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Article

Turning AI Capability into Performance: How AI Understanding and AI Skills Shape Employee Productivity through Employee–AI Collaboration in a Chinese Smart Hospital

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Abstract: Hospital investment in artificial intelligence (AI) rarely produces productivity gains by itself. Drawing on the technology acceptance model and person–environment fit theory, this study asks whether two capability-oriented employee conditions, understanding of AI and practical AI skills, improve employee productivity directly, or whether their value depends on being converted into day-to-day collaboration with AI systems. Survey data were collected from 694 employees of a tertiary public hospital in China. The measurement model was validated in SmartPLS 4, and the structural hypotheses were tested with path analysis on composite scores, using Monte Carlo confidence intervals for the indirect effects. AI understanding ($\beta = 0.434$) and AI skills ($\beta = 0.312$) both predicted employee–AI collaboration, and collaboration was the strongest predictor of productivity ($\beta = 0.426$, $p < .001$). The direct capability–productivity paths were positive but comparatively small (understanding: $\beta = 0.169$, $p < .001$; skills: $\beta = 0.073$, $p = .041$), while the indirect paths through collaboration were significant in each case and carried 52% and 64% of the respective total effects. The pattern is consistent with complementary partial mediation: knowing what AI can do, and being able to operate it, pay off chiefly when they are enacted in collaborative work practice. The findings move the explanatory weight from acceptance attitudes to enacted collaboration, and they imply that hospital training and system design should be evaluated by whether they change how employees work with AI, not merely what employees know about it.
Keywords: artificial intelligence; human–AI collaboration; AI skills; AI understanding; employee productivity; smart hospital; mediation analysis

1. Introduction

Chinese public hospitals have adopted AI at a pace that few other service organisations can match. Imaging support, triage recommendation, pharmacy checking, intelligent scheduling, and automated record review are now routine components of the "smart hospital" programmes promoted across the country's tertiary institutions. The investment logic behind these programmes is straightforward: AI is expected to make hospital employees more productive. The evidence for that expectation is far less straightforward. Field studies of generative AI show meaningful performance gains, but the gains concentrate among workers who stay actively engaged in steering and applying the technology (Brynjolfsson et al., 2025; Noy & Zhang, 2023). In clinical settings, the effect of AI on work outcomes appears to depend on whether systems can be integrated into professional reasoning and existing routines rather than on the sophistication of the systems themselves (Hassan et al., 2024; Sokol et al., 2025).

The policy environment sharpens the question. National programmes for hospital "intelligentisation" have made AI deployment a graded, audited component of tertiary-hospital evaluation in China, which means that adoption at the organisational level is largely settled by mandate. What is not settled by mandate is what happens at the level of the individual employee. A physician, nurse, or administrator confronted with an AI-enabled system still decides, task by task, how much weight to give its outputs, how to fold them into professional judgement, and how much effort to invest in learning the tool well. These micro-decisions accumulate into the difference between an AI infrastructure that raises output and one that adds screens without adding value. Understanding what determines them is consequently a practical problem for hospital management and a theoretical problem for technology adoption research at the same time.

Technology adoption research offers only a partial account of this integration problem. The dominant tradition, built on the technology acceptance model and its successors, explains variance in the intention to use a system from perceptions such as usefulness and ease of use (Davis, 1989; Venkatesh et al., 2003). Intention, however, is a weak proxy for what happens after deployment in a hospital, where the use of AI-enabled systems is often embedded in mandated workflows and the meaningful variation lies in how well employees work with the technology, not whether they touch it. Recent work on AI in organisations has therefore begun to treat employee–AI collaboration, defined as the coordinated, complementary joint execution of tasks by employees and AI systems, as a construct in its own right (Chowdhury et al., 2022; Kong et al., 2023). Quantitative evidence on whether collaboration actually carries the effect of employee capability on performance remains thin, particularly at the employee level in healthcare. A prior review by the present authors proposed an acceptance–collaboration–productivity pathway for Chinese smart hospitals but could only synthesise existing studies rather than test that pathway directly (Song et al., 2025); the present study supplies the empirical test.

Two capability-oriented conditions are repeatedly proposed as prerequisites for productive AI use, and they are not the same thing. AI understanding refers to an employee's mental model of what AI systems can do, what they cannot do, and how their outputs should be read in context (Knop et al., 2022; Pinski et al., 2023). AI skills denote the practical capacity to operate AI-supported tools, prepare inputs, and act on outputs in the flow of work (Chuang, 2024; Morandini et al., 2023). A radiologist may understand the scope of a detection algorithm yet struggle to use it efficiently under time pressure; an administrator may operate a scheduling tool fluently without understanding when its recommendations should be overridden. Whether these two conditions translate into productivity directly, or only through the quality of collaboration they enable, is an open empirical question with direct consequences for how hospitals should spend their training budgets.

This study addresses that question with survey data from 694 employees of a large tertiary (Grade III, Class A) public hospital in China. Three questions guide the analysis. First, do AI understanding and AI skills have direct associations with employee productivity? Second, do they predict employee–AI collaboration? Third, does collaboration mediate the capability–productivity relationship?

The study makes three contributions. It provides employee-level evidence on the mechanism linking AI capability to work outcomes, finding a complementary mediation pattern in which understanding and skills matter for productivity chiefly, though not exclusively, through collaboration. It separates two capability constructs that are often collapsed into a single literacy measure, and shows that they contribute to collaboration with different weights. It also extends the human–AI collaboration literature into a mandated-use, high-accountability hospital context, where collaboration quality rather than adoption choice is the operative variable.

The remainder of the paper is organised as follows. Section 2 develops the theoretical background and hypotheses. Section 3 describes the method. Section 4 reports the results, and Section 5 discusses their theoretical and practical implications, together with limitations and directions for further research.

2. Theoretical Background and Hypotheses

2.1 Employee–AI Collaboration in Smart Hospitals

Employee–AI collaboration captures how far employees and AI systems jointly accomplish work tasks through coordination, role complementarity, and mutual contribution to task execution (Chowdhury et al., 2022; Kong et al., 2023). The construct is behavioural rather than attitudinal. It captures what employees and systems do together, not how employees feel about the technology, and it is conceptually distinct from use frequency: an employee can interact with an AI system many times a day in a superficial, compliance-driven way while collaborating with it poorly (Kong et al., 2023). Collaboration implies that computational strengths (speed, pattern recognition, routine processing) are combined with human strengths such as contextual judgement and accountability in a manner that improves the joint product.

Hospitals are a demanding setting for this kind of joint work. AI systems in hospitals are rarely autonomous; they assist with imaging interpretation, triage, medication checking, and administrative processing, and employees must decide when to rely on outputs, how to read them, and how to fold them into decisions for which humans remain professionally responsible (Sezgin, 2023). The value of hospital AI therefore hinges on the quality of human–AI interaction at the point of task execution. Organisational research converges on this view: collaboration-oriented accounts of AI value creation place the human contribution at the centre of the system, whereas deployment-oriented accounts that treat the technology as self-sufficient give a weaker account of where performance comes from (Jiang et al., 2023; Makarius et al., 2020; Simón et al., 2024).

Collaboration also develops. Conceptual frameworks of human–AI collaboration treat it as phased rather than fixed, progressing from narrow, tightly bounded interaction toward more integrated arrangements in which task distribution adjusts to situation and competence (Jiang et al., 2023; Weisz et al., 2025). In healthcare specifically, levels of AI integration have been distinguished as assisted, augmented, and autonomous configurations, which differ in how much of a task the system carries and how much human judgement stays in the loop (Garbuio & Lin, 2019). Two implications follow for the model tested here. Collaboration quality varies meaningfully across employees within the same technology environment, which makes it a sensible individual-level construct. Its development appears to depend on employee-side resources: what people know about the systems and what they can do with them. That dependence motivates treating capability as its antecedent.

2.2 Theoretical Grounding

The technology acceptance model (TAM) provides the first anchor for the framework. TAM and its extensions hold that beliefs about a technology shape use, and that performance consequences follow from use rather than from beliefs directly (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003). Applied to workplace AI, this logic implies that employee capability, meaning what employees know about AI and what they can do with it, should influence productivity through the behavioural engagement it enables. In an environment where basic system use is mandated, the behavioural variable of interest shifts from adoption to the quality of collaborative use. TAM thus supplies a specific, testable expectation: capability effects on performance should run substantially through enacted collaboration.

The TAM tradition also cautions against reading capability as sufficient. Perceived usefulness and ease of use predict intention well, yet the intention–behaviour link weakens in organisational settings where use is not fully voluntary, and the behaviour–performance link has been studied far less than the antecedent side of the model (Venkatesh & Davis, 2000). Post-adoption research consequently needs behavioural constructs richer than binary use. Employee–AI collaboration serves that purpose here: it is the form of use through which acceptance-related resources could plausibly become performance.

Person–environment fit theory supplies the second anchor. Work outcomes improve when individual abilities align with the demands of the work environment (Kristof-Brown et al., 2005). AI-intensive hospital work changes those demands: tasks now require interpreting algorithmic output, judging its reliability, and coordinating one's own contribution with that of a system. Employees whose understanding and skills match these demands achieve better demands–abilities fit, which should express itself in smoother human–AI coordination and, through it, in higher productivity (Makarius et al., 2020; Simón et al., 2024). Fit theory distinguishes several alignments (with the task, with the technology, with the group), and AI-transformed hospital work engages all of them, since collaboration with a system is embedded in team routines and departmental workflows rather than performed in isolation (Kristof-Brown et al., 2005). Both theoretical lenses converge on the same structural claim: collaboration is the proximal mechanism, capability is the distal input.

2.3 Hypothesis Development

2.3.1 AI Understanding and Productivity

Employees with an accurate mental model of AI are expected to work more effectively in AI-saturated environments. Understanding supports informed decisions about task delegation, that is, which subtasks to hand to the system and which to keep, and it reduces two costly errors: over-reliance on outputs that deserve scepticism and under-use of functions that would save time (Pinski et al., 2023; Theis et al., 2023). Learning about AI has also been linked to stronger AI skills and closer working engagement with AI systems (Kumar & Mittal, 2024). On these grounds a direct association with productivity is plausible, although the strength of that association once collaborative behaviour is taken into account remains uncertain.

H1. AI understanding is positively related to employee productivity.

2.3.2 AI Skills and Productivity

AI skills concern execution. Employees who can operate AI-supported tools fluently, prepare appropriate inputs, and act on outputs without friction should complete AI-assisted tasks faster and with fewer errors (Chuang, 2024; Hornikel et al., 2021). Skill development has been described as the human-side complement without which AI investment fails to convert into performance (Chowdhury et al., 2023), and skilled employees appear more resilient when technologies are updated, sustaining performance through change (Kong et al., 2024; Morandini et al., 2023). A direct productivity effect is therefore expected.

H2. AI skills are positively related to employee productivity.

2.3.3 AI Understanding and Collaboration

Collaboration requires calibrated reliance, and calibration requires comprehension. Employees who understand what a system can and cannot do are better placed to divide labour with it sensibly, to question its outputs when questioning is warranted, and to integrate its recommendations into decisions rather than treating them as noise or as gospel (Knop et al., 2022; Pinski et al., 2023). In safety-critical work more broadly, information about what a system can do and where it is likely to fail has been identified as a precondition for accepting and productively engaging with AI support (Theis et al., 2023), and understanding-related conditions feature prominently in accounts of successful human–AI socialisation in organisations (Chowdhury et al., 2022; Makarius et al., 2020).

H3. AI understanding is positively related to employee–AI collaboration.

2.3.4 AI Skills and Collaboration

Skill lowers the cost of every collaborative act. Employees who can operate AI tools confidently engage with them more willingly and more often, and their interactions are of higher quality: inputs are better prepared, outputs are interpreted faster, and workflow adjustments are made rather than resisted (Hornikel et al., 2021; Morandini et al., 2023). Skills and collaboration also appear to reinforce one another over time, with competence enabling collaboration and collaborative experience building further competence (Sezgin, 2023). Balanced technical and adaptive skill sets have been linked to more effective human–AI teaming in service organisations (Simón et al., 2024).

H4. AI skills are positively related to employee–AI collaboration.

2.3.5 Collaboration and Productivity

Evidence from field settings indicates that AI improves output when workers and systems complement each other. Productivity gains from generative AI have been documented precisely where workers remain in the loop, directing and editing the system's contribution (Brynjolfsson et al., 2025; Noy & Zhang, 2023). In organisational studies, effective employee–AI collaboration is argued to improve coordination and to lower the cognitive burden of task execution, each of which should feed task performance (Jiang et al., 2023; Marikyan et al., 2022). Information sharing and trust are likewise treated as the core enablers of AI-supported collaboration, although that evidence sits at the inter-organisational rather than the employee level (Weisz et al., 2025).

H5. Employee–AI collaboration is positively related to employee productivity.

2.3.6 The Mediating Role of Collaboration

The theoretical case assembled above implies a specific architecture. Capability is a resource; collaboration is the behaviour through which the resource is spent. If TAM's use-mediates-belief logic and the fit-theoretic account are correct, then understanding and skills should raise productivity mainly by raising the quality of collaborative work with AI, and their direct effects should weaken, perhaps to insignificance, once collaboration is modelled (Chowdhury et al., 2022; Kong et al., 2023). This is an empirically falsifiable claim: a strong direct capability effect alongside a null indirect path would contradict it.

H6. Employee–AI collaboration mediates the relationship between AI understanding and employee productivity.

H7. Employee–AI collaboration mediates the relationship between AI skills and employee productivity.

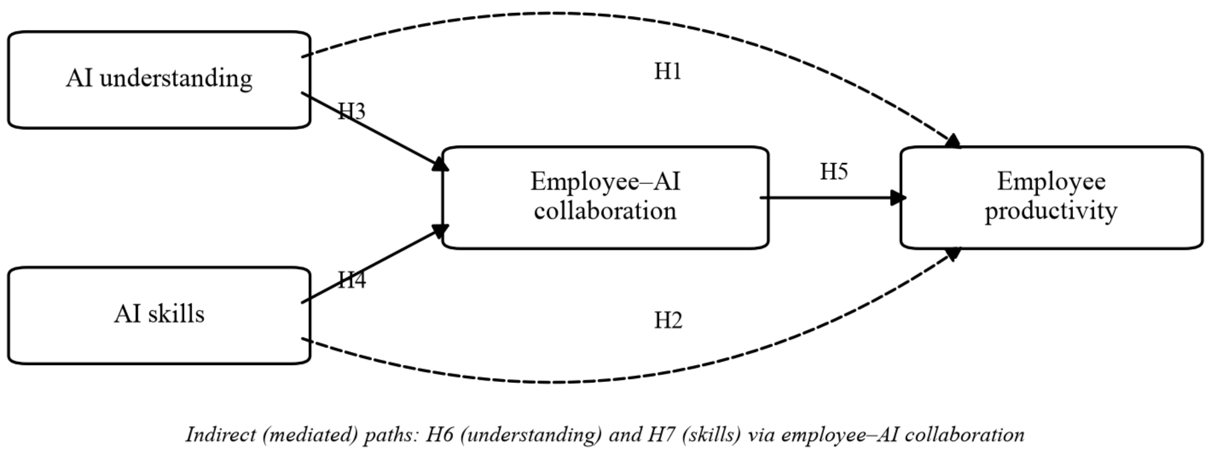

Figure 1. *Conceptual model linking AI understanding and AI skills to employee productivity through employee–AI collaboration.*

3. Method

3.1 Design and Setting

A cross-sectional survey design was used. Data were collected in a large Grade III, Class A (tertiary) general public hospital in China that has implemented AI-enabled systems across clinical and administrative functions, including imaging support, intelligent triage, pharmacy checking, and automated record processing. A single-site design was chosen deliberately: it holds the AI infrastructure, governance arrangements, and implementation history constant across respondents, so that variation in the study constructs reflects differences among employees rather than differences among technology environments.

3.2 Participants and Procedure

The target population comprised hospital employees in four occupational strata: physicians, nurses, pharmaceutical and technical staff, and administrative and logistics staff. Proportionate stratified sampling was implemented with the cooperation of the hospital's human resources department so that each stratum was represented in line with its share of the workforce. The questionnaire was administered online through the Wenjuanxing platform over approximately three months in 2025, using an anonymous link and QR code distributed through official channels; most respondents completed it by smartphone. Ethical approval was obtained from the researchers' university and the hospital before data collection, participation was voluntary and anonymous, and informed consent was recorded before the questionnaire opened.

Recruitment was coordinated with department heads so that the survey window avoided periods of unusual workload, and reminders were issued through routine administrative channels. Response quality was monitored during collection: the platform enforced complete responses, and predefined screening rules covering straight-line answering, contradictory response patterns, and implausible completion times were specified before the data were examined.

A total of 740 questionnaires were submitted. Screening removed 46 cases for invalid response patterns, chiefly straight-lining and implausibly rapid completion, leaving 694 valid responses (retention rate 93.8%). Excluded cases averaged 190 seconds of completion time against 360 seconds for retained cases, supporting the interpretation that removals reflected disengaged responding. The valid sample was predominantly female (76.7%), consistent with public-hospital staffing profiles; 60.7% held a bachelor's degree, 26.4% a master's degree, and 7.3% a doctorate, and mean organisational tenure was approximately 12.9 years. A priori power analysis conducted in G*Power for a five-predictor regression specification, deliberately more demanding than the three-predictor equation estimated here, indicated a minimum of 138 cases at a power of 0.95 ($\alpha = 0.05$, $f^2 = 0.15$), a requirement the achieved sample exceeds five-fold.

3.3 Measures

All substantive items were scored on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Established English-language scales were adapted to the hospital context, translated into Chinese, and back-translated to verify conceptual equivalence. The instrument was then reviewed by subject experts, pre-tested with hospital employees, and refined through a pilot study (n = 53 valid responses) in the same hospital; pilot-stage psychometric screening removed weak items before the main survey.

AI understanding was measured with eight items on how well employees comprehend what AI does in their work, covering its functions, appropriate applications, and boundaries, adapted from the workplace AI socialisation literature (Chowdhury et al., 2022). AI skills were measured with seven items on operating AI-enabled tools fluently, making sense of their outputs, and applying them appropriately in routine hospital tasks (Chowdhury et al., 2023; Morandini et al., 2023). Employee–AI collaboration was measured with ten items covering coordination, mutual role support, and shared task contribution between employee and system, with item structure informed by Kong et al. (2023) and wording adjusted to public-hospital workflows. Employee productivity was measured with four items on perceived effectiveness in daily work (task completion, work quality, workload management, and contribution to organisational goals), adapted from Kassa and Worku (2025). Demographic items recorded gender, education, department, job category, professional title, tenure, AI use frequency, and AI-related training. The survey instrument also carried scales measuring constructs outside the scope of this study; these are not analysed here.

3.4 Common Method Considerations

Because all data were self-reported in a single instrument, procedural and statistical remedies for common method bias were applied (Podsakoff et al., 2003). Procedurally, anonymity was guaranteed, item blocks were separated, and respondents were assured there were no right or wrong answers. Statistically, a Harman-type single-factor test across the full instrument showed the first unrotated factor explaining 38.1% of variance, below the 50% threshold, and full-collinearity testing among the study constructs returned a maximum construct-level VIF of 1.92, well below the 3.3 criterion (Kock, 2015). Method variance is therefore unlikely to account for the results.

3.5 Analytical Approach

A two-stage analytical strategy was followed. Data screening and descriptive analysis were conducted in SPSS 26.0. The measurement model, covering indicator reliability, internal consistency, convergent validity, and discriminant validity for the reflective scales, was assessed in SmartPLS 4, applying the evaluation criteria recommended for variance-based models (Hair et al., 2019). The structural hypotheses were then tested with path analysis on unit-weighted composite scores: standardised coefficients were estimated by ordinary least squares for the two structural equations (collaboration on the capability constructs; productivity on the capability constructs and collaboration), with two-tailed tests and 95% confidence intervals. Because the specified path model is saturated, global fit indices are not informative and inference rests on the coefficient estimates. The specific indirect effects were evaluated with the Monte Carlo confidence-interval method, using 20,000 replications of the product of the constituent path estimates (MacKinnon et al., 2004; Preacher & Selig, 2012), and mediation types were classified following the decision logic of Zhao et al. (2010).

4. Results

4.1 Descriptive Statistics

Table 1 reports construct-level means, standard deviations, and correlations. Respondents reported fairly high AI understanding (M = 3.53) and productivity (M = 3.67), moderate collaboration (M = 3.41), and distinctly lower AI skills (M = 3.01). The gap between understanding and skills is itself informative: employees in this hospital know more about AI than they can comfortably do with it. All correlations among the four constructs were positive and significant, and collaboration correlated most strongly with both AI understanding and productivity (r = 0.56 in each case). Skewness and kurtosis values fell within conventional descriptive ranges.

Table 1

Descriptive Statistics and Correlations Among Constructs (N = 694)

Construct	M	SD	1	2	3	4
1. AI understanding	3.53	0.54	—			
2. AI skills	3.01	0.65	0.39	—		
3. Employee–AI collaboration	3.41	0.62	0.56	0.48	—	
4. Employee productivity	3.67	0.59	0.43	0.34	0.56	—

Non-response bias was examined by comparing early and late respondents on the study constructs and key demographics; no significant differences emerged, which reduces concern that participation timing reflects systematic differences in AI-related attitudes. Construct-level skewness (−0.43 to 0.25) and kurtosis (0.01 to 0.79) indicated no distributional irregularities severe enough to complicate estimation.

4.2 Measurement Model

Indicator reliability was acceptable. Outer loadings ranged from 0.542 to 0.886 across the four constructs; most exceeded 0.70. Three indicators (AU1 = 0.570, AU2 = 0.542, and ASK5 = 0.552) fell in the 0.50–0.70 range and were retained because the affected constructs met all reliability and convergent validity criteria and because the items cover substantively important content whose removal would narrow the construct domain (Hair et al., 2019). Internal consistency was strong for every construct: Cronbach's alpha ranged from 0.872 to 0.939 and composite reliability from 0.904 to 0.948, all within the 0.70–0.95 band that indicates reliability without redundancy. Average variance extracted exceeded 0.50 throughout (Fornell & Larcker, 1981), from 0.546 for AI understanding to 0.723 for productivity. Table 2 summarises these statistics.

Table 2

Measurement Model: Reliability and Convergent Validity

Construct	Items	Loadings	α	CR	AVE
AI understanding	8	0.542–0.858	0.879	0.904	0.546
AI skills	7	0.552–0.854	0.890	0.913	0.605
Employee–AI collaboration	10	0.730–0.861	0.939	0.948	0.648
Employee productivity	4	0.793–0.886	0.872	0.912	0.723

Discriminant validity was assessed with the heterotrait–monotrait ratio (Henseler et al., 2015). The largest HTMT value was 0.618, between collaboration and productivity, well below the conservative 0.85 threshold (Table 3). Indicator-level VIF values (maximum 3.62) and predictor-level VIF values in the structural equations (maximum 1.64) indicated no collinearity concerns.

Table 3

Discriminant Validity: HTMT Ratios

Construct pair	HTMT
AI understanding ↔ AI skills	0.457
AI understanding ↔ Collaboration	0.617
AI understanding ↔ Productivity	0.499
AI skills ↔ Collaboration	0.523
AI skills ↔ Productivity	0.402
Collaboration ↔ Productivity	0.618

4.3 Structural Model

Table 4 reports the path estimates; Figure 2 displays the model. Both capability constructs predicted collaboration: AI understanding at $\beta = 0.434$ ($t = 13.48$, $p < .001$) and AI skills at $\beta = 0.312$ ($t = 9.67$, $p < .001$), supporting H3 and H4. Collaboration in turn predicted productivity strongly ($\beta = 0.426$, $t = 10.70$, $p < .001$), supporting H5. The direct capability–productivity paths were positive but markedly smaller. AI understanding retained a significant direct effect ($\beta = 0.169$, $t = 4.45$, $p < .001$), supporting H1, and the direct effect of AI skills was significant though modest ($\beta = 0.073$, $t = 2.04$, $p = .041$), supporting H2. For comparison, the total effects of understanding and skills on productivity, estimated without the mediator, were 0.354 and 0.206, respectively; more than half of each association is absorbed once collaboration enters the equation.

Read together, the coefficients describe a clear division of labour within the model. Capability operates upstream: understanding and skills jointly shape whether employees and AI systems actually work together well. Collaboration operates downstream, converting that joint work into perceived output. The direct residuals that remain are real but small: knowing about AI, or being able to operate it, yields some productivity advantage on its own, yet most of the capability–productivity association travels through the collaborative channel.

The model explained 39.1% of the variance in collaboration and 33.5% of the variance in productivity. Effect sizes reinforced the path results: for collaboration, f^2 was 0.263 for understanding and 0.135 for skills, medium-sized contributions by conventional standards; for productivity, collaboration contributed $f^2 = 0.166$ while the direct capability contributions were small ($f^2 = 0.029$ for understanding and 0.006 for skills).

Table 4

Structural Model Results (N = 694)

Hypothesis	Path	β	t	p	95% CI	Decision
H1	AI understanding → Productivity	0.169	4.45	< .001	[0.094, 0.243]	Supported
H2	AI skills → Productivity	0.073	2.04	.041	[0.003, 0.144]	Supported
H3	AI understanding → Collaboration	0.434	13.48	< .001	[0.371, 0.498]	Supported
H4	AI skills → Collaboration	0.312	9.67	< .001	[0.248, 0.375]	Supported
H5	Collaboration → Productivity	0.426	10.70	< .001	[0.348, 0.504]	Supported

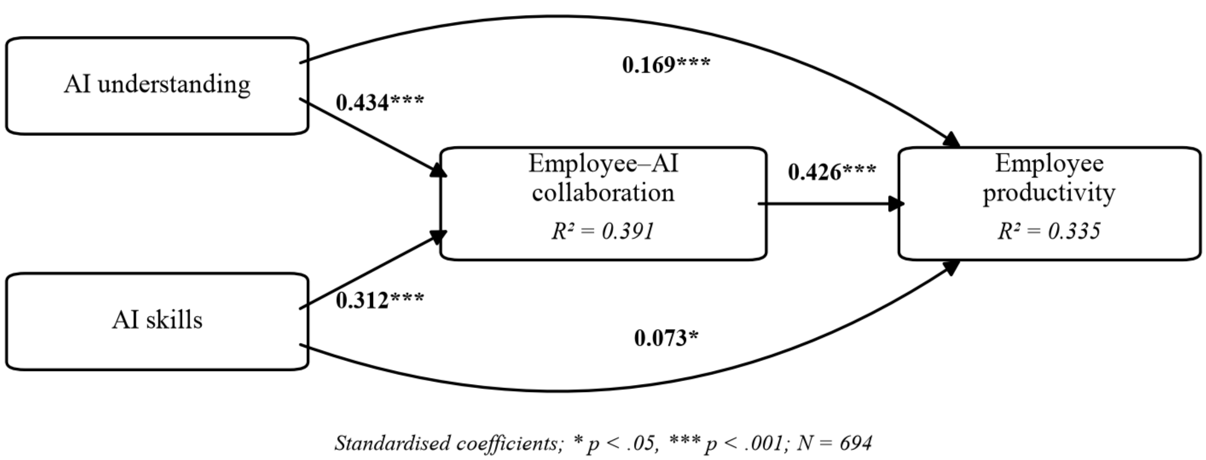

Figure 2. *Structural model results with standardised path coefficients (* p < .05, *** p < .001; N = 694).*

4.4 Mediation Analysis

The specific indirect effects were both positive and significant (Table 5). The indirect path from AI understanding through collaboration to productivity was β = 0.185 (95% Monte Carlo CI [0.144, 0.230], $p < .001$); combined with a significant direct path of the same sign, this constitutes complementary partial mediation in the classification of Zhao et al. (2010), supporting H6. The indirect path from AI skills was β = 0.133 (95% Monte Carlo CI [0.098, 0.171], $p < .001$); with a small significant direct path, the pattern is again complementary partial mediation, supporting H7. Descriptively, the mediated share of the total effect (variance accounted for) was 52.3% for understanding and 64.6% for skills. Collaboration is not the only route from capability to productivity in these data, but it is the main one, and for skills very much the dominant one.

Table 5

Mediation Results: Indirect Effects via Employee–AI Collaboration

Path	Direct β (p)	Indirect β (p)	95% CI (indirect)	Total effect	VAF	Interpretation
AU → EAC → EP	0.169 (< .001)	0.185 (< .001)	[0.144, 0.230]	0.354	0.523	Complementary partial mediation
ASK → EAC → EP	0.073 (.041)	0.133 (< .001)	[0.098, 0.171]	0.206	0.646	Complementary partial mediation

5. Discussion

5.1 Principal Findings

Three results carry the argument. Employee–AI collaboration was the strongest proximal predictor of productivity in the model. Both AI understanding and AI skills predicted collaboration substantially, with understanding the stronger of the two. Both capability constructs retained direct effects on productivity, but these were modest, and for skills barely distinguishable from zero, while the indirect paths through collaboration were large and precise, carrying half to two-thirds of the total effects. Capability, in these data, produces some output on its own; it produces most of its output when it is spent on collaborative work practice.

This pattern is theoretically coherent rather than surprising. TAM's core insight is that beliefs and competencies act on outcomes through use behaviour (Davis, 1989; Venkatesh et al., 2003); in a mandated-use hospital, the behaviourally meaningful variable is collaborative quality, and the capability effects duly route through it. The fit-theoretic reading is complementary: understanding and skills constitute demands-abilities fit with AI-transformed work, and fit expresses itself in coordination before it expresses itself in output (Kristof-Brown et al., 2005; Makarius et al., 2020). What the data add to both accounts is magnitude. A 52% mediated share for understanding and a 64% share for skills mean the collaborative channel is not one pathway among several of similar size; it is the principal conduit, with the direct residuals small in effect-size terms ($f^2 \leq 0.029$).

The relative weight of the two capability dimensions is also informative. Understanding outpredicted skills for collaboration (β = 0.434 versus β = 0.312) and retained the larger direct effect, suggesting that an accurate mental model of what AI can and cannot do is the single most productive employee-side resource in this setting. Skills mattered too, but almost entirely through collaboration (VAF = 64%), and the sample's mean skill score (3.01) sat markedly below its mean understanding score (3.53). Employees appear to know more about AI than they can execute. Comprehension is the stronger lever in the model, yet skill is the scarcer commodity in the workforce, a combination that argues for developing both rather than choosing between them.

5.2 Theoretical Implications

The smallness of the direct effects deserves interpretation, and the context supplies a plausible reading. In this hospital, as in most Chinese tertiary institutions, core AI functions are embedded in required workflows: an order passes through pharmacy checking whether or not the pharmacist admires the algorithm. Under such conditions, private knowledge that is never enacted has few channels through which to affect output; the productivity-relevant differences arise chiefly in the quality of enacted interaction, which is what the collaboration construct measures. The direct residual for understanding ($\beta = 0.169$) plausibly reflects unmediated benefits such as better judgement about when to question or override system output, while the near-threshold direct path for skills ($\beta = 0.073$, $p = .041$) suggests that executional competence has little productivity value that is not already expressed in collaborative practice.

The findings speak first to the adoption literature. Models in the TAM tradition have been extended repeatedly with new antecedent beliefs, yet the outcome side of the chain, namely what accepted technology does to performance and through what behaviour, has received far less attention (Venkatesh et al., 2003). The results here indicate that in post-adoption organisational settings the productive action is downstream of acceptance: two classic capability antecedents mattered for productivity mainly through enacted collaboration. Studies that regress performance directly on acceptance-type constructs will recover the total effects but misattribute them, collapsing a largely behavioural mechanism into what looks like a belief–performance link.

The results also give the employee–AI collaboration construct sharper theoretical standing. Prior work has proposed collaboration as the locus of AI value creation (Chowdhury et al., 2022; Kong et al., 2023; Simón et al., 2024), but quantitative demonstrations that it carries capability effects have been scarce in healthcare. The complementary mediation documented here, with VAF at or above half for both capability dimensions, supplies that demonstration and justifies treating collaboration as a mediating mechanism rather than a correlate.

Comparison with prior evidence is instructive. Related work has linked AI knowledge and competence to delegation quality and to collaboration itself (Kumar & Mittal, 2024; Pinski et al., 2023), but has rarely carried the chain through to a performance outcome; the results here suggest that capability–performance associations largely summarise a mediated process. Conversely, the strong collaboration–productivity path aligns with experimental and field evidence that human-in-the-loop arrangements drive AI's output effects (Brynjolfsson et al., 2025; Noy & Zhang, 2023), and it extends that evidence from voluntary, task-bounded settings to a mandated, workflow-embedded one. The consistency across such different designs strengthens the case that collaboration quality is the operative variable wherever AI and human work intersect.

Separating understanding from skills proved empirically worthwhile. The two constructs were only moderately related (HTMT = 0.457), satisfied the discriminant validity criterion, and behaved differently in the model: understanding carried the larger paths throughout, while the skills effect was almost wholly mediated. Composite "AI literacy" measures that merge knowledge and competence would have obscured this asymmetry, and with it the practical conclusions that follow.

5.3 Practical Implications

The findings also travel, with care, beyond healthcare. Mandated-use environments are becoming the norm for workplace AI: banks, logistics operators, and public agencies deploy systems that employees cannot decline, and in each case the open question is what separates productive users from unproductive ones. The answer suggested here, the conversion of capability into collaborative practice, is not hospital-specific in its logic, although its magnitude may vary with task discretion, accountability structures, and the maturity of the deployed systems. Comparative tests across industries would be a natural extension.

For hospital managers, the central message is that capability investments should be judged by their effect on collaborative work practice, not by knowledge outcomes. Training programmes that end with an assessment of what staff know about AI stop one step short of where value is created. Programmes are more likely to pay off when they are role-based and applied, rehearsing the actual delegation, interpretation, and override decisions of specific job families, and when their success metric is observed change in how AI is used within workflows.

The skills deficit deserves particular attention. With mean skills at 3.01 against understanding at 3.53, this workforce's constraint is executional. Hands-on practice environments, super-user networks within departments, and protected time for skill consolidation are the interventions this profile calls for. Information departments and vendors share responsibility: interfaces and explanation formats that lower the skill threshold for productive interaction can help convert existing understanding into collaborative practice, since users' willingness to act on AI output depends heavily on how intelligibly that output is presented (Hassan et al., 2024).

A sequencing implication follows from the mediation structure. Capability-building and collaboration-enabling measures are complements, and the order in which they are deployed matters. Training delivered before the surrounding workflow supports collaboration produces knowledge with nowhere to go; the small direct residuals in these data indicate how little capability returns on its own. A more effective sequence pairs each capability intervention with an immediate collaborative outlet: training on a decision-support function scheduled in the same month the function is embedded at the relevant decision point, or skill certification tied to participation in a live AI-assisted workflow rather than to a written test. Departments can operationalise this by auditing, for each deployed AI function, whether staff possess the skill to use it and whether the workflow gives that skill a place to be exercised; a gap on either side is, on the logic of this study's mediation result, a plausible reason for the function to contribute little to output.

Workflow design is the third lever. Because collaboration, not exposure, drives productivity, managers should look beyond usage statistics such as logins and invocation counts, and monitor whether AI outputs are actually incorporated into decisions and task execution. Embedding AI touchpoints at natural decision moments, clarifying when staff may override system recommendations, and reviewing collaboration quality in routine performance conversations are practical steps consistent with the evidence.

5.4 Limitations and Future Research

Four limitations bound these conclusions. The design is cross-sectional, so the mediation model is causally ordered by theory, not by data; reciprocal dynamics, such as collaboration building skills and productivity feeding confidence, are plausible and unmodelled. Longitudinal or experience-sampling designs would allow the temporal claims to be tested directly. Second, all constructs were self-reported, and the structural estimates rest on composite scores, which do not partial out measurement error; given the high scale reliabilities ($\alpha \geq 0.87$), attenuation should be modest, but it runs against the hypotheses rather than for them. The method-bias diagnostics were reassuring (38.1% single-factor variance; maximum full-collinearity VIF of 1.92), yet perceived productivity is not measured output, and future work should pair survey measures with archival performance indicators where hospital data systems permit. Third, the evidence comes from one tertiary public hospital in China. Single-site designs control the technology environment but leave institutional generalisability open; replication across hospital tiers, ownership types, and health systems is needed before the mediation pattern can be treated as general. Fourth, the model is deliberately parsimonious. Other employee-side conditions, trust in AI foremost among them (Glikson & Woolley, 2020), and organisational moderators such as leadership support or training climate were outside its scope, and integrating them may reveal boundary conditions for the mediation documented here.

Future research might also unpack collaboration itself. The construct was measured here as an overall quality of joint task execution; finer-grained work could distinguish delegation, verification, and co-production behaviours, and ask which of them transmits capability to productivity most efficiently across professional groups.

6. Conclusion

AI systems do not make hospital employees productive; working well with AI systems does. In data from 694 employees of a Chinese tertiary public hospital, AI understanding and AI skills raised productivity mainly through the employee–AI collaboration they enabled, with direct effects that were real but small by comparison. The finding relocates the managerial problem: the question that matters after deployment is not whether staff accept AI or know about it, but whether their knowledge and competence are being converted, daily and concretely, into collaborative work practice. Hospitals that measure and manage that conversion, through applied training, skill-lowering interface design, and workflow integration, are the ones positioned to collect the productivity returns their AI investments were meant to deliver.

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