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Trust in Artificial Intelligence and AI Adoption Intention in Enterprises

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ABSTRACT: Artificial intelligence (AI) adoption has become a strategic priority for enterprises seeking to improve productivity, decision-making, automation, and competitiveness. However, employees may hesitate to adopt AI when they perceive risks related to reliability, privacy, ethics, security, and overreliance. This study examines the determinants of trust in AI and its effect on AI adoption intention in enterprises. Drawing on the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and Trust Theory, the study investigates the effects of perceived usefulness, perceived ease of use, perceived risk, and organizational support on trust in AI and AI adoption intention. Data were collected from 400 respondents and analyzed using partial least squares structural equation modeling. The results show that perceived usefulness, perceived ease of use, and organizational support positively influence trust in AI, while perceived risk negatively affects trust in AI. Trust in AI has a strong positive effect on AI adoption intention and fully mediates the relationships between all antecedent variables and adoption intention. The findings extend AI adoption literature by positioning trust in AI as a central psychological mechanism linking technology perceptions and organizational conditions to adoption intention. Practical implications are provided for enterprises seeking to build trustworthy and responsible AI adoption environments.

KEYWORDS: AI adoption intention; Trust in AI; Perceived usefulness; Perceived ease of use; Perceived risk; Organizational support.

1. INTRODUCTION

Artificial intelligence (AI) has become an increasingly important technology for enterprises seeking to improve productivity, decision-making, customer service, process automation, innovation, and competitive advantage. AI applications are now used in many business functions, including marketing analytics, customer relationship management, human resource management, accounting, logistics, production planning, risk assessment, and strategic decision-making. Unlike traditional information systems, AI can learn from data, generate recommendations, automate complex tasks, and interact with users in human-like ways. Therefore, AI adoption is no longer only a technological issue but also an organizational and behavioral issue.

Despite the rapid diffusion of AI technologies, many enterprises still face challenges in encouraging employees and managers to accept and use AI systems. Recent evidence shows that AI use in workplaces is expanding, but trust, AI literacy, responsible use, and organizational guidance remain uneven. A global study by the University of Melbourne and KPMG found that many workers use AI tools but do not always verify AI outputs, highlighting the importance of trust calibration, training, and governance in organizational AI adoption (Gillespie et al., 2025).

Trust in AI is especially important because AI systems often operate through complex algorithms that are difficult for ordinary users to understand. Employees may hesitate to adopt AI if they perceive it as unreliable, opaque, risky, biased, or threatening to their job autonomy. Conversely, when employees believe that AI systems are competent, reliable, transparent, and beneficial, they are more likely to accept and use them. Prior research has emphasized that trust plays a critical role in human-AI interaction and can influence whether individuals accept, rely on, or reject AI-based recommendations (Glikson & Woolley, 2020; Afroogh et al., 2024). Recent studies also suggest that trust in AI is dynamic and may change as users gain more experience and knowledge about AI technologies (Daly et al., 2025).

Although the literature on technology acceptance has widely examined perceived usefulness, perceived ease of use, performance expectancy, effort expectancy, and behavioral intention, the specific role of trust in AI adoption within enterprises remains underdeveloped. Traditional models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) provide useful foundations for explaining technology acceptance (Davis, 1989; Venkatesh et al., 2003). However, AI differs from conventional technologies because it can make autonomous recommendations, process sensitive data, learn from users, and affect organizational decisions. Therefore, AI adoption requires not only perceptions of usefulness and ease of use but also trust in the AI system's reliability, transparency, fairness, and alignment with organizational goals.

Trust in Artificial Intelligence and AI Adoption Intention in Enterprises

This study addresses three research gaps. First, prior research has often examined AI adoption from a general technology acceptance perspective, while trust in AI has not been sufficiently integrated as a central explanatory mechanism in enterprise settings. Second, many studies have focused on individual consumers or students, whereas enterprise adoption involves employees and managers who evaluate AI in relation to work tasks, organizational support, data risks, and performance outcomes. Third, the role of perceived risk and organizational support in shaping trust in AI remains underexplored, especially in emerging economy contexts where enterprises may adopt AI rapidly but lack mature AI governance systems.

Accordingly, this study aims to develop a research model explaining AI adoption intention in enterprises by examining the effects of perceived usefulness, perceived ease of use, perceived risk, and organizational support on trust in AI and AI adoption intention. The study contributes to the literature in three ways. First, it extends TAM and UTAUT by positioning trust in AI as a key mechanism linking technology perceptions and organizational conditions to adoption intention. Second, it contributes to trust in AI literature by examining trust in an enterprise context rather than only in consumer or general human-AI interaction settings. Third, it provides practical implications for enterprises by showing how AI adoption can be strengthened through useful AI applications, user-friendly systems, risk reduction, transparent governance, and organizational support.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. Theoretical background and key concepts

This study is grounded in three theoretical perspectives: the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and Trust Theory.

The Technology Acceptance Model argues that perceived usefulness and perceived ease of use are key determinants of users' attitudes and intentions toward technology adoption (Davis, 1989). Perceived usefulness refers to the extent to which users believe that a technology improves job performance, while perceived ease of use refers to the extent to which the technology is perceived as easy to learn and operate. In the AI context, employees may be more willing to adopt AI when they believe it can improve task performance, reduce workload, enhance decision quality, and be used without excessive complexity.

The Unified Theory of Acceptance and Use of Technology extends technology acceptance research by emphasizing performance expectancy, effort expectancy, social influence, and facilitating conditions as determinants of behavioral intention and technology use (Venkatesh et al., 2003). In enterprise settings, AI adoption is shaped not only by individual perceptions but also by organizational resources, training, managerial support, and infrastructure. Therefore, organizational support is particularly important because employees may need guidance, technical assistance, ethical policies, and managerial encouragement to adopt AI responsibly.

Trust Theory provides an additional foundation for explaining AI adoption. Trust refers to users' willingness to rely on a system under conditions of uncertainty and vulnerability. In human-AI interaction, trust may include beliefs about AI competence, reliability, predictability, benevolence, integrity, transparency, and risk control (Glikson & Woolley, 2020; McKnight et al., 2011). Because AI can influence decisions and automate tasks, employees may need to trust AI before they are willing to accept and use it in their work.

In this study, trust in AI refers to employees' belief that AI systems used in enterprises are reliable, competent, transparent, safe, and useful for work-related decision-making. AI adoption intention refers to employees' willingness and intention to use AI tools or AI-enabled systems in their job tasks. The proposed model includes perceived usefulness, perceived ease of use, perceived risk, and organizational support as antecedents of trust in AI, and trust in AI as a key predictor of AI adoption intention.

2.2. Perceived usefulness and trust in AI

Perceived usefulness is expected to positively influence trust in AI. Employees are more likely to trust AI systems when they believe that these systems help improve work performance, enhance productivity, support decision-making, reduce repetitive tasks, and provide valuable recommendations. In enterprise contexts, AI systems are often evaluated based on whether they generate practical benefits for employees and organizations. If AI tools provide accurate analyses, useful suggestions, and better task outcomes, users may develop stronger confidence in the system.

This argument is consistent with TAM, which emphasizes perceived usefulness as a central determinant of technology acceptance (Davis, 1989). In AI contexts, usefulness may also shape trust because users often infer system competence from performance benefits. Prior research indicates that performance-related evaluations are important for trust in AI and AI acceptance (Glikson & Woolley, 2020; Choung et al., 2022). Therefore, when employees perceive AI as useful for their work, they are more likely to trust it.

H1: Perceived usefulness positively influences trust in AI.

2.3. Perceived ease of use and trust in AI

Perceived ease of use is expected to positively influence trust in AI. AI systems that are easy to learn, easy to operate, and easy to integrate into daily work are more likely to reduce user anxiety and uncertainty. When employees can understand how to interact with AI tools, interpret AI outputs, and apply AI recommendations without excessive effort, they may perceive the system as more controllable and trustworthy.

According to TAM, perceived ease of use influences technology acceptance directly and indirectly through perceived usefulness (Davis, 1989). In the AI context, ease of use is also important because complex or opaque systems may reduce user confidence. Employees may distrust AI when they find it difficult to understand its interface, logic, or recommendations. Conversely, user-friendly AI systems can strengthen trust by increasing perceived control and reducing cognitive burden. Prior studies on AI adoption and technology acceptance have confirmed that effort-related perceptions are important predictors of AI acceptance (Venkatesh et al., 2003; Rana et al., 2024).

H2: Perceived ease of use positively influences trust in AI.

2.4. Perceived risk and trust in AI

Perceived risk is expected to negatively influence trust in AI. In enterprises, AI adoption may create concerns about data privacy, algorithmic bias, inaccurate recommendations, cybersecurity risks, job displacement, accountability, and overdependence on automated systems. Employees may hesitate to trust AI if they believe that AI outputs are unreliable, difficult to verify, or potentially harmful to job performance and organizational decisions.

Trust in AI literature emphasizes that trust and distrust are not simply opposite states but may coexist depending on users' perceptions of system reliability, uncertainty, and risk (Afroogh et al., 2024; Scharowski et al., 2024). AI systems can generate value, but they also create risks when users over-rely on inaccurate or biased outputs. Recent workplace evidence highlights that many employees use AI without adequately checking accuracy, which increases the importance of risk awareness and governance (Gillespie et al., 2025). Therefore, perceived risk is expected to reduce trust in AI.

H3: Perceived risk negatively influences trust in AI.

2.5. Organizational support and trust in AI

Organizational support is expected to positively influence trust in AI. Employees are more likely to trust AI when their organization provides training, technical support, ethical guidelines, data governance, managerial encouragement, and clear communication about AI use. In enterprise settings, AI adoption does not depend only on the technology itself; it also depends on whether employees feel supported in learning, experimenting, and using AI responsibly.

UTAUT emphasizes facilitating conditions as an important factor in technology adoption (Venkatesh et al., 2003). In AI adoption, facilitating conditions include infrastructure, training, policies, leadership support, and technical assistance. Organizational support may reduce uncertainty and strengthen employees' confidence that AI systems are properly implemented, monitored, and aligned with organizational goals. Recent studies on organizational AI adoption also emphasize that successful AI integration requires not only technical tools but also organizational readiness, user support, and governance mechanisms (Romeo & Lacko, 2025).

H4: Organizational support positively influences trust in AI.

2.6. Trust in AI and AI adoption intention

Trust in AI is expected to positively influence AI adoption intention. When employees trust AI systems, they are more willing to use them for work-related tasks, rely on their recommendations, and integrate them into daily decision-making. Trust reduces uncertainty and perceived vulnerability, making users more comfortable with AI-assisted processes.

Prior research has consistently emphasized the importance of trust in human-AI interaction and AI acceptance. Glikson and Woolley (2020) argue that trust is critical for successful AI integration because users must decide whether to rely on AI outputs. Afroogh et al. (2024) also show that trust and distrust influence the diffusion and acceptance of AI across domains. Recent organizational research further suggests that trust in AI influences willingness to adopt AI technologies in workplaces (Daly et al., 2025).

H5: Trust in AI positively influences AI adoption intention.

2.7. Mediating role of trust in AI

Trust in AI is expected to mediate the relationship between technology perceptions, organizational support, perceived risk, and AI adoption intention. Perceived usefulness and ease of use may increase trust by signaling that AI is beneficial, understandable, and controllable. Organizational support may increase trust by reducing uncertainty and providing employees with resources for responsible AI use. Conversely, perceived risk may reduce trust and thereby weaken adoption intention.

This mediating mechanism is consistent with the integration of TAM, UTAUT, and Trust Theory. Technology perceptions and organizational conditions shape employees' trust in AI, and trust then influences their willingness to adopt AI. Recent research also suggests that trust is a central mechanism explaining how attitudes toward AI translate into organizational AI adoption (Daly et al., 2025).

H6: Trust in AI mediates the relationships between perceived usefulness, perceived ease of use, perceived risk, organizational support, and AI adoption intention.

The proposed research model includes six latent constructs: Perceived usefulness, Perceived ease of use, Perceived risk, Organizational support, Trust in AI and AI adoption intention.

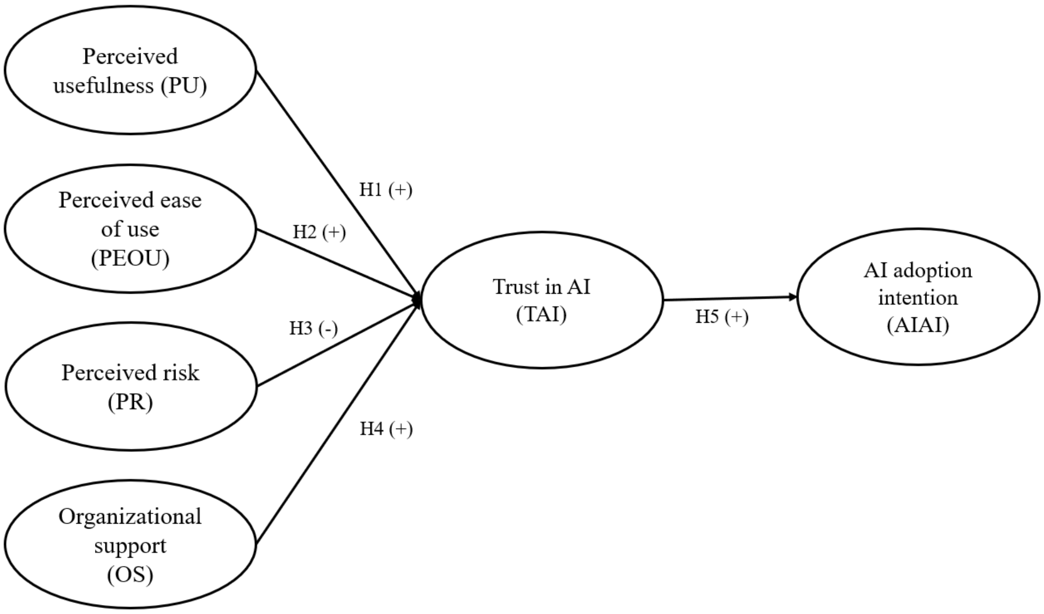

Figure 1: The proposed research model
(Source: Author)

3. RESEARCH METHODOLOGY

3.1. Research design

This study adopts a quantitative, cross-sectional survey design. This approach is suitable because the study aims to test hypothesized relationships among latent constructs and examine the mediating role of trust in AI. A structured questionnaire will be used to collect data from employees and managers working in enterprises that have adopted or are preparing to adopt AI-enabled tools. Partial least squares structural equation modeling (PLS-SEM) will be used because the research model includes multiple latent constructs, direct effects, and mediation effects, and the study is prediction-oriented (Hair et al., 2022).

3.2. Research context and sample

The study can be conducted among enterprises in Vietnam, especially firms undergoing digital transformation or using AI-enabled applications in business operations. Vietnam is an appropriate context because many enterprises are increasingly adopting digital technologies, data analytics, automation, chatbots, and AI-based platforms to improve competitiveness. However, many firms still face limitations in AI literacy, governance, employee training, and trust in AI systems. The target respondents are employees, supervisors, department heads, managers, and senior managers who have knowledge of AI use in their organizations. The suggested sample size is 350–500 valid responses, which is suitable for PLS-SEM and allows subgroup analysis by industry, firm size, job position, AI experience, and digital transformation level.

3.3. Sampling and data collection

The study may use purposive sampling combined with convenience sampling. Purposive sampling ensures that respondents have sufficient exposure to AI-enabled systems or digital work processes. Convenience sampling can be implemented through business associations, professional networks, chambers of commerce, alumni networks, online employee communities, and participating enterprises. Before the main survey, a pilot test should be conducted with 30–50 respondents to assess item clarity, wording, and contextual relevance. The final questionnaire can be distributed online using Google Forms or similar platforms. Respondents should be informed that participation is voluntary, their answers are confidential, and data will be used only for academic purposes.

3.4. Measurement scales

All constructs were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The measurement items were adapted from validated scales in technology acceptance, trust in technology, perceived risk, and organizational support literature. Perceived usefulness and perceived ease of use were measured using six items adapted from Davis (1989) and Venkatesh et al. (2003). Perceived risk was measured using six items adapted from Featherman and Pavlou (2003), Afroogh et al. (2024), and Gillespie et al. (2025). Organizational support was measured using six items adapted from Venkatesh et al. (2003) and Eisenberger et al. (1986). Trust in AI was measured using seven items adapted from McKnight et al. (2011), Glikson and Woolley (2020), Choung et al. (2022), and Scharowski et al. (2024). AI adoption intention was measured using six items adapted from Davis (1989) and Venkatesh et al. (2003).

3.5. Data analysis

Data will be analyzed using SPSS and SmartPLS 4. First, data screening will remove incomplete responses, duplicate responses, and careless answers. Second, descriptive statistics will summarize respondent and firm characteristics. Third, common method bias will be assessed using Harman's single-factor test and full collinearity VIF (Podsakoff et al., 2003; Kock, 2015). Fourth, the measurement model will be evaluated using outer loadings, Cronbach's alpha, composite reliability, average variance extracted, and HTMT (Fornell & Larcker, 1981; Henseler et al., 2015; Hair et al., 2022). Fifth, the structural model will be assessed using path coefficients, t-statistics, p-values, VIF, R^2, Q^2, and f^2. Finally, the mediating effect of trust in AI will be tested using bootstrapping with 5,000 subsamples (Preacher & Hayes, 2008; Hair et al., 2022).

4. RESULTS

Because empirical data have not yet been collected, this section provides a scientific reporting structure that can be completed after data analysis.

4.1. Sample description

Table 1 presents the demographic and organizational profile of 400 respondents. The sample is relatively balanced by gender, with 53.0% male and 47.0% female respondents. Most respondents are aged 25–34 years (41.0%) and 35–44 years (31.0%), indicating an active working-age group. Regarding education, 58.0% hold a bachelor's degree and 23.0% have postgraduate qualifications. Employees/specialists account for the largest group (37.5%), followed by middle managers (24.5%). Most respondents have more than three years of work experience. In terms of AI exposure, 43.0% report moderate experience, while 20.0% report high experience. Overall, the sample is suitable for examining trust in AI and AI adoption intention in enterprises.

Table 1 - Sample Description

Characteristic	Category	Frequency	Percentage
Gender	Male	212	53.0%
	Female	188	47.0%
Age	Under 25	48	12.0%
	25–34	164	41.0%
	35–44	124	31.0%
	45 and above	64	16.0%
Education	College or below	76	19.0%
	Bachelor's degree	232	58.0%
	Postgraduate degree	92	23.0%
Job position	Employee/Specialist	150	37.5%
	Team leader/Supervisor	92	23.0%
	Department head/Middle manager	98	24.5%
	Director/Senior manager	60	15.0%
Work experience	Under 1 year	36	9.0%
	1–3 years	104	26.0%
	4–6 years	126	31.5%
	More than 6 years	134	33.5%
AI experience	No experience	44	11.0%
	Low experience	104	26.0%
	Moderate experience	172	43.0%
	High experience	80	20.0%
Industry	Manufacturing	72	18.0%
	Trade/Retail	76	19.0%
	Banking/Finance	68	17.0%
	Services	92	23.0%
	IT/Digital services	52	13.0%
	Logistics/Others	40	10.0%
Firm size	Micro enterprise	48	12.0%

	Small enterprise	126	31.5%
	Medium enterprise	144	36.0%
	Large enterprise	82	20.5%
Ownership type	Private domestic firm	250	62.5%
	State-owned enterprise	42	10.5%
	Foreign-invested enterprise	72	18.0%
	Joint venture/Other	36	9.0%
Level of AI adoption	Not yet adopted, but planning	60	15.0%
	Initial adoption	136	34.0%
	Moderate adoption	150	37.5%
	Advanced adoption	54	13.5%

(Source: Author)

4.2. Measurement model assessment

The measurement model demonstrates satisfactory reliability and convergent validity. As shown in Table 2, all outer loadings ranged from 0.815 to 0.927, exceeding the recommended threshold of 0.70. Cronbach's alpha values ranged from 0.926 to 0.953, while composite reliability values ranged from 0.942 to 0.963, confirming strong internal consistency across all constructs. In addition, AVE values ranged from 0.728 to 0.811, all above the 0.50 threshold. These results indicate that PU, PEOU, PR, OS, TAI, and AIAI achieved adequate reliability and convergent validity for subsequent analysis.

Table 2. Reliability and Validity

Construct	**Items**	**Outer Loadings**	**Cronbach's α**	**CR**	**AVE**
PU	6	0.818-0.889	0.926	0.942	0.730
PEOU	6	0.838-0.903	0.934	0.948	0.753
PR	6	0.876-0.927	0.953	0.962	0.809
OS	6	0.875-0.916	0.953	0.962	0.810
TAI	7	0.815-0.890	0.938	0.949	0.728
AIAI	6	0.885-0.917	0.953	0.963	0.811

(Source: Author)

Discriminant validity was assessed using the Fornell–Larcker criterion and the HTMT ratio. As shown in Table 3, the square roots of AVE for AIAI, OS, PEOU, PR, PU, and TAI ranged from 0.853 to 0.90 and were higher than their corresponding inter-construct correlations. In addition, all HTMT values were below the recommended threshold of 0.85, with the highest value observed between TAI and AIAI. These results confirm that the constructs are empirically distinct, supporting adequate discriminant validity for further structural model analysis.

Table 3. Heterotrait–Monotrait Ratio (HTMT)

	AIAI	OS	PEOU	PR	PU	TAI
AIAI	**0.9**	0.191	0.307	-0.302	0.207	0.557
OS	0.201	**0.9**	-0.074	-0.005	-0.012	0.289
PEOU	0.326	0.08	**0.867**	-0.026	0.016	0.393
PR	0.314	0.024	0.046	**0.899**	-0.024	-0.344
PU	0.219	0.041	0.028	0.052	**0.854**	0.268
TAI	0.589	0.303	0.418	0.36	0.286	**0.853**

Note: Correlations and HTMT ratio are at the lower and upper of the diagonal, respectively; the square roots of AVE are highlighted in bold

(Source: Author)

4.3. Common method bias

Because this study uses self-reported survey data, common method bias should be examined. Harman's single-factor test can be used as an initial diagnostic. If the first factor explains less than 50% of total variance, common method bias is unlikely to be a serious concern. In addition, full collinearity VIF values below 3.3 indicate that common method bias is not severe in PLS-SEM

(Kock, 2015). Procedural remedies should also be applied, including anonymity, voluntary participation, and separation of construct items in the questionnaire.

4.4. Structural model assessment

The structural model was assessed using explanatory power, predictive relevance, path coefficients, multicollinearity, effect sizes, and mediation effects. As shown in Table 4, the model explains 31.1% of the variance in trust in AI (TAI) and 24.9% of the variance in AI adoption intention (AIAI). The Q^2 values for TAI and AIAI were both 0.311 and 0.249, respectively, exceeding zero and confirming the model's predictive relevance. However, the reported SRMR value of 0.403 is substantially higher than the recommended threshold of 0.08, indicating that model fit should be rechecked before final reporting.

The hypothesis testing results show that all proposed direct effects were statistically significant. Perceived usefulness positively influenced trust in AI ($\beta = 0.320$, $p < 0.001$), supporting H1. Perceived ease of use had the strongest positive effect on trust in AI ($\beta = 0.403$, $p < 0.001$), supporting H2. Perceived risk negatively affected trust in AI ($\beta = -0.325$, $p < 0.001$), supporting H3. Organizational support also positively influenced trust in AI ($\beta = 0.257$, $p < 0.001$), supporting H4. In addition, trust in AI had a strong positive effect on AI adoption intention ($\beta = 0.557$, $p < 0.001$), supporting H5.

The VIF values ranged from 1.000 to 1.780, below the threshold of 3, indicating that multicollinearity was not a concern. Regarding effect sizes, trust in AI had the largest effect on AI adoption intention ($f^2 = 0.450$), followed by perceived ease of use on trust in AI ($f^2 = 0.284$), perceived risk on trust in AI ($f^2 = 0.186$), organizational support on trust in AI ($f^2 = 0.180$), and perceived usefulness on trust in AI ($f^2 = 0.116$).

The mediation results confirm that trust in AI significantly mediated the effects of perceived usefulness, perceived ease of use, perceived risk, and organizational support on AI adoption intention. All indirect effects were statistically significant at $p < 0.001$. The VAF values of 100% indicate full mediation, suggesting that these antecedents influence AI adoption intention entirely through trust in AI. Overall, the findings confirm the central role of trust in AI in explaining AI adoption intention in enterprises.

Table 4. Structural Model Assessment and Hypothesis Testing Result

Latent variables		**R^2**	**Q^2**			
AIAI		0.249	0.249			
TAI		0.311	0.311			
SRMR: 0.403						
Hypothesis	**Path**	**β**	**p-value**	**VIF**	**f^2**	**VAF (%)**
H1: Yes	PU → TAI	0.32	0.000	1	0.116	-
H2: Yes	PEOU → TAI	0.403	0.000	1	0.284	-
H3: Yes	PR → TAI	-0.325	0.000	1.78	0.186	-
H4: Yes	OS → TAI	0.257	0.000	1.355	0.180	-
H5: Yes	TAI → AIAI	0.557	0.000	1.406	0.450	-
H6a: Yes	PU → TAI → AIAI	0.143	0.000	-	-	100
H6b: Yes	PEOU → TAI → AIAI	0.225	0.000	-	-	100
H6c: Yes	PR → TAI → AIAI	-0.181	0.000	-	-	100
H6e: Yes	OS → TAI → AIAI	0.143	0.000	-	-	100

(Source: Author)

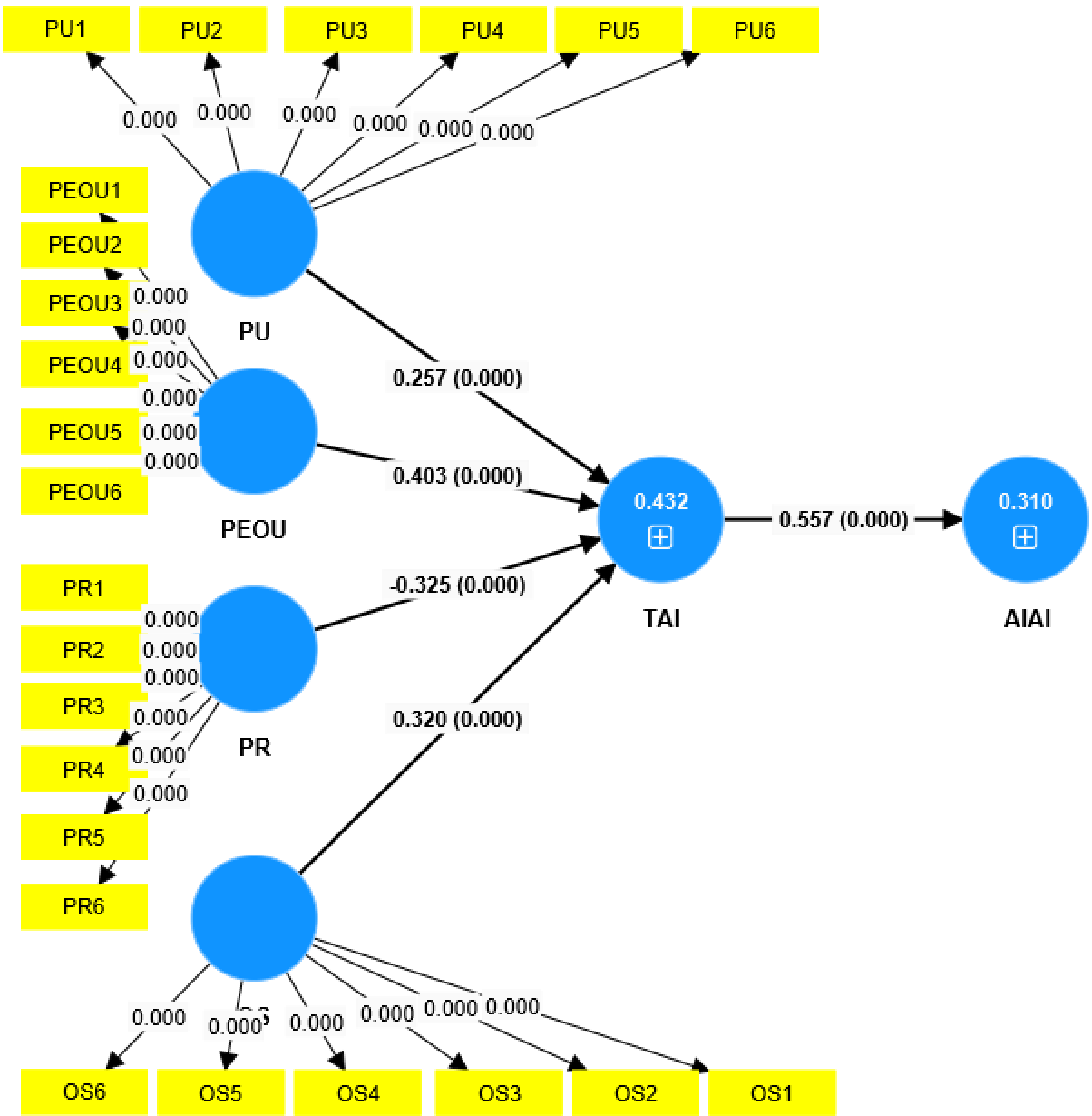

Figure 2. Final Structural Model after Bootstrapping

Note: Path coefficients (β) and explained variances (R^2) are based on SmartPLS 4 bootstrapping results.

5. DISCUSSION

This study examined AI adoption intention in enterprises by integrating perceived usefulness, perceived ease of use, perceived risk, organizational support, and trust in AI. The results provide empirical support for the proposed model and confirm the central role of trust in AI in explaining employees' willingness to adopt AI systems in organizational settings. Overall, all proposed hypotheses were supported, indicating that employees' trust in AI is shaped by both technology-related perceptions and organizational conditions, and that trust in AI is a direct driver of AI adoption intention.

First, perceived usefulness was found to have a positive effect on trust in AI. This finding suggests that employees are more likely to trust AI systems when they perceive that AI helps improve work effectiveness, decision quality, productivity, and problem-solving capability. This result is consistent with the Technology Acceptance Model, which identifies perceived usefulness as a key determinant of technology acceptance (Davis, 1989). It also aligns with Choung et al. (2022) and Glikson and Woolley (2020), who argued that users' confidence in AI is partly formed through perceived system competence and performance value. In enterprise contexts, usefulness may signal that AI is not merely a technological novelty but a practical work-supporting tool.

Second, perceived ease of use showed the strongest positive effect on trust in AI. This result indicates that employees are more likely to trust AI when they find AI tools easy to learn, understandable, and convenient to integrate into daily work. This finding is consistent with Davis (1989) and Venkatesh et al. (2003), who emphasized the importance of effort-related perceptions in technology adoption. In the AI context, ease of use is especially important because AI systems may be perceived as complex, opaque, or difficult to control. Therefore, user-friendly AI interfaces and clear guidance can reduce uncertainty and strengthen employees' confidence in AI.

Third, perceived risk negatively influenced trust in AI. This finding confirms that concerns about data privacy, unreliable outputs, ethical issues, security risks, and overreliance on AI can weaken employees' trust. This result is consistent with Featherman and Pavlou (2003), who emphasized that perceived risk can reduce technology acceptance. It also supports recent AI trust studies showing that trust and distrust are shaped by concerns about fairness, transparency, accountability, and system reliability (Afroogh et al., 2024; Scharowski et al., 2024). In enterprises, this finding highlights that AI adoption requires not only technical implementation but also risk governance and responsible AI practices.

Fourth, organizational support positively affected trust in AI. This result suggests that employees are more likely to trust AI when their organizations provide training, technical support, clear guidelines, and managerial encouragement. This finding is consistent with UTAUT, which emphasizes facilitating conditions as an important factor in technology adoption (Venkatesh et al., 2003). It also aligns with Eisenberger et al. (1986), who argued that perceived organizational support strengthens employees' confidence and positive work attitudes. In the AI adoption context, organizational support reduces uncertainty and helps employees understand how to use AI responsibly and effectively.

Fifth, trust in AI had a strong positive effect on AI adoption intention. This confirms that employees are more willing to use AI systems when they believe that AI is reliable, competent, dependable, and useful for work-related decisions. This finding is consistent with Glikson and Woolley (2020), who emphasized trust as a critical condition for human reliance on AI. It also supports Afroogh et al. (2024), who suggested that trust is a central factor in AI acceptance and diffusion.

Finally, the mediation results show that trust in AI fully mediates the effects of perceived usefulness, perceived ease of use, perceived risk, and organizational support on AI adoption intention. This is the key contribution of the study. The finding suggests that technology perceptions and organizational conditions do not automatically lead to AI adoption intention; rather, they influence adoption intention through the formation of trust. Theoretically, this study extends TAM and UTAUT by positioning trust in AI as a central psychological mechanism in enterprise AI adoption. Practically, enterprises should improve AI usefulness, simplify AI use, reduce perceived risks, and strengthen organizational support to build employee trust and encourage AI adoption.

6. CONCLUSION, IMPLICATIONS, LIMITATIONS AND FUTURE RESEARCH

6.1. Conclusion

This study examined AI adoption intention in enterprises by focusing on the central role of trust in AI. Drawing on the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and Trust Theory, the study tested how perceived usefulness, perceived ease of use, perceived risk, and organizational support influence trust in AI and, subsequently, AI adoption intention. The empirical results supported all proposed hypotheses. Perceived usefulness, perceived ease of use, and organizational support positively influenced trust in AI, while perceived risk negatively affected trust in AI. Trust in AI, in turn, had a strong positive effect on AI adoption intention. The mediation results further confirmed that trust in AI fully mediated the effects of perceived usefulness, perceived ease of use, perceived risk, and organizational support on AI adoption intention. These findings indicate that enterprise AI adoption is not only determined by technological benefits or organizational support, but also by whether employees develop sufficient trust in AI systems.

6.2. Theoretical implications

This study provides several theoretical contributions. First, it extends technology acceptance research by positioning trust in AI as a central psychological mechanism in enterprise AI adoption. While TAM and UTAUT emphasize usefulness, ease of use, and facilitating conditions, the findings show that these factors influence adoption intention mainly through trust in AI. Second, the study contributes to trust in AI literature by demonstrating that trust is shaped by both positive technology perceptions and perceived risks. Employees are more likely to trust AI when they perceive it as useful and easy to use, but their trust declines when they perceive privacy, reliability, ethical, or security risks. Third, the study integrates individual-level and organizational-level explanations of AI adoption. The significant role of organizational support confirms that AI adoption is not merely an individual decision, but also depends on training, technical support, clear guidelines, and managerial encouragement.

6.3. Managerial implications

The findings provide important implications for enterprise managers. First, firms should improve the perceived usefulness of AI by clearly demonstrating how AI enhances productivity, decision quality, problem solving, and work efficiency. Employees are more likely to trust AI when they see direct work-related benefits. Second, AI systems should be designed and implemented in a user-friendly way. Since perceived ease of use has the strongest effect on trust in AI, enterprises should provide simple interfaces, practical tutorials, hands-on training, and continuous technical support. Third, managers must actively reduce perceived risk. This requires clear AI governance policies, data protection procedures, ethical guidelines, output verification mechanisms, and human oversight. Fourth, organizational support should be strengthened through AI training programs, managerial communication, learning opportunities, and resources for responsible AI use. Overall, building trust should be treated as a core managerial task in AI adoption strategies.

6.4. Policy implications

For policymakers and business support agencies, the results suggest that AI adoption programs should go beyond encouraging firms to invest in AI technologies. Policy initiatives should also focus on AI literacy, responsible AI governance, data protection, ethical AI use, and employee trust-building. Training programs for enterprises, especially SMEs, should help managers and employees understand AI benefits, risks, limitations, and responsible use practices. Business associations, chambers of commerce, and professional organizations can develop practical guidelines for safe, transparent, and trustworthy AI adoption. Such support is particularly important in emerging economies, where many enterprises may adopt AI tools rapidly but lack sufficient governance systems and human resource capabilities.

6.5. Limitations

This study has several limitations. First, the cross-sectional design limits the ability to make strong causal claims. Although the model is theoretically grounded and empirically supported, longitudinal data would better explain how trust in AI develops over time. Second, the study uses self-reported survey data, which may involve common method bias or subjective evaluation. Future studies should combine employee perceptions with objective indicators of AI use or organizational performance. Third, the sample focuses on enterprises in a specific context, which may limit generalizability across countries, industries, and institutional environments. Fourth, the model includes selected antecedents of trust in AI, while other factors such as AI literacy, digital leadership, perceived transparency, ethical climate, AI anxiety, and regulatory trust may also influence AI adoption intention.

6.6. Future research

Future research should extend this study in several directions. First, longitudinal studies should examine how employees' trust in AI changes as they gain more experience with AI systems. Second, comparative studies across industries, firm sizes, ownership types, and countries would help identify boundary conditions of AI adoption. Third, future studies may examine additional mediating or moderating variables, such as AI literacy, digital leadership, perceived transparency, innovation climate, technology readiness, organizational learning, or ethical AI climate. Finally, future research should distinguish among different types of AI applications, such as generative AI, predictive analytics, robotic process automation, AI chatbots, and AI-based decision-support systems, because trust and adoption intention may vary across AI use cases.

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