sectional survey was conducted among 547 healthcare professionals working in hospitals across China. Data were analyzed using structural equation modeling, including confirmatory factor analysis, path analysis, and bootstrap mediation testing. Multi-group structural equation modeling was also used to compare healthcare professionals with different levels of AI familiarity. The integrated model explained 49.4% of the variance in behavioral intention, and all twelve hypothesized paths were statistically significant. Technology anxiety was negatively associated with perceived ease of use (β = -0.553, $p<0.001$), perceived behavioral control (β = -0.371, $p<0.001$), attitude (β = -0.339, $p<0.001$), and subjective norms (β = -0.451, $p<0.001$), and it was also associated with behavioral intention through multiple indirect pathways. Multi-group analysis showed that the association between perceived ease of use and perceived usefulness was stronger among professionals with low AI familiarity, while the remaining paths remained stable across groups. AI adoption intention in hospital HRM appears to involve more than rational evaluations of usefulness and ease of use. Emotional states, such as technology anxiety, also play a role. Reducing technology anxiety and improving ease of use for users with lower AI familiarity are therefore important steps for promoting AI adoption intention. These findings highlight the value of addressing emotional factors alongside cognitive beliefs when introducing AI tools in healthcare organizations.

**Keywords** Technology acceptance model · Theory of planned behavior · Technology anxiety · AI adoption intention · Healthcare professionals · Hospital human resource management

**Abbreviations**

| | |
|---|---|
| AI | Artificial intelligence |
| ATT | Attitude toward using |

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| | |
|---|---|
| AVE | Average variance extracted |
| BI | Behavioral intention |
| C.R. | Critical ratio |
| CFI | Comparative fit index |
| CI | Confidence interval |
| CR | Composite reliability |
| DF | Degrees of freedom |
| HRM | Human resource management |
| PBC | Perceived behavioral control |
| PEOU | Perceived ease of use |
| PU | Perceived usefulness |
| RMSEA | Root mean square error of approximation |
| S.E. | Standard error |
| SN | Subjective norms |
| SRMR | Standardized root mean square residual |
| TA | Technology anxiety |
| TAM | Technology acceptance model |
| TLI | Tucker-Lewis index |
| TPB | Theory of planned behavior |

## Introduction

Artificial intelligence (AI) has emerged as a prominent factor across industries worldwide, driven by its capacity to automate repetitive operations, enhance decision-making, and boost productivity[1,2]. The digital transformation of healthcare is rapidly expanding AI's role from clinical applications into operational management. It is expected to substantially reshape how hospitals organize and deploy their workforce[3]. In the contemporary healthcare landscape, the success of modern hospitals is increasingly dependent on their workforce, which remains their most invaluable asset[1]. In recent years, AI has begun to change Human Resource Management (HRM). It now supports key functions such as recruitment, employee engagement, and performance evaluation[4–6]. AI technologies present significant opportunities to enhance the efficiency and efficacy of HR operations, optimize decision-making, and ultimately improve patient care[7–9]. The post-pandemic era has further emphasized the continued necessity for healthcare organizations to adopt AI, particularly as they face workforce shortages and the limitations of traditional HR methods, which can be laborious, resource-demanding, and occasionally inadequate in addressing the unique challenges of the healthcare sector[1,10]. Hospital HRM involves high-stakes tasks where inefficiencies may directly affect staff well-being, operational costs, and patient care quality[11]. While existing research has focused extensively on clinical AI applications, the adoption of AI in hospital HRM, a domain involving high-stakes personnel decisions, remains insufficiently examined.

As AI becomes more deeply embedded in hospital administrative environments, it is becoming increasingly crucial to understand the factors that influence healthcare professionals' acceptance and adoption behaviors. Healthcare organizations are increasingly adopting advanced AI systems in HR administration to perform tasks that were previously done by humans in complex and demanding medical settings[9,12]. Despite the considerable potential of AI in hospital HRM, its successful integration is critically dependent on healthcare professionals' perceptions and acceptance[13].

In healthcare settings, technology adoption is rarely driven solely by rational considerations. The high-stakes nature of medical work means that technology evaluations are deeply shaped by emotional, social, and contextual forces[14]. One key emotional factor is technology anxiety, which refers to an individual's apprehension or

fear when using technology[15]. Unlike general computer anxiety, AI-related anxiety in hospital HRM is likely to involve deeper concerns, such as algorithmic opacity, loss of professional judgment, and the perceived threat to clinical and administrative roles[9,16] These deeper concerns highlight the complexity of AI adoption in healthcare HRM, which involves technical feasibility as well as professionals' cognitive, emotional, and normative evaluations. To our knowledge, these complexities have not yet been thoroughly explored, especially in the context of Chinese healthcare professionals. Although organizations globally have implemented technology tools to effectively and systematically manage their functional departments, only a limited number of healthcare organizations are currently in the process of adopting these tools in their HR functions[12].

Previous studies investigating technology adoption in healthcare have typically employed classic frameworks, such as the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB)[17,18]. However, few studies have integrated context-specific emotional factors, particularly technology anxiety, into a single composite model for the hospital HRM context. Most either apply TAM or TPB in isolation, or examine only cognitive or social predictors, leaving the role of emotional antecedents underexplored[19,20]. It is therefore imperative to conduct a thorough investigation into how AI can be integrated into the HR operations of the healthcare sector, with particular attention to the psychological and behavioral drivers that shape adoption[21,22]. To address these knowledge gaps, the present study investigates the key psychological and behavioral drivers behind AI adoption among Chinese healthcare professionals. TAM and TPB serve as the core frameworks, which are extended with technology anxiety as a context-specific emotional antecedent. TPB explains behavior according to three cognitive constructs, namely attitude, subjective norms, and perceived behavioral control, and has been widely adopted in technology acceptance research because of its strong explanatory power[23]. However, TPB alone does not account for emotional factors such as technology anxiety, which is expected to be crucial in high-stakes healthcare environments. Therefore, the present study focuses on the following research questions:

RQ1: To what extent are the integrated TAM-TPB predictors and technology anxiety associated with Chinese healthcare professionals' intention to adopt AI tools in hospital HRM?

RQ2: What role does technology anxiety play within the integrated TAM-TPB model in relation to healthcare professionals' adoption intention?

RQ3: To what extent does the integrated TAM-TPB model with technology anxiety explain the variance in healthcare professionals' adoption intention?

This study advances understanding of AI adoption intention in hospital HRM.

## AI in hospital human resource management

The integration of AI into healthcare HRM is emerging as a transformative force, aiming to enhance efficiency, reduce costs, and ultimately improve patient care quality[24]. Administrative tasks in hospital HRM have long been labor-intensive, and aligning workforce plans with care delivery has proven difficult[24]. Data-driven AI tools offer a way to address many of these long-standing pressures[25]. In practice, AI now touches recruitment, talent management, scheduling, training, and performance evaluation. For example, natural language processing and machine learning can screen résumés and match candidates, sharply reducing the time spent on hiring[26]. Predictive analytics can also forecast staffing needs from patient volume trends, which helps control labor costs and smooth operations[27,28]. Training becomes more personalized, and employee data can be mined to flag turnover risks early[7,29]. Among these uses, AI-assisted performance evaluation and retention prediction probably carry the highest stakes. They directly touch careers and professional identity, which helps explain why they also provoke the strongest anxiety[12,30].

For all this potential, putting AI fully into practice in hospital HRM is not straightforward. Data privacy and security rank among the most immediate worries, because AI systems often handle sensitive staff information and must comply with data protection rules[31,32]. Bias is another persistent concern: when models are trained on biased historical data, they risk reinforcing inequalities in hiring and appraisal[33,34]. Employee resistance, often rooted in fears about job loss or doubts about automated decisions, remains a further obstacle[8,35]. The success of AI in

healthcare HRM hinges on healthcare professionals' acceptance and adoption intentions, which are themselves shaped by factors such as technology anxiety.

## Theoretical foundations

To adequately address the complexities of technology adoption in this context, an integrated theoretical framework is essential. This study primarily draws upon the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the concept of technology anxiety. The review proceeds in a systematic sequence: it first situates AI within hospital HRM, then presents TAM and TPB and their integration, introduces technology anxiety as an affective antecedent, and finally consolidates these elements into the research gap and the integrated model.

## Technology acceptance model (TAM)

The Technology Acceptance Model (TAM), originally developed by Davis[36], identifies two cognitive beliefs as the main drivers of technology adoption: perceived usefulness (PU) and perceived ease of use (PEOU). PU captures the extent to which a person expects a system to improve their job performance, while PEOU reflects the expectation that using the system will be relatively effortless[37]. Together, these two beliefs are thought to shape a user's attitude, which then feeds into their behavioral intention to use the technology. TAM has been applied across a wide range of information technologies, including healthcare information systems[17,18]. The model is valued for its simplicity and strong empirical grounding, but it has also been criticized for paying insufficient attention to social and control-related factors[20]. This limitation is especially relevant in healthcare. In such settings, technology adoption decisions are rarely made alone; rather, they are embedded within organizational hierarchies, peer networks, and institutional norms[14]. Any effort to understand adoption in this context therefore calls for theoretical extensions that bring in the social and organizational forces at play.

## Theory of planned behavior (TPB)

Ajzen[23] extended the Theory of Reasoned Action by introducing perceived behavioral control (PBC) as an additional predictor of both intention and behavior, resulting in the Theory of Planned Behavior (TPB). In TPB, behavioral intention is seen as a function of three factors: attitude, subjective norms (SN), and PBC. The model has been applied in many technology adoption studies, including work on healthcare technology acceptance[17].

TPB improves on TAM by accounting for social and control factors, but it still leaves out technology-specific beliefs such as PU and PEOU, as well as emotional factors like technology anxiety[19]. In the hospital HRM context, TPB has some clear strengths. When healthcare professionals decide whether to adopt AI for tasks like scheduling, performance reviews, or recruitment, they rarely act alone. Their choices are shaped by clinical team dynamics, expectations from hospital leadership, and the organizational resources available to them[38]. The gains from digital technologies are seldom realized through the technology alone; they typically depend on complementary organizational capabilities[39]. Digital literacy and professional autonomy also differ widely across healthcare roles, which makes perceived behavioral control especially important to consider in this population[40]. Subjective norms can be especially powerful in hospitals. Healthcare professionals work in tightly coupled clinical teams, where peer endorsement or rejection can travel fast within professional networks. Hospital hierarchies amplify this effect. When senior clinicians express skepticism or support for an AI tool, their views tend to spread through the clinical ranks[41,42].

### Technology anxiety and affect-cognition theories

Technology anxiety is defined as an individual's affective response of apprehension, fear, or unease when considering or actually using technology[15]. Unlike general attitudes, anxiety represents a specific negative emotional state that can inhibit technology adoption and usage. In the context of AI in hospital HRM, technology anxiety may stem from concerns about job displacement, a lack of understanding of AI systems, fear of making critical errors, or discomfort with algorithmic decision-making in people-related processes[35,43]. Research has consistently demonstrated that technology anxiety negatively affects perceived ease of use[19,44] and perceived behavioral control[45]. Given the high-stakes nature of hospital HRM and the professional identity concerns of healthcare workers, technology anxiety is likely to be a significant barrier to AI adoption[46]. General computer anxiety concerns the operational difficulty of using technology. By contrast, AI-specific anxiety in hospital HRM involves deeper concerns: algorithmic opacity, loss of professional judgment in personnel decisions, and the perceived threat of AI to clinical and administrative roles built over years of practice[47,48]. When AI-driven decisions lack transparency, an accountability gap can open up between the system's outputs and the professional being evaluated. In hospital HRM, this gap is especially acute because performance evaluations carry real career consequences, which can push technology anxiety well beyond what is typically seen in clinical AI adoption[30]. In these settings, anxiety does not come only from unfamiliarity with the technology. It also stems from deeper concerns about job loss, reduced professional autonomy, and the possibility that AI errors in personnel decisions could harm colleagues' careers or compromise patient care[8,35]. Although the broader literature on AI anxiety discusses these dimensions in greater depth, the present study focuses on four core concerns that are directly operationalized here: difficulty understanding how AI systems work, worry about making mistakes, concern that AI will negatively affect one's work, and worry that AI will make HRM less human-centred.

Affect-cognition theories help explain why emotions like anxiety can do more than just affect cognitive and control beliefs; they can also directly shape attitudes and social perceptions. According to the Affect-as-Information theory[49], people often rely on their current feelings as a source of information when making judgments. Negative feelings, such as anxiety, can act as a warning signal, making evaluations of the technology itself more negative. The Mood-Congruent Recall theory[50] adds that people tend to recall memories that match their current emotional state. This means anxiety can selectively activate negative associations with AI, which further reinforces negative attitudes. Furthermore, anxiety can alter how individuals perceive and respond to social cues and norms. When anxious, they may become more self-focused and less attentive to external social pressures. They may also interpret ambiguous social signals in a way that confirms their existing fears[51]. Consequently, technology anxiety can directly influence the formation or perception of subjective norms. It can make individuals less open to positive social influence, or more likely to perceive negative social pressure regarding AI adoption[52].

### Research gap and integrated model development

Despite the growing body of research on AI adoption, significant gaps remain. First, most existing studies focus on clinical AI applications rather than administrative and HR functions. Second, TAM and TPB have been extensively applied. However, their integration with emotional factors such as technology anxiety remains underdeveloped, particularly in healthcare HRM. Several features of the healthcare context call for extending established theories. Staff vary considerably in their digital literacy, personnel decisions face growing demands for algorithmic transparency, and concerns about data privacy are especially heightened. Third, limited research has examined these dynamics among Chinese healthcare professionals.

More precisely, while some studies have incorporated AI anxiety, they often focus on student or general user groups[35,51,53]. These studies neglect the intricate psychological and social influences on medical professionals working in a highly specialized and high-stakes environment[43,46]. This study bridges these gaps by developing and testing an integrated model. The model combines core TAM constructs (PU, PEOU, ATT, BI) and TPB

constructs (SN, PBC), and incorporates technology anxiety (TA) as an additional antecedent. Figure 1 presents the integrated model and the hypothesized relationships among these constructs.

## Hypotheses development

Based on the theoretical foundations and the integrated model, we formulate the following hypotheses. For the core TAM relationships, perceived ease of use is expected to positively influence perceived usefulness (H1); perceived usefulness and perceived ease of use should each positively influence attitude (H2, H3). Consistent with the TPB, attitude (H4), subjective norms (H5), and perceived behavioral control (H6) are expected to positively influence behavioral intention.

Furthermore, in organizational settings where performance improvements are paramount, perceived usefulness is hypothesized to have a direct positive effect on behavioral intention, beyond the indirect path through attitude (H7)[36,54]. Extending the TAM-TPB nexus, we theorize perceived ease of use as a significant antecedent of perceived behavioral control (H8). When healthcare professionals perceive an AI system as intuitive and easy to operate, the psychological barriers to usage are lowered, and their self-efficacy—a core component of PBC—is enhanced[55]. A system that is easy to learn and navigate thus empowers users with the belief that they have the skills to manage it successfully. Empirical evidence from integrated TAM-TPB studies supports this relationship[56,57].

Technology anxiety is hypothesized to negatively influence perceived ease of use (H9) and perceived behavioral control (H10). This is because anxiety impairs cognitive processing and undermines individuals' confidence in their ability to operate AI systems successfully[19,44,45]. Drawing on affect-as-information theory, technology anxiety is also hypothesized to directly and negatively influence attitude (H11) and subjective norms (H12). Negative emotions can directly color an individual's overall evaluation of AI, leading to a more negative attitude even before comprehensive cognitive appraisal of its usefulness or ease of use[55,57]. Moreover, anxious individuals may become more self-protective and less receptive to social pressure. They may also selectively interpret social cues in a way that confirms their existing fears about AI, thereby perceiving weaker social support[35,51]. Table 1 summarizes all twelve hypotheses.

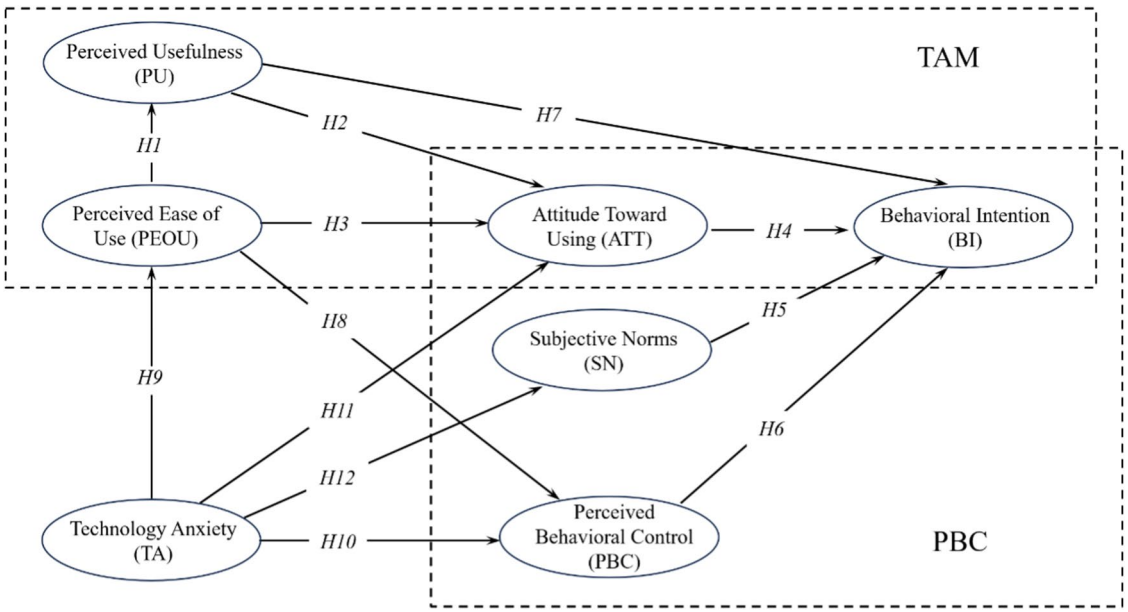


**Fig. 1** Integrated conceptual model and hypothesized relationships.

**Table 1** Summary of research hypotheses.

| Hypothesis | Path | Statement |
|---|---|---|
| TAM Relationships | | |
| H1 | PEOU → PU | Perceived ease of use positively influences perceived usefulness |
| H2 | PU → ATT | Perceived usefulness positively influences attitude |
| H3 | PEOU → ATT | Perceived ease of use positively influences attitude |
| H7 | PU → BI | Perceived usefulness positively influences behavioral intention |
| TPB Relationships | | |
| H4 | ATT → BI | Attitude positively influences behavioral intention |
| H5 | SN → BI | Subjective norms positively influence behavioral intention |
| H6 | PBC → BI | Perceived behavioral control positively influences behavioral intention |
| Extending the TAM-TPB Nexus | | |
| H8 | PEOU →PBC | Perceived ease of use positively influences perceived behavioral control over using AI tools in hospital HRM. |
| Technology Anxiety Relationships | | |
| H9 | TA → PEOU | Technology anxiety negatively influences perceived ease of use |
| H10 | TA → PBC | Technology anxiety negatively influences perceived behavioral control |
| H11 | TA → ATT | Technology anxiety negatively influences attitude |
| H12 | TA → SN | Technology anxiety negatively influences subjective norms |

# Methods

## Study design and participants

This study employed a cross-sectional survey design (Table 2). Participants were healthcare professionals working in hospitals in China, including physicians, nurses, pharmacists, medical technicians, and administrative staff. A convenience sampling approach was used. No formal sampling frame was available; participants were recruited through Credamo, an online survey platform, which screened respondents by occupation. Respondents' hospitals were located in all seven geographic regions of China (East, Central, North, South, Southwest, Northeast, and Northwest China); Table 3 reports the distribution.

## Data collection

Data were gathered through a structured online questionnaire on Credamo, a survey platform widely adopted in Chinese academic research. The survey ran from January to February 2026 and included screening questions to check eligibility. Eligible participants were adults aged 18 or older currently employed as healthcare professionals in mainland Chinese hospitals, including physicians, nurses, pharmacists, medical technicians, and administrative staff. All items were mandatory, so no submitted response contained missing data, and the platform allowed only one response per account, which prevented duplicate submissions. To improve data quality, we embedded attention check items; participants who failed these checks were removed. We also set a minimum completion time of three minutes to filter out overly rushed responses, and removed responses showing straight-lining or patterned responding. In total, 600 responses were received. After discarding 53 invalid responses, 547 valid responses were retained, yielding an effective response rate of 91.1%. The study was approved by the Ethics Committee of the Third Affiliated Hospital of Zhejiang Chinese Medical University (No. ZSLL-KY-2026-014-01). Informed consent was obtained from all participants, and confidentiality and anonymity were assured; full details are reported in the Declarations section.

**Table 2** Construct definitions and measurement items.

| Construct | Operational Definition | Code | Measurement Items | Source |
|---|---|---|---|---|
| Perceived Usefulness (PU) | Degree to which a professional believes AI in HRM enhances job performance | PU1 | I believe AI improves HR department efficiency by automating repetitive tasks like attendance statistics and payroll calculations. | 36,54 |
| | | PU2 | I believe AI provides valuable references for recruitment and performance decisions by analyzing historical data. | |
| | | PU3 | I believe AI optimizes staff scheduling and improves HR allocation effectiveness. | |
| | | PU4(R) | AI will not significantly help hospital HRM (reverse-coded). | |
| Perceived Ease of Use (PEOU) | Degree to which using AI in HRM is perceived as effortless. | PEOU1 | Learning to operate AI tools for hospital HRM would be easy for me. | 36,54 |
| | | PEOU2 | I believe mastering AI tools for hospital HRM would not require excessive effort. | |
| | | PEOU3 | I believe Hospital HR personnel can easily get started with AI to assist their work. | |
| | | PEOU4 | I believe interacting with AI tools/systems for hospital HRM is clear and understandable. | |
| Subjective Norms (SN) | Perceived social pressure to perform or not perform the behavior (using AI in hospital HRM). | SN1 | I believe hospital leadership may support the introduction of AI technology in HRM. | 23,59 |
| | | SN2 | Colleagues or peers who significantly influence my work believe that AI tools/systems should be used in hospital HRM. | |
| | | SN3 | I feel that my hospital expects me to use AI tools/systems in hospital HRM. | |
| Perceived Behavioral Control (PBC) | Perceived ease or difficulty of performing the behavior (using AI in hospital HRM), reflecting past experience and anticipated obstacles. | PBC1 | For me, learning and operating AI HRM systems at work is easy. | 23,59 |
| | | PBC2 | I am confident in my ability to effectively use AI HRM systems at work. | |
| | | PBC3 | I believe I have enough knowledge and resources to support my use of AI HRM systems. | |
| | | PBC4 | Whether to use AI HRM systems at work is entirely within my control. | |
| Technology Anxiety (TA) | An individual's affective response of apprehension, fear, or unease when considering or actually using technology. | TA1 | I am worried that I cannot understand or keep up with the operational logic of AI HRM tools/systems. | 51,58 |
| | | TA2 | I am worried about making mistakes when using AI HRM tools/systems in the hospital and being unable to correct them. | |
| | | TA3 | I am worried that AI HRM tools/systems may negatively impact my work. | |
| | | TA4 | I am worried that the intervention of AI will make the HRM process less human-centered. | |
| Attitude Toward Using (ATT) | An individual's positive or negative evaluation of performing the behavior (using AI in hospital HRM). | ATT1 | I think introducing AI in hospital HRM is generally a good idea. | 23,59 |
| | | ATT2 | Overall, I look forward to and welcome the introduction of AI tools/systems in hospital HRM. | |
| | | ATT3 | Overall, I support exploring and applying AI technology in hospital HR work. | |
| Behavioral Intention (BI) | The strength of an individual's intention to perform a specific behavior (using AI in hospital HRM). | BI1 | If the hospital introduces a reliable AI HRM system, I am willing to actively try to use it. | 54,57 |
| | | BI2 | I plan to incorporate the AI HRM system into my daily workflow after it operates stably. | |
| | | BI3 | If I find it helpful after trial, I am willing to give positive feedback on the introduced AI HRM system. | |

## Measures

Before the core scales, the questionnaire presented six illustrative applications of AI in hospital HRM (recruitment and initial screening, performance analysis, training and development, turnover-risk warning, scheduling, and employee self-service Q&A). Respondents rated each application on urgency and implementation difficulty. Because no single definition of AI in hospital HRM is yet generally accepted, the survey did not impose one; the six applications described above served as a shared frame of reference. These items were not used in the structural model. Our model comprises seven key constructs: perceived usefulness (PU), perceived ease of use (PEOU), subjective norms (SN), perceived behavioral control (PBC), technology anxiety (TA), attitude toward using (ATT), and behavioral intention (BI). We drew measurement items from established scales in the literature and adapted the wording to fit the specific context of AI tools in hospital HRM. All items were rated on a five-point Likert scale from 1 ("strongly disagree") to 5 ("strongly agree"). The questionnaire was pre-tested with three

**Table 3** Demographic profile of participants.

| Item | Options | Frequency | Percentage(%) |
|---|---|---|---|
| Gender | Male | 232 | 42.4% |
| | Female | 315 | 57.6% |
| Age | ≤20 years | 3 | 0.5% |
| | 21–30 years | 284 | 51.9% |
| | 31–40 years | 153 | 28.0% |
| | 41–50 years | 69 | 12.6% |
| | 51–60 years | 36 | 6.6% |
| | >60 years | 2 | 0.4% |
| Professional Role | Physician | 233 | 42.6% |
| | Nurse | 99 | 18.1% |
| | Pharmacist | 32 | 5.9% |
| | Medical Technician | 66 | 12.1% |
| | Administrative Staff (Non-HR) | 51 | 9.3% |
| | HR Professional | 56 | 10.2% |
| | Others | 10 | 1.8% |
| Hospital Level | Tertiary | 352 | 64.4% |
| | Secondary | 129 | 23.6% |
| | Primary | 40 | 7.3% |
| | Unrated | 26 | 4.8% |
| Hospital Ownership | Public | 485 | 88.7% |
| | Private | 62 | 11.3% |
| Geographic region | East China | 158 | 28.9% |
| | Central China | 98 | 17.9% |
| | North China | 89 | 16.3% |
| | South China | 72 | 13.2% |
| | Southwest China | 56 | 10.2% |
| | Northeast China | 42 | 7.7% |
| | Northwest China | 32 | 5.9% |
| Work Experience | ≤5 years | 288 | 52.7% |
| | 6–10 years | 80 | 14.6% |
| | 11–15 years | 74 | 13.5% |
| | 16–20 years | 42 | 7.7% |
| | >20 years | 63 | 11.5% |
| Professional Title | Senior | 13 | 2.4% |
| | Associate Senior | 52 | 9.5% |
| | Intermediate | 168 | 30.7% |
| | Junior | 222 | 40.6% |
| | None | 92 | 16.8% |
| Position | Ordinary Staff | 376 | 68.7% |
| | Grassroots Manager | 99 | 18.1% |
| | Middle Manager | 69 | 12.6% |
| | Senior Manager | 3 | 0.5% |
| Education | Doctoral degree | 27 | 4.9% |
| | Master's degree | 143 | 26.1% |
| | Bachelor's degree | 318 | 58.1% |
| | Associate's degree | 56 | 10.2% |
| | High school and below | 3 | 0.5% |

**Table 3** (continued)

| Item | Options | Frequency | Percentage(%) |
|---|---|---|---|
| AI Familiarity | Very familiar | 43 | 7.9% |
| | Somewhat familiar | 294 | 53.7% |
| | Moderately familiar | 197 | 36.0% |
| | Slightly familiar | 13 | 2.4% |
| | Completely unfamiliar | 0 | 0% |

AI familiarity was measured with a single item: "How would you describe your own level of knowledge or familiarity with artificial intelligence (AI) technology?" The five response options were: "very familiar" (understands the underlying technical principles and can apply AI proactively), "somewhat familiar" (has used multiple AI tools), "moderately familiar" (has used only a few common AI tools, such as smart translation or smart search), "slightly familiar" (has only heard of the concept), and "completely unfamiliar." Because that option was selected by no respondent, the four remaining categories were combined a priori into two groups for the multi-group analysis: "very familiar" and "somewhat familiar" formed the high-familiarity group ($n=337$), and "moderately familiar" and "slightly familiar" formed the low-familiarity group ($n=210$).

academic experts in health informatics and technology adoption, along with five hospital practitioners. The pretest aimed to ensure content validity, clarity, and contextual relevance. Based on their feedback, minor wording modifications were made. Table 2 presents the construct definitions and measurement items. The four technology anxiety items capture this construct through concerns that are salient in hospital HRM: difficulty understanding the operational logic of AI systems (TA1), worry about making mistakes that cannot be corrected (TA2), concern that AI will negatively affect one's work (TA3), and worry that AI will make HRM less human-centred (TA4). They were selected for their direct relevance to hospital HRM rather than to cover the full conceptual space of AI anxiety[51,58].

### Statistical analysis

The data were analyzed with IBM SPSS 26.0 and AMOS 28.0. Descriptive statistics were first computed for all measurement items. Internal consistency reliability was assessed using Cronbach's alpha. Confirmatory factor analysis was conducted to evaluate the measurement model, and structural equation modeling was used to test the hypothesized relationships. Bootstrap mediation testing with 5,000 resamples and 95% bias-corrected confidence intervals was performed to examine indirect effects. Multi-group structural equation modeling was used to compare path coefficients between high and low AI familiarity groups after testing measurement invariance. AI familiarity was measured with a single item offering five response options. No respondent selected "completely unfamiliar," so the remaining four categories were grouped a priori into high familiarity ("very familiar" and "somewhat familiar," $n=337$) and low familiarity ("moderately familiar" and "slightly familiar," $n=210$). Full item wording and response options are provided in the note to Table 2.

## Results

### Sample characteristics

Table 3 summarizes the demographic profile of the participants. Of the 547 healthcare professionals included in the analysis, 57.6% were women. The largest age group was 21–30 years (51.9%), followed by 31–40 years (28.0%). Physicians accounted for 42.6% of the sample, and nurses made up 18.1%. Most respondents worked in tertiary hospitals (64.4%) and public institutions (88.7%). A majority (52.7%) had five years or less of work experience.

## Descriptive statistics

Table 4 presents the descriptive statistics for all measurement items. Overall, healthcare professionals reported fairly positive views of AI in hospital HRM. Perceived usefulness averaged between 3.90 and 4.06, while perceived ease of use fell between 3.71 and 3.88, pointing to moderate-to-high ease-of-use perceptions. The highest ratings emerged for attitude toward using AI, where means ranged from 4.04 to 4.07, suggesting a strongly favorable overall evaluation. Behavioral intention means ranged from 3.70 to 3.74. Technology anxiety exhibited the lowest means (2.47–2.60), indicating that anxiety levels were generally low. All items showed acceptable skewness values (absolute values < 2) and kurtosis values (absolute values < 7).

## Data quality assessment

We examined non-response bias by comparing early and late respondents on key demographics and construct measures, and found no significant differences[60]. In addition, Harman's single-factor test was conducted to check for common method bias. The single factor explained 35.705% of the total variance, which is below the 40% threshold[61], suggesting that common method bias was not a serious concern in this study.

## Reliability and validity

Internal consistency reliability was assessed using Cronbach's alpha. All values exceeded the accepted threshold of 0.70[62], ranging from 0.798 for behavioral intention to 0.838 for subjective norms. Content validity was established through adaptation from established scales and pre-testing with experts. Exploratory factor analysis extracted seven components with eigenvalues greater than 1, which together explained 69.061% of the total variance. Confirmatory factor analysis showed good measurement model fit: $\chi^2 = 388.463$, df = 254, $\chi^2/df = 1.529$,

**Table 4** Descriptive statistics of measurement items ($N = 547$).

| Item | Mean | Std. Deviation | Skewness | Kurtosis |
|---|---|---|---|---|
| PU1 | 4.01 | 0.903 | -1.337 | 2.226 |
| PU2 | 4.06 | 0.871 | -1.249 | 2.032 |
| PU3 | 4.04 | 0.821 | -1.094 | 1.876 |
| PU4(R) | 3.90 | 0.793 | -0.902 | 1.596 |
| PEOU1 | 3.85 | 0.745 | -0.757 | 1.022 |
| PEOU2 | 3.71 | 0.871 | -0.695 | 0.386 |
| PEOU3 | 3.77 | 0.821 | -0.829 | 1.098 |
| PEOU4 | 3.88 | 0.832 | -0.800 | 1.021 |
| SN1 | 3.84 | 0.899 | -0.764 | 0.300 |
| SN2 | 3.81 | 0.903 | -0.943 | 0.978 |
| SN3 | 3.76 | 0.967 | -0.900 | 0.619 |
| PBC1 | 3.90 | 0.789 | -0.815 | 1.349 |
| PBC2 | 3.97 | 0.784 | -1.008 | 2.137 |
| PBC3 | 3.99 | 0.812 | -1.134 | 2.136 |
| PBC4 | 3.85 | 0.759 | -1.001 | 1.914 |
| TA1 | 2.47 | 0.993 | 0.528 | -0.284 |
| TA2 | 2.53 | 1.015 | 0.562 | -0.420 |
| TA3 | 2.52 | 1.064 | 0.507 | -0.475 |
| TA4 | 2.60 | 1.099 | 0.303 | -0.843 |
| ATT1 | 4.04 | 0.788 | -1.137 | 2.140 |
| ATT2 | 4.06 | 0.797 | -1.118 | 1.883 |
| ATT3 | 4.07 | 0.847 | -1.324 | 2.494 |
| BI1 | 3.74 | 0.923 | -0.745 | 0.474 |
| BI2 | 3.70 | 0.861 | -0.712 | 0.685 |
| BI3 | 3.73 | 0.800 | -0.512 | 0.388 |

PU4 was reverse-scored before analysis. The reported mean for PU4(R) reflects the score after reverse-scoring adjustment, so higher values indicate greater perceived usefulness.

**Table 5** Reliability and convergent validity.

| Construct | Item | Standardized Factor Loading (λ) | Cronbach's Alpha (α) | Composite reliability (CR) | Average variance extracted (AVE) |
|---|---|---|---|---|---|
| PU | PU1 | 0.716 | 0.818 | 0.820 | 0.533 |
| | PU2 | 0.715 | | | |
| | PU3 | 0.776 | | | |
| | PU4(R) | 0.711 | | | |
| PEOU | PEOU1 | 0.713 | 0.827 | 0.835 | 0.561 |
| | PEOU2 | 0.696 | | | |
| | PEOU3 | 0.708 | | | |
| | PEOU4 | 0.867 | | | |
| SN | SN1 | 0.732 | 0.838 | 0.841 | 0.638 |
| | SN2 | 0.815 | | | |
| | SN3 | 0.845 | | | |
| PBC | PBC1 | 0.710 | 0.818 | 0.819 | 0.531 |
| | PBC2 | 0.751 | | | |
| | PBC3 | 0.733 | | | |
| | PBC4 | 0.719 | | | |
| TA | TA1 | 0.720 | 0.830 | 0.831 | 0.552 |
| | TA2 | 0.741 | | | |
| | TA3 | 0.802 | | | |
| | TA4 | 0.706 | | | |
| ATT | ATT1 | 0.744 | 0.807 | 0.810 | 0.587 |
| | ATT2 | 0.793 | | | |
| | ATT3 | 0.761 | | | |
| BI | BI1 | 0.760 | 0.798 | 0.800 | 0.571 |
| | BI2 | 0.767 | | | |
| | BI3 | 0.740 | | | |

**Table 6** Discriminant validity and latent variable correlation matrix.

| Construct | PU | PEOU | SN | PBC | TA | ATT | BI |
|---|---|---|---|---|---|---|---|
| PU | **0.730** | | | | | | |
| PEOU | 0.609 ** | **0.749** | | | | | |
| SN | 0.420 ** | 0.379 ** | **0.799** | | | | |
| PBC | 0.560 ** | 0.519 ** | 0.434 ** | **0.728** | | | |
| TA | -0.552 ** | -0.492 ** | -0.390 ** | -0.538 ** | **0.743** | | |
| ATT | 0.620 ** | 0.550 ** | 0.581 ** | 0.542 ** | -0.557 ** | **0.766** | |
| BI | 0.630 ** | 0.529 ** | 0.490 ** | 0.499 ** | -0.528 ** | 0.641 ** | **0.756** |

Bold diagonal values are the square root of AVE. **$p < 0.01$.

CFI = 0.978, TLI = 0.974, RMSEA = 0.031, SRMR = 0.0364. Although the chi-square statistic was significant ($p < 0.001$), this is common with large samples[63].

Convergent validity was assessed through standardized factor loadings, composite reliability (CR), and average variance extracted (AVE). As shown in Table 5, nearly all standardized factor loadings exceeded 0.70. The only exception was PEOU2 (λ = 0.696), which was retained because it was very close to the threshold. All CR values exceeded 0.70 (0.800–0.841), and all AVE values exceeded 0.50 (0.531–0.638). Discriminant validity was supported by the Fornell-Larcker criterion[64], with the square root of the AVE for each construct exceeding its correlations with other constructs (Table 6).

**Table 7** Standardized regression weights and hypothesis testing results.

| Hypothesis | Path | Standardized Estimate (β) | S.E. | C.*R*. (t-value) | *P*-value | Conclusion |
|---|---|---|---|---|---|---|
| H1 | PEOU → PU | 0.660 | 0.043 | 12.077 | *** | Supported |
| H2 | PU → ATT | 0.309 | 0.067 | 4.731 | *** | Supported |
| H3 | PEOU → ATT | 0.207 | 0.059 | 2.869 | 0.004 | Supported |
| H4 | ATT → BI | 0.327 | 0.075 | 5.147 | *** | Supported |
| H5 | SN → BI | 0.167 | 0.047 | 3.650 | *** | Supported |
| H6 | PBC → BI | 0.125 | 0.063 | 2.442 | 0.015 | Supported |
| H7 | PU → BI | 0.321 | 0.073 | 5.336 | *** | Supported |
| H8 | PEOU→ PBC | 0.359 | 0.045 | 6.226 | *** | Supported |
| H9 | TA → PEOU | -0.553 | 0.048 | -10.429 | *** | Supported |
| H10 | TA → PBC | -0.371 | 0.042 | -6.213 | *** | Supported |
| H11 | TA → ATT | -0.339 | 0.042 | -5.936 | *** | Supported |
| H12 | TA → SN | -0.451 | 0.046 | -8.335 | *** | Supported |

β = standardized regression weight. S.E. and C.R. (t-value) are derived from the unstandardized solution (C.R. = unstandardized estimate / unstandardized S.E.) and therefore do not reconcile with β by simple division. *** $p < 0.001$.

**Table 8** Squared multiple correlations ($R^2$) for endogenous constructs.

| Endogenous Construct | $R^2$ |
|---|---|
| Perceived Ease of Use (PEOU) | 0.305 |
| Perceived Usefulness (PU) | 0.435 |
| Subjective Norms (SN) | 0.204 |
| Perceived Behavioral Control (PBC) | 0.413 |
| Attitude (ATT) | 0.492 |
| Behavioral Intention (BI) | 0.494 |

## Structural model and hypothesis testing

The structural model demonstrated good fit with the data: $\chi^2/df = 2.088$ ($\chi^2 = 549.205$, df = 263), CFI = 0.953, TLI = 0.946, RMSEA = 0.045 (90% CI: 0.039–0.050), and SRMR = 0.0767. All fit indices met the recommended criteria[63].

Table 7 presents the standardized regression weights and hypothesis testing results. Among the TAM relationships, perceived ease of use positively predicted perceived usefulness (H1: β = 0.660, $p < 0.001$) and attitude (H3: β = 0.207, $p = 0.004$), while perceived usefulness positively predicted attitude (H2: β = 0.309, $p < 0.001$). Perceived usefulness also showed a direct positive association with behavioral intention (H7: β = 0.321, $p < 0.001$). Among the TPB predictors, attitude was the strongest (H4: β = 0.327, $p < 0.001$), followed by subjective norms (H5: β = 0.167, $p < 0.001$) and perceived behavioral control (H6: β = 0.125, $p = 0.015$). Perceived ease of use significantly predicted perceived behavioral control (H8: β = 0.359, $p < 0.001$).

Technology anxiety showed significant negative associations with perceived ease of use (H9: β = -0.553, $p < 0.001$), perceived behavioral control (H10: β = -0.371, $p < 0.001$), attitude (H11: β = -0.339, $p < 0.001$), and subjective norms (H12: β = -0.451, $p < 0.001$).

Table 8 reports the squared multiple correlations ($R^2$). Technology anxiety alone accounted for 30.5% of the variance in perceived ease of use and 20.4% in subjective norms. Perceived ease of use alone explained 43.5% of the variance in perceived usefulness (β = 0.660). Perceived ease of use and technology anxiety together explained 41.3% of the variance in perceived behavioral control. The combined effects of perceived usefulness, perceived ease of use, and technology anxiety accounted for 49.2% of the variance in attitude. Most notably, the integrated model explained 49.4% of the variance in behavioral intention.

## Mediation analysis

To further clarify the mechanisms through which technology anxiety and the cognitive beliefs relate to behavioral intention, indirect effects were examined as supplementary analyses derived from the hypothesized structural paths, rather than as separate a priori hypotheses. A bootstrap mediation analysis with 5,000 resamples and 95% bias-corrected confidence intervals was then conducted. Technology anxiety had significant negative indirect effects on behavioral intention through attitude (β = -0.097, 95% CI [-0.178, -0.045], $p < 0.001$), perceived behavioral control (β = -0.041, 95% CI [-0.087, -0.007], $p = 0.016$), and subjective norms (β = -0.066, 95% CI [-0.129, -0.022], $p = 0.001$). Technology anxiety also showed significant indirect effects on attitude through perceived ease of use (β = -0.085, 95% CI [-0.171, -0.024], $p = 0.007$) and on perceived behavioral control through perceived ease of use (β = -0.141, 95% CI [-0.215, -0.089], $p < 0.001$).

Perceived ease of use showed significant positive indirect effects on behavioral intention through attitude (β = 0.065, 95% CI [0.015, 0.153], $p = 0.007$), perceived behavioral control (β = 0.043, 95% CI [0.009, 0.092], $p = 0.013$), and perceived usefulness (β = 0.205, 95% CI [0.110, 0.331], $p < 0.001$). Perceived usefulness also had a significant indirect effect on behavioral intention through attitude (β = 0.123, 95% CI [0.060, 0.218], $p < 0.001$). All nine indirect effects were statistically significant (Table 9).

## Multi-group analysis

Respondents were divided into high AI familiarity ($n = 337$) and low AI familiarity ($n = 210$) groups. Measurement invariance was tested before comparing structural paths. The configural invariance model fitted the data well (CFI = 0.967, RMSEA = 0.026), and the metric invariance model did not differ significantly from it (ΔCFI = 0.000, ΔRMSEA = -0.001), supporting full equivalence of factor loadings across groups. The scalar invariance model showed a ΔCFI of -0.011, which was marginally outside the strict criterion of 0.01[65] but within the more lenient threshold of 0.02[66]; ΔRMSEA was only 0.004, below the 0.015 cutoff[67]. Metric invariance supported structural path comparisons; scalar invariance was only partially supported, pointing to possible intercept differences across groups. The findings are therefore limited to comparisons of structural relationships, and latent mean comparisons would require stronger evidence of invariance.

Only one path differed significantly between groups. The association between perceived ease of use and perceived usefulness was stronger in the low AI familiarity group (β = 0.656) than in the high AI familiarity group (β = 0.586), with a critical ratio of -2.428 ($p < 0.05$). The remaining eleven paths showed no significant differences (all |C.R.| < 1.96, $p > 0.05$), indicating that the core psychological mechanisms of the model remained stable across familiarity levels (Table 10).

**Table 9** Results of mediation analysis.

| Mediation Path | Estimate | 95% Bias-corrected CI | | *p*-value |
|---|---|---|---|---|
| | | Lower | Upper | |
| TA → ATT → BI | -0.097 | -0.178 | -0.045 | 0.000 |
| TA → PEOU → ATT | -0.085 | -0.171 | -0.024 | 0.007 |
| TA → PEOU → PBC | -0.141 | -0.215 | -0.089 | 0.000 |
| TA → PBC → BI | -0.041 | -0.087 | -0.007 | 0.016 |
| TA → SN → BI | -0.066 | -0.129 | -0.022 | 0.001 |
| PEOU → ATT → BI | 0.065 | 0.015 | 0.153 | 0.007 |
| PEOU → PBC → BI | 0.043 | 0.009 | 0.092 | 0.013 |
| PEOU → PU → BI | 0.205 | 0.110 | 0.331 | 0.000 |
| PU → ATT → BI | 0.123 | 0.060 | 0.218 | 0.000 |

Bootstrap sample size = 5,000. Bias-corrected percentile method. CI = confidence interval.

**Table 10** Multi-group structural path comparison.

| Hypothesized path | Low Familiarity β | High Familiarity β | C.*R*. | *p*-value | Significant |
|---|---|---|---|---|---|
| H1: PEOU → PU | 0.656 | 0.586 | -2.428 | <0.05 | Yes |
| H2: PU → ATT | 0.330 | 0.276 | -0.765 | >0.05 | No |
| H3: PEOU → ATT | 0.207 | 0.213 | -0.328 | >0.05 | No |
| H4: ATT → BI | 0.415 | 0.286 | -0.489 | >0.05 | No |
| H5: SN → BI | 0.119 | 0.210 | 1.224 | >0.05 | No |
| H6: PBC → BI | 0.056 | 0.176 | 0.719 | >0.05 | No |
| H7: PU → BI | 0.330 | 0.208 | -1.042 | >0.05 | No |
| H8: PEOU → PBC | 0.344 | 0.352 | 0.117 | >0.05 | No |
| H9: TA → PEOU | -0.569 | -0.454 | 0.350 | >0.05 | No |
| H10: TA → PBC | -0.321 | -0.362 | -0.608 | >0.05 | No |
| H11: TA → ATT | -0.338 | -0.322 | 0.764 | >0.05 | No |
| H12: TA → SN | -0.331 | -0.449 | -1.393 | >0.05 | No |

β = standardized path coefficient from the unconstrained model. C.R. = Critical Ratio for the difference between parameters. |C.R.| > 1.96, $p < 0.05$; |C.R.| > 2.58, $p < 0.01$.

## Discussion

We set out to test whether an integrated TAM-TPB model, extended with technology anxiety, could meaningfully predict healthcare professionals' intentions to adopt AI in hospital HRM. Across a sample of 547 Chinese healthcare professionals, all twelve hypothesized paths were supported, and the model accounted for 49.4% of the variance in behavioral intention. This level of explanatory power is comparable to what has been reported in earlier TAM-TPB studies in healthcare contexts. These findings converge with prior integrated TAM-TPB work in which usefulness and ease of use emerge as the leading cognitive predictors of acceptance[17,56\], and diverge from it by showing that technology anxiety, which earlier studies did not model, is associated with adoption intention through several indirect pathways. One plausible reason for the leading role of usefulness and ease of use is that AI-HRM tools reach staff as instruments embedded in routine administrative work, so that judgements about them are formed mainly on the basis of what they help users accomplish and how readily they can be operated.

As expected from classic TAM predictions, perceived ease of use showed a strong positive association with perceived usefulness, and both of these cognitive beliefs positively predicted attitudes toward AI. We also found a direct path from perceived usefulness to behavioral intention, reinforcing the idea that in organizational settings, the instrumental benefits of a technology may be associated with stronger adoption intentions even when emotional enthusiasm is not particularly high. In other words, healthcare professionals appear willing to engage with AI-HRM tools when they see tangible gains in efficiency, decision-making, or workforce management. The TPB side of the model held up as well. Among the three TPB predictors, attitude was the strongest, which fits with the view that a favorable personal evaluation remains a primary motivator. At the same time, the significant roles of subjective norms and perceived behavioral control highlight that adoption is also associated with the organizational climate and with whether individuals feel they have the skills and resources to use the technology effectively.

This study adds to prior work by focusing explicitly on technology anxiety. As expected, anxiety showed significant negative links with perceived ease of use, perceived behavioral control, attitude, and subjective norms. Notably, anxiety was not confined to effort-related beliefs but extended to evaluative and social ones as well, which suggests that affective responses to AI spread across the belief system rather than remaining tied to a single dimension. This pattern is consistent with the logic of affect-as-information and mood-congruent theories, which suggest that emotional states can color how people evaluate new tools and how they interpret the social signals around them. In the supplementary mediation analysis, technology anxiety was associated with lower adoption intention through five distinct indirect pathways. Taken together, the findings suggest that anxiety enters the acceptance process through the beliefs that users already hold, rather than through a channel of its own. Conversely, ease of use showed clear positive indirect effects. This asymmetry indicates that interface design operates upstream, shaping usefulness and attitude rather than only the immediate interaction.

The multi-group analysis showed that the overall model structure held up well regardless of how familiar people were with AI. Only one path differed: the association between ease of use and usefulness was stronger among those with less AI familiarity. This aligns neatly with the classic TAM idea that novices lean more heavily on ease-of-use heuristics when forming usefulness judgments, a pattern that may reflect the fewer alternative cues available to less familiar users, although this account remains untested here. Beyond this difference, the remaining paths showed no significant between-group differences, which suggests that the model's core structure does not depend on prior familiarity, while the generalizability of these mechanisms beyond the present sample remains to be established. The moderation pattern is consistent with the practical observation that novices rely more on intuitive interfaces when judging whether a system is useful.

## Theoretical and practical implications

The findings extend the integrated TAM-TPB framework by positioning technology anxiety as an affective antecedent that sits alongside the model's cognitive, social, and control-related constructs. Rather than operating as a single direct predictor, anxiety was associated with behavioral intention through several indirect pathways, which clarifies the mechanism by which emotional factors enter the acceptance process. The results also extend this line of research to Chinese healthcare professionals, a population in which the integration of TAM, TPB, and technology anxiety has rarely been examined.

For practice, the findings suggest that technical training alone may not be enough to prepare staff to use AI tools in hospital HRM. Given that anxiety was associated with lower ease of use, perceived control, attitude, and perceived social support, implementation should address emotional barriers alongside technical ones, through transparent communication about how the systems work, supportive supervision, and user-friendly design. These measures are especially relevant for less AI-familiar staff, for whom ease of use mattered most, and for settings where adoption remains at least partly a matter of individual choice. Even when AI-HRM systems are mandated, employees' willingness to engage still matters: reluctant or superficial use can slow implementation and reduce efficiency gains. Addressing technology anxiety and building positive attitudes therefore remains relevant in mandatory contexts as well.

## Limitations and future research

Several limitations should be noted. The cross-sectional design limits causal inference. All measures were self-reported, which may introduce social desirability bias. Although Harman's single-factor test suggested that common method bias was not a serious concern, it cannot completely rule out this possibility. The exploratory and confirmatory factor analyses were both run on the same 547 cases, so the confirmatory fit indices may be somewhat optimistic. Across the two AI familiarity groups, invariance was established at the level of factor loadings but not fully at the level of item intercepts (scalar invariance: $\Delta$CFI = -0.011); the multi-group findings should therefore be read as comparisons of structural relationships rather than of the absolute levels of the constructs. The sample was recruited online and consisted entirely of Chinese healthcare professionals. Participants may have been younger, more digitally literate, or more interested in AI than the broader workforce. Although respondents came from all seven geographic regions of China, the convenience sampling approach means that the sample should not be assumed to represent Chinese healthcare professionals as a whole. Future studies using probability sampling are needed to assess the generalizability of these findings. We also measured behavioral intention rather than actual use, and this gap is especially relevant in hospital settings where deployment decisions often rest with administrators rather than individual staff. When administrative AI tools are introduced as top-down mandates, individual behavioral intention may carry less weight, because staff are expected to use the systems regardless of their own attitudes or anxiety. Our findings therefore speak most directly to settings where adoption remains at least partly a matter of individual choice. Finally, the four-item technology anxiety measure captures four specific concerns (difficulty understanding AI, fear of mistakes, negative effects on work,

and reduced human-centredness) and does not separately represent broader dimensions of AI-specific anxiety such as opacity, job displacement, or threats to professional autonomy and accountability; a multi-dimensional measure could examine these facets in future research. Future work could adopt longitudinal or mixed-methods designs, include objective usage data, and examine organizational factors such as leadership support and digital infrastructure.

## Conclusions

This study suggests that cognitive factors alone may not adequately account for AI adoption intention in hospital HRM. Technology anxiety appears to be an important emotional factor, showing both direct and indirect associations with attitudes, perceived control, and perceived social support. The integrated TAM-TPB model with technology anxiety offers a robust account of adoption intentions, explaining nearly half of the variance. For hospital administrators and policymakers, these findings point to the need for strategies that go beyond technical training. Reducing anxiety through transparent communication, supportive supervision, and user-friendly system design should be regarded as essential components of AI implementation. By addressing emotional barriers alongside cognitive ones, healthcare organizations can build a more receptive environment for AI tools and ultimately improve the integration of these technologies into daily HRM practice.

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**Data availability** The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

**Code availability** No custom or bespoke computational tools or code were used in this study. All analyses were performed using standard commercial statistical software (IBM SPSS Statistics 26.0 and IBM SPSS AMOS 28.0).

## Declarations

**Competing interests** The authors declare no competing interests.

**Ethics approval and consent to participate** This study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of the Third Affiliated Hospital of Zhejiang Chinese Medical University (No. ZSLL-KY-2026-014-01). Informed consent was obtained from all participants. They received detailed briefings on the study's purpose, procedures, and privacy protections. Consent forms were signed before data collection, and participants were assured of their right to withdraw at any time without consequences. All participants were adults aged 18 years or older, and no minors were involved in this study. Data from withdrawn participants were excluded from the analysis. Data confidentiality was protected.

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