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Quantitative Research Article

Examining Organizational and Human Drivers of Artificial Intelligence Adoption for Enhancing Operational Performance in Thai Technology Enterprises

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Abstract

Background/ problem: While artificial intelligence (AI) is transforming global business, adoption in Thailand's tech sector depends on human factors like adaptability and leadership. These reflect behavioral traits such as change readiness, learning motivation, and organizational culture.
Objective/ purpose: This study examined the influence of AI adoption on operational performance within technology firms in Thailand. Six hypotheses were tested to assess the influence of competitive pressure, external support, top management commitment, employee adaptability, and organizational readiness on AI adoption. In turn, the effect of AI adoption on operational performance was examined.
Design and Methodology: The study surveyed 450 employees in technology companies across Thailand, employing judgmental, convenience, and snowball sampling techniques. An item-objective congruence index validated the instruments, and a pilot test (n = 50) confirmed its reliability via Cronbach's alpha. Data were analyzed using confirmatory factor analysis and structural equation modeling techniques).
Results: The findings show that competitive pressure (β = .18, p = .009), top management commitment (β = .18, p = .005), and organizational readiness (β = .12, p = .021) significantly affected AI adoption. However, external support (β = .09, p = .148) and employee adaptability (β = .07, p = .284) did not have significant effects. AI adoption significantly affected operational performance (β = .50, p < .001).
Conclusion and Implications: This study highlights the role of competitive pressure, leadership, and organizational readiness in AI adoption. Promoting transformational leadership and offering training could enhance employee adaptability and support successful implementation.

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Artificial intelligence (AI) has become a transformative force across multiple industries, including manufacturing, healthcare, finance, and education, with the technology sector being one of its primary adopters (Phongsatha, 2024). The adoption of AI enhances operational performance by streamlining processes, optimizing supply chains, and facilitating data-driven decision-making (Duan et al., 2019; Mavlutova et al., 2022). However, the successful implementation of AI is not solely dependent on technical capabilities but also on key organizational and managerial factors (Venkatesh et al., 2012). In Thailand, while AI adoption is gaining momentum, firms still face challenges in fully integrating AI into their operations due to factors such as lack of leadership support, organizational readiness, and external pressures (Lada et al., 2023). Key determinants influencing AI adoption include competitive pressure, external support, top management commitment, employee adaptability, and organizational readiness (Badghish & Soomro, 2024; Lada et al., 2023). Organizations operating in highly competitive environments may adopt

AI to maintain their strategic advantage (Verma et al., 2021), while support from external entities such as technology vendors and government agencies plays a crucial role in facilitating adoption (Zhu et al., 2006). Furthermore, leadership commitment ensures the alignment of AI initiatives with organizational goals and provides necessary resources for successful implementation (Noonpakdee, 2024). Despite extensive research on AI adoption in developed economies, limited studies have explored competitive pressure, external support, top management commitment, employee adaptability, organizational readiness and AI adoption in the context of Thailand's technology enterprises, highlighting the need for further investigation (Phongsatha, 2024).

This study aimed to bridge this research gap by examining the impact of organizational and external factors on AI adoption and its subsequent effects on operational performance in Thai technology firms. By focusing on competitive pressure, top management commitment, external support, employee adaptability, and organizational readiness, the study provides a comprehensive understanding of how these factors drive AI integration (Badghish & Soomro, 2024; Lada et al., 2023). The findings offer valuable insights for businesses, policymakers, and industry leaders, enabling them to optimize AI strategies and foster innovation in Thailand's digital economy.

Literature Review

This study explored the key factors influencing AI adoption in Thailand's technology sector, including competitive pressure, external support, top management commitment, employee adaptability, and organizational readiness. Grounded in the technology acceptance model (TAM), the resource-based view (RBV), and human resource management (HRM) theory, the research examined how both organizational and individual capabilities drive AI adoption and enhance operational performance.

Technology Acceptance Model

To ground this research, this study applied the technology acceptance model (TAM), which explains technology adoption based on *perceived ease of use* and *perceived usefulness* (Davis, 1989). The technology acceptance model helps understand how competitive pressure, top management commitment, and organizational readiness influence employees' perceptions of AI, impacting its adoption. External support and employee adaptability also shape these perceptions (Phongsatha, 2024). By using TAM, this study explores the psychological and organizational factors driving AI adoption in Thailand's technology firms, linking AI adoption to improved operational performance.

The Resource-Based View

The resource-based view (RBV) offers a valuable lens to examine how firms leverage internal capabilities to achieve competitive advantage. Within this perspective, leadership commitment and employee adaptability are seen as strategic assets that enable the successful adoption of AI. These internal resources contribute not only to the technical implementation of AI but also to the organizational culture and readiness for innovation. Resource-based view suggests that firms with strong intangible assets—such as managerial competencies, adaptive workforce, and a learning-oriented culture—are better positioned to capitalize on technological advancements like AI (Wade & Hulland, 2004).

Human Resource Management

From a human resource management (HRM) standpoint, Ulrich's human resource competency model (Ulrich et al., 2010) highlights the need for HR professionals and organizational leaders to act as strategic partners, capability builders, and change champions. Employee adaptability—a key variable in this study—can be better understood through this model, which emphasizes the importance of equipping the workforce with competencies to manage and embrace change. In practice, this involves fostering agility, learning capacity, and resilience across the organization.

Competitive Pressure

Competitive pressure significantly influences AI adoption, driving organizations to innovate and enhance operations to stay competitive (Lada et al., 2023; Payakkapong et al., 2017). Firms in highly competitive environments are more likely to adopt AI for strategic advantages, such as optimizing operations and improving decision-making (Mikalef & Gupta, 2021). Empirical evidence shows that companies facing intense competition invest in AI to remain relevant and leverage technological benefits (Xu et al., 2024). AI enables firms to detect trends, enhance customer experiences, and strengthen market positions (Badghish & Soomro, 2024). These dynamics underscore how competition fuels innovation in AI adoption (Lada et al., 2023). In the Thai context, research indicates that competitive pressure, along with factors such as organizational readiness and management commitment, significantly influences AI adoption among SMEs in the Bangkok Metropolitan Area, the capital of Thailand (Verma et al., 2021), leading to the following hypothesis:

H1: Competitive pressure has a positive effect on AI adoption.

External Support

External support, provided by industry partners, government initiatives, and technological ecosystems, plays a crucial role in AI adoption (Lada et al., 2023). Organizations with access to external resources, such as funding and expertise, are more likely to integrate AI effectively (Yang et al., 2024). Collaborations with technology providers enhance AI implementation by reducing risks and providing essential knowledge (Ingalagi et al., 2021). Government policies promoting innovation and financial incentives further encourage AI investment (Alshaer, 2023). In Thailand, digital transformation initiatives have driven AI adoption among technology enterprises (Noonpakdee, 2024). Thus, external support is a key enabler of AI integration, leading to the following hypothesis:

H2: External support has a positive effect on AI adoption.

Top Management Commitment

Top management commitment is crucial for fostering a culture of technological innovation and ensuring the allocation of necessary resources for AI adoption (Garg & Agarwal, 2014). Strong leadership commitment enables organizations to prioritize AI by setting strategic directions, mobilizing resources, and creating an environment conducive to change (Phongsatha, 2024). When executives actively support AI initiatives, employees are more likely to accept and utilize AI tools (Lada et al., 2023). Research shows that engaged leadership improves AI implementation success by aligning strategies with business objectives and reducing resistance to change (Peifer et al., 2022; Sharma et al., 2022). In Thailand’s technology sector, top management plays a key role in overcoming AI adoption challenges, enhancing operational performance, and maintaining competitiveness (Phongsatha, 2024). Additionally, a study by Phakamach et al. (2023) highlights the importance of top management in the digital transformation journey, especially in Thailand's SMEs. Therefore, this study proposes the following hypothesis:

H3: Top management commitment has a positive effect on AI adoption.

Employee Adaptability

Employee adaptability, defined as the ability to adjust to new technologies and evolving work environments, is crucial for effective AI utilization (Ingalagi et al., 2021). In Thai context, organizations with adaptable employees are more likely to embrace AI, as they are open to learning and applying new skills necessary for leveraging AI capabilities (Phichitchaisopa & Naenna, 2013). Adaptability fosters continuous learning and innovation, easing AI implementation challenges (Reiman et al., 2021). Research shows that adaptable employees facilitate smoother AI transitions, enhance collaboration, and improve knowledge sharing (Sony & Mekoth, 2022). In Thailand’s technology sector, fostering adaptability is essential for overcoming resistance to AI and optimizing operational performance (Phongsatha, 2024). Therefore, this study proposes the following hypothesis:

H4: Employee adaptability has a positive effect on AI adoption.

Organizational Readiness

Organizational readiness refers to an organization's preparedness to implement new technologies, including resource availability, employee skills, technological infrastructure, and cultural alignment (Lada et al., 2023). Organizations with high readiness levels are more likely to adopt AI successfully, as they possess the necessary capabilities to integrate AI into operations (Çınar et al., 2021). A supportive environment fosters innovation and reduces resistance to change, facilitating smoother AI adoption (Lada et al., 2023). Research shows that well-defined technological strategies, management support, and a strong resource foundation enhance AI implementation success (Shahadat et al., 2023). In Thailand's technology sector, fostering organizational readiness is crucial for overcoming adoption challenges and maximizing AI's impact on operational performance (Verma et al., 2024). Therefore, this study proposes the following hypothesis:

H5: Organizational readiness has a positive effect on AI adoption.

Artificial Intelligence Adoption

The adoption of artificial intelligence enables firms to optimize processes, enhance decision-making, and improve productivity through automation and data analysis (Badghish & Soomro, 2024). Companies that successfully implement AI experience gains in efficiency, quality, and customer satisfaction, contributing to superior operational performance (Duan et al., 2019). AI-driven real-time insights and predictive analytics help organizations anticipate market trends and respond proactively to customer needs (Badghish & Soomro, 2024). Research shows that AI adoption reduces operational costs, shortens cycle times (Lada et al., 2023), and enhances service speed and quality (Phongsatha, 2024). In Thai technology enterprises, AI adoption is crucial for maintaining a competitive edge in a digital-driven economy (Verma et al., 2024). Hence, this study proposes the following hypothesis:

H6: Artificial intelligence adoption has a positive effect on operational performance.

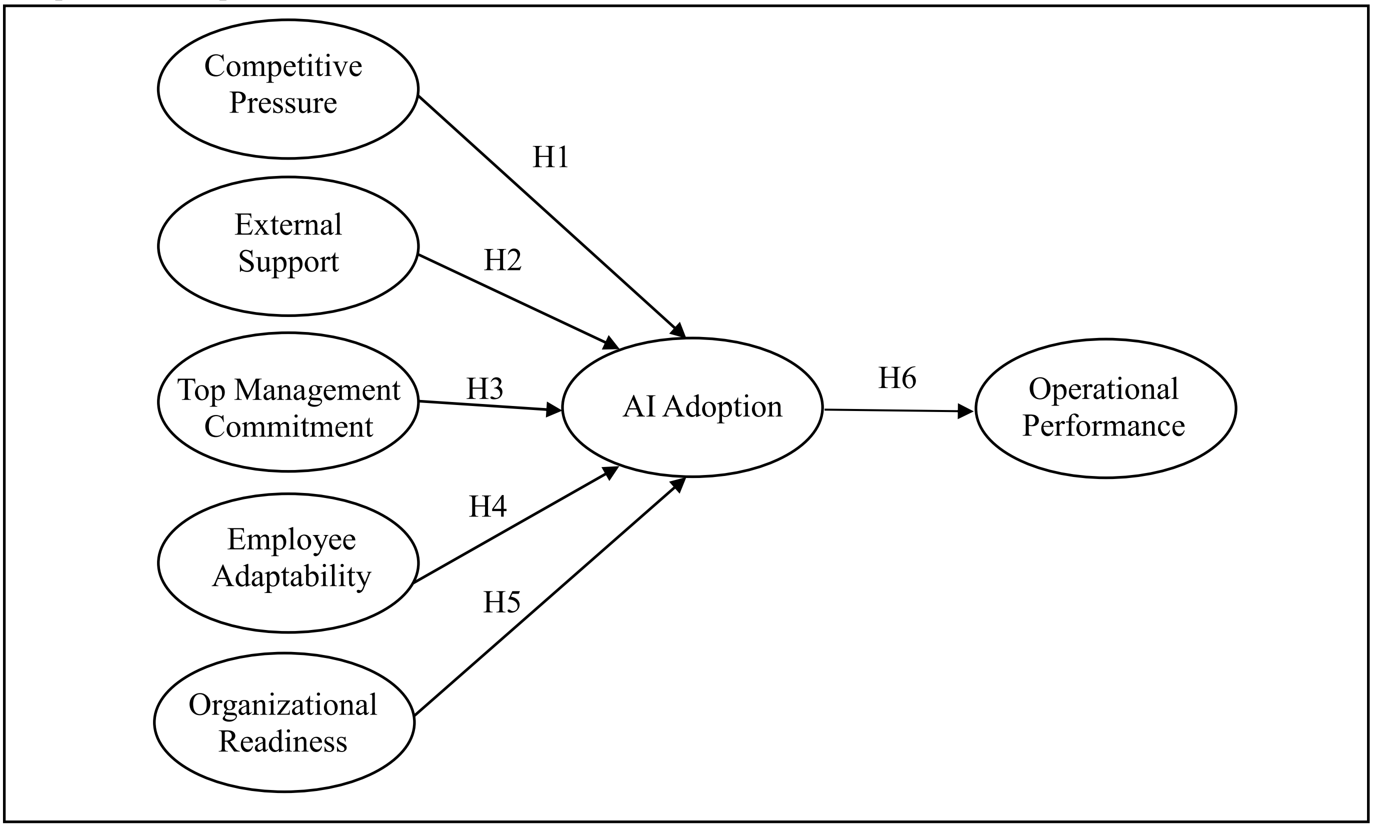
Operational Performance

Operational performance refers to the efficiency and effectiveness of an organization in utilizing its resources to achieve desired outcomes, which encompasses productivity, quality, responsiveness, and customer satisfaction (Badghish & Soomro, 2024). Enhancing operational performance is vital for sustaining competitive advantage and achieving long-term success (Verma et al., 2024). Key influencing factors include process optimization, technology adoption, and workforce engagement (Domenek et al., 2022). AI plays a crucial role by automating processes, improving data analysis, and enhancing decision-making, leading to increased efficiency and cost reduction (Badghish & Soomro, 2024). Studies show that AI adoption boosts productivity and shortens cycle times (Peretz-Andersson et al., 2024). Additionally, organizational culture and employee engagement contribute to performance improvements (Phongsatha, 2024). A study by Verma et al. (2024) highlights that Thai SMEs with higher organizational readiness, including resource availability and technological infrastructure, are more prepared to implement AI solutions effectively, leading to enhanced operational performance.

Conceptual Framework

This study's conceptual framework integrated insights from two prior studies and was contextualized within Thailand's technology sector, based on a sample of 450 employees from AI-engaged firms. Lada et al. (2023) examined 196 SMEs across various sectors in Malaysia to identify critical factors influencing AI adoption. Meanwhile, Badghish and Soomro (2024) investigated AI adoption among SMEs in Saudi Arabia, collecting 220 responses—115 from medium-sized businesses and 105 from small businesses. Using the technology–organization–environment (TOE) framework, their study found that factors such as relative advantage, compatibility, and government support significantly influenced AI adoption. Their multi-group analysis revealed that firm size moderated these relationships, with medium-sized firms showing a stronger link between relative advantage and AI adoption compared to smaller firms. Merging these perspectives, the present framework examined how competitive pressure, top management commitment, and employee adaptability influenced AI adoption and, in turn, enhanced operational performance. Figure 1 presented the conceptual framework of this study.

Figure 1
Proposed Conceptual Framework



Method

Research Design

This study adopted a quantitative research design to examine the factors influencing AI adoption and its impact on operational performance among employees in Thailand's technology sector. A structured questionnaire consisting of 26 items was developed based on established literature, using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The target population comprised employees from AI-engaged technology companies who held at least a bachelor's degree and had a minimum of one year of work experience. A total sample of 450 respondents was obtained through judgmental, convenience, and snowball sampling between February and June 2024. To ensure measurement validity and reliability, the instrument underwent expert evaluation through the item-objective congruence (IOC) method and a pilot test with 50 respondents. All constructs achieved Cronbach's alpha values above .70. Data analysis employed confirmatory factor analysis (CFA) and structural equation modeling (SEM). The analysis tested both direct and indirect relationships among constructs to provide insights into AI adoption strategies and operational performance outcomes.

Target Population and Sample Size

The target population for this study consists of employees working in technology-related sectors. The study specifically targets employees who have at least a bachelor's degree and a minimum of one year of experience in their respective organizations. This demographic is chosen to ensure that participants have sufficient knowledge and experience regarding the implementation and impact of artificial intelligence (AI) technologies in their workplaces. According to Hair et al. (2010), a sample size of 200 or more is considered adequate for SEM when models are not overly complex. To achieve a representative sample, a total sample size of 450 employees was determined.

Measurement Items Development

The research instrument employed in this study was a structured questionnaire comprising items adapted from previously validated sources. All responses were captured using a 5–point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Each construct was measured by multiple items, and a representative sample item is presented for each. For competitive pressure (CP), a sample item is: 'Our business faced competitive pressure to implement AI' (Rahman et al., 2022). For external support (ES), a representative item is: 'My firm receives support from external services' (Ingalagi et al., 2021). The top management commitment (TMC) construct included items such as: 'Top management is actively engaged throughout the life cycle of AI' (Garg & Agarwal, 2014). Employee adaptability (EA) was represented by the item: 'I acquire new skills for AI implementation" (Ingalagi et al., 2021). The construct of organizational readiness (OR) included the item: 'We have all the readiness resources for AI-based business operation' (Shahadat et al., 2023). For AI adoption (AI), a sample item was: 'My firm is willing to adopt AI to improve firm performance'. Lastly, for operational performance (OPF), a typical item was: 'Productive processes have become more efficient'. These items collectively measured the core variables relevant to the study's investigation into AI adoption and its impact within the organizational context.

The research instrument underwent a two-step validation process. First, content validity was assessed using the index of item-objective congruence (IOC). Three experts—two academic researchers specializing in technology adoption and one chief executive officer from an AI-adopting technology firm—evaluated each item for relevance, clarity, and alignment with the intended constructs, retaining items with IOC scores of .60 or above (Rovinelli & Hambleton, 1977). Subsequently, a pilot test was conducted with 50 employees from Thai technology firms. The results demonstrated strong internal consistency across all constructs, with Cronbach's alpha values as follows: competitive pressure ($\alpha = .82$), external support ($\alpha = .79$), top management commitment ($\alpha = .85$), employee adaptability ($\alpha = .81$), organizational readiness ($\alpha = .83$), AI adoption ($\alpha = .88$), and operational performance ($\alpha = .86$), confirming acceptable reliability (Nunnally & Bernstein, 1994).

The original survey, developed in English, was translated into Thai using a back-translation method to ensure linguistic accuracy and conceptual equivalence (Maneesriwongul & Dixon, 2004). Two bilingual experts independently translated the survey into Thai, and a separate set of bilingual experts back-translated it into English. Discrepancies were reviewed and resolved through consensus. This process ensured clarity, cultural appropriateness, and content accuracy in the Thai version of the questionnaire.

Data Collection and Sampling

Data collection was conducted from February to June 2024 using a combination of judgmental, convenience, and snowball sampling methods to ensure a well-rounded and representative sample (Kline, 2015). The process began with judgmental sampling, where AI-engaged technology companies were deliberately selected based on their relevance to the study's focus—namely, organizations actively implementing or exploring artificial intelligence solutions. Selection criteria included firm size, sector engagement in digital transformation, and public recognition of AI initiatives. Once eligible organizations were identified, convenience sampling was employed to recruit participants who were readily accessible within these firms. This approach enabled the researchers to gather diverse perspectives from employees with different roles and levels of involvement in AI projects. To further enhance the sample and reach participants who might not be easily accessible through direct recruitment, snowball sampling was utilized. Initial respondents were asked to refer colleagues who met the inclusion criteria—specifically, those holding at least a bachelor's degree and possessing a minimum of one year of work experience in the technology sector. This method facilitated access to a broader range of respondents across various departments and organizational levels, resulting in a final sample of 450 employees.

Data Analysis

This study employed confirmatory factor analysis (CFA) and structural equation modeling (SEM) to validate the measurement model and test the proposed hypotheses. CFA was used to confirm the factor structure, ensuring that the observed variables aligned with their corresponding latent constructs (Bagozzi & Yi, 2012). Model fit was assessed using fit indices such as the comparative fit index (CFI), Tucker–Lewis index (TLI), and root mean square error of approximation (RMSEA) following the guidelines of Hair et al. (2010). Once the measurement model was validated, SEM was conducted to examine the direct and indirect relationships among the constructs, integrating both factor and regression analyses to provide a comprehensive understanding of AI adoption and its influence on operational performance. Path coefficients were estimated to assess the significance of each hypothesis and to determine the overall explanatory power of the model (Kline, 2015).

Ethical Considerations

This study was conducted in accordance with the ethical principles. Informed consent was taken from all participants before their participation, ensuring their voluntary involvement. Confidentiality and anonymity were maintained throughout the study, and data were used solely for research purposes.

Results

Demographic Information

The demographic analysis in Table 1 shows that the majority of the 450 respondents were male (53.33%). Most participants were aged 26–35 years (53.33%), held a bachelor's degree (71.11%), and worked in firms with 100–499 employees (44.44%). This composition highlights the dominant characteristics within the sample, providing a well-rounded perspective on the respondent profile

Table 1
Sample Demographic (n=450)

Sample characteristic		Frequency	Percentage
Gender	Male	240	53.33
	Female	210	46.67
Age	25 years old or below	90	20.00
	26-35 years old	240	53.33
	36-45 years old	100	22.22
	46 years old or over	20	4.45
Level of education	Bachelor’s degree	320	71.11
	Master’s degree	110	24.44
	Doctoral degree	20	4.45
Firm size by number of employees	≤ 99 employees	150	33.33
	100 - 499 employees	200	44.44
	≥ 500 employees	100	22.23
Total		450	100.00

Confirmatory Factor Analysis

The confirmatory factor analysis (CFA) results confirm strong model reliability and validity across all measured variables. Cronbach's alpha scores exceed .70, ensuring internal consistency (Hair et al., 2010). Factor loadings range from .72 to .92, surpassing the recommended .70 threshold and confirming convergent validity (Kline, 2015). Composite reliability (CR) values exceed .85, indicating strong reliability, while average variance extracted (AVE) values are all above .50, meeting the criteria for convergent validity (Fornell & Larcker, 1981). These findings confirm the robustness of the measurement model, as detailed in Table 2.

Table 2
Confirmatory Factor Analysis, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire	No. of Items	Cronbach's (*n*=450)	Factor Loading	CR	AVE
Competitive pressure	Rahman et al. (2022)	3	.92	.85 – .91	.92	.79
External support	Ingalagi et al. (2021)	4	.89	.80 – .87	.89	.69
Top management commitment	Garg and Agarwal (2014)	5	.88	.72 – .86	.89	.62
Employee adaptability	Ingalagi et al. (2021)	4	.91	.81 – .88	.91	.73
Organizational readiness	Shahadat et al. (2023)	3	.93	.88 – .92	.93	.82
AI adoption	Badghish and Soomro (2024)	3	.84	.77 – .83	.85	.65
Operational performance	Domenek et al. (2022)	4	.91	.83 – .87	.91	.73

Discriminant Validity

The discriminant validity results in table 3 confirm that each construct is distinct from the others. The square roots of the average variance extracted (AVE), displayed diagonally, exceed the correlations among constructs, meeting Fornell and Larcker's (1981) criteria. For example, AI (.80) is greater than its correlations with CP (.37) and ES (.32), demonstrating clear construct separation. Similarly, operational performance (OPF) and employee adaptability (EA) show strong discriminant validity, with OPF at .85 and EA at .85. These findings validate the uniqueness of each construct, reinforcing the model's reliability.

Table 3
Discriminant Validity

	AI	CP	ES	TMC	EA	ORR	OPF
AI	.80						
CP	.37	.89					
ES	.32	.59	.83				
TMC	.35	.49	.44	.78			
EA	.33	.58	.39	.53	.85		
ORR	.26	.27	.26	.25	.38	.90	
OPF	.46	.56	.41	.43	.45	.23	.85

Note. The diagonally listed value is the AVE square roots of the variables. AI = AI adoption, CP = competitive pressure, EA = employee adaptability, ES = external support, OPF = operational performance, ORR = organizational readiness, and TMC = top management commitment

Structural Equation Model

The goodness-of-fit results presented in Table 4 confirm the strong alignment of the model after adjustments, with the measurement model demonstrating a good fit. Specifically, the CMIN/DF value of 1.65 is below the threshold of 3.00, as recommended by Hair et al. (2010). Additionally, the fit indices exceed the acceptable thresholds: GFI (.92), AGFI (.91), NFI (.94), CFI (.97), and TLI (.97) all exceed .90, aligning with the guidelines set by Hair et al. (2010), Arbuckle (1995), and others. The RMSEA value of .04 further supports model adequacy, meeting the < .04 threshold proposed by Browne and Cudeck (1993). These indices confirm that the model fits the data well, providing strong support for the measurement model's validity.

Initially, the structural model did not meet fit criteria (CMIN/DF = 3.81, GFI = .81, RMSEA = .07). However, after adjustments, CMIN/DF improved to 1.83, GFI to .92, and RMSEA to .04, aligning the model with acceptable fit standards. These improvements confirm that the final structural model accurately represents the empirical data.

Table 4

Goodness of Fit for Measurement and Structural Models

Index	Acceptable Values	Measurement Model	Structural Model	
		Statistical Values	Statistical Values Before Adjustment	Statistical Values After Adjustment
CMIN/DF	< 3.00 (Hair et al., 2010)	460.49/278 = 1.65	1116.23/293 = 3.81	510.93/278 = 1.83
GFI	≥ .90 (Hair et al., 2010)	.92	.81	.92
AGFI	≥ .90 (Hair et al., 2010)	.91	.77	.90
NFI	≥ .90 (Arbuckle, 1995)	.94	.87	.94
CFI	≥ .90 (Hair et al., 2010)	.97	.90	.97
TLI	≥ .90 (Hair et al., 2010)	.97	.89	.96
RMSEA	< .04 (Browne & Cudeck, 1993)	.04	.07	.04
Model summary		In harmony with empirical data	Not in harmony with empirical data	In harmony with empirical data

Note. CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI, normalized fit index, TLI = Tucker-Lewis index, CFI = comparative fit index, and RMSEA = root mean square error of approximation

Table 5

Hypotheses Testing Results

Hypothesis	Paths	Standardized Path Coefficients (β)	S.E.	*t*–value	Interpretation of the Tests Result
H1	CP→AI	.18	.06	2.59**	Supported
H2	ES → AI	.09	.06	1.44	Not Supported
H3	TMC → AI	.18	.07	2.78**	Supported
H4	EA→AI	.07	.07	1.07	Not Supported
H5	ORR→ AI	.12	.04	2.30*	Supported
H6	AI →OPF	.50	.05	9.68***	Supported

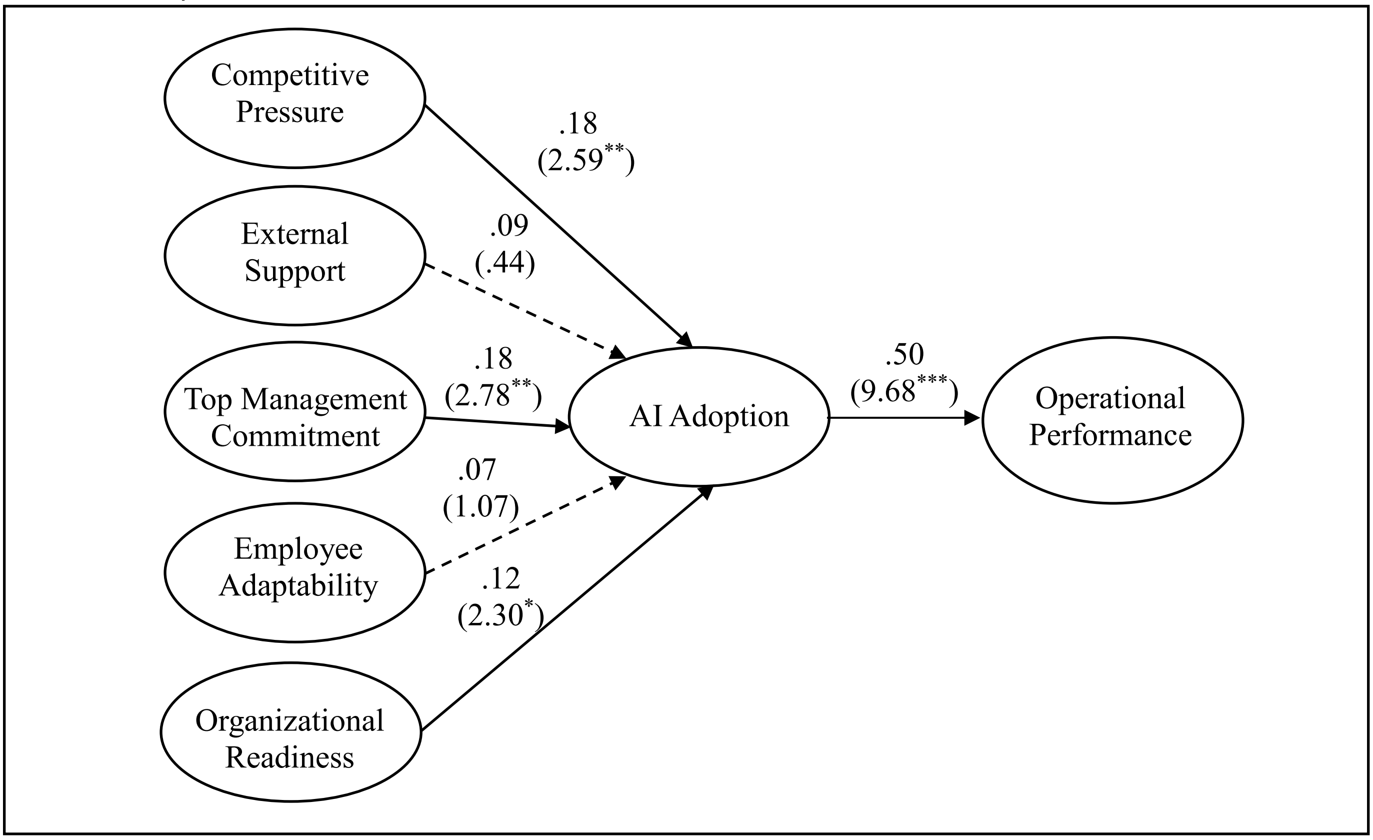
Note. *p < .05; **p < .01; ***p < .001, AI = AI adoption, CP = competitive pressure, EA = employee adaptability, ES = external support, OPF = operational performance, ORR = organizational readiness, and TMC = top management commitment

Hypotheses Testing Results

The hypothesis testing results in Figure 2 and Table 5 were derived from the structural model analysis using structural equation modeling (SEM). This analysis examined the relationships between competitive pressure, external support, top management commitment, employee adaptability, and organizational readiness on AI adoption, as well as the subsequent impact of AI adoption on operational performance. Standardized path coefficients (β), standard errors (S.E.), and *t*-values were calculated, with significance assessed at $p < .05$ (Hair et al., 2010). The SEM effectively evaluates complex relationships among multiple constructs, ensuring robust analytical insights (Hair et al., 2010).

Figure 2

The Results of Structural Model



Note. Dashed lines, not significant; solid lines, significant. *$p < .05$; **$p < .01$; ***$p < .001$

Discussion and Conclusion

Discussion of Main Results

This study investigated the organizational drivers of artificial intelligence (AI) adoption and its subsequent impact on operational performance. Drawing from the technology acceptance model (TAM), the resource-based view (RBV), and human resource management (HRM) theory, the research sought to empirically validate a conceptual model explaining how internal and external organizational factors influenced AI integration. The findings revealed that competitive pressure, top management commitment, and organizational readiness significantly influenced AI adoption, while external support and employee adaptability did not. Furthermore, AI adoption demonstrated a strong positive effect on operational performance, affirming its strategic value within organizations.

Competitive pressure emerged as a significant predictor of AI adoption ($\beta = .18$, $p = .009$), consistent with the notion that external market forces can influence strategic decision-making. From the lens of TAM, the perceived usefulness and urgency of AI technology may be heightened in competitive environments, which accelerates adoption behaviors (Lada et al., 2023; Mikalef & Gupta, 2021).

Top management commitment ($\beta = .18$, $p = .005$) was also a significant determinant, aligning with both the technology acceptance model and the resource-based view. Top management commitment significantly influences technology adoption by shaping employees' perceptions of usefulness and ease of use, which aligns with the technology acceptance model. Additionally, from the resource-based view, committed top management is seen as a valuable organizational resource that drives strategic capability and sustained competitive advantage in AI adoption. Strategic leadership plays a crucial role in resource mobilization, risk mitigation, and cultivating a vision for AI integration (Garg & Agarwal, 2014; Phongsatha, 2024). The resource-based view underscores the value of managerial capabilities as intangible organizational resources that are valuable, rare, and difficult to imitate.

Organizational readiness had the strongest impact on AI adoption ($\beta = .12$, $p = .021$). This construct encompassed the availability of infrastructure, skilled personnel, and financial resources—core components of what RBV identifies as firm-specific capabilities. These results confirm that AI initiatives are more likely to succeed in organizations equipped with the necessary internal resources (Çınar et al., 2021).

In contrast, external support ($\beta = .09$, $p = .148$) and employee adaptability ($\beta = .07$, $p = .284$) did not significantly influence AI adoption. These findings challenge certain assumptions in the literature suggesting the role of third-party support and employee flexibility (Ingalagi et al., 2021; Yang et al., 2024). From an HRM perspective, while employee adaptability is often touted as essential for innovation, it appears insufficient in the absence of organizational structures and leadership commitment. Similarly, external consultants and vendors may offer guidance, but without strong internal alignment, their impact remains limited.

Finally, the adoption of AI significantly enhanced operational performance ($\beta = .50$, $p < .001$). This aligns with extant literature (Badghish & Soomro, 2024; Duan et al., 2019) highlighting AI's contributions to operational efficiency, cost reduction, and strategic agility. The RBV explains this by positioning AI capabilities as part of an organization's unique resource bundle that enables superior performance and competitive advantage.

Limitations

This study has several limitations that provide opportunities for future research. First, the sample was limited to Thai technology enterprises, which restricts the generalizability of the findings to other industries or cultural contexts. Future research could explore AI adoption across diverse sectors and regions to enhance external validity. Additionally, the study utilized judgmental and convenience sampling, which may introduce biases in the selection process, potentially affecting the representativeness of the sample. Judgmental sampling may have led to the inclusion of certain enterprises based on the researcher's discretion, while convenience sampling may have skewed results based on the availability of participants. Future studies could consider using probability sampling to reduce biases and enhance the generalizability of the results. The study also employed a cross-sectional research design, which limits insights into long-term adoption trends; longitudinal studies could provide a deeper understanding of how AI adoption evolves over time. Moreover, the survey-based approach introduces the possibility of response and selection biases, and future studies could adopt mixed-method approaches to provide a more comprehensive perspective. Lastly, factors such as regulatory policies, industry-specific challenges, and ethical considerations were not thoroughly examined and should be explored in future research to offer a more holistic understanding of AI adoption in organizations.

Implications for Behavioral Science

This study offered significant implications for behavioral science, particularly in the context of AI adoption within organizations. By integrating technology acceptance model, resource-based view, and human resource management, the research emphasized the psychological and organizational factors that influenced AI adoption. The findings highlighted that top management commitment (TMC) and organizational readiness (OR) were critical drivers of AI adoption (AI), aligning with TAM's assertion that perceived usefulness (PU) and perceived ease of use (PEOU) significantly shaped technology acceptance (Davis, 1989). This supported the idea that leadership behavior and organizational culture were crucial in fostering an environment conducive to technology adoption (Garg & Agarwal, 2014). By incorporating the RBV, the study expanded the behavioral perspective to include firm-level resources, emphasizing that organizational readiness (OR), rather than individual perceptions, played a central role in facilitating AI adoption. Moreover, the study challenged traditional views in HRM by demonstrating that top management commitment had a more substantial influence on AI adoption than employee adaptability (EA), thereby suggesting that leadership behavior outweighed individual-level traits in driving technological integration (Garg & Agarwal, 2014; Phongsatha, 2024).

The findings also underscored the importance of external factors such as competitive pressure (CP) in influencing AI adoption. This supported the behavioral science notion that environmental stimuli interacted with individual and organizational decision-making processes to drive technology integration (Shahadat et al., 2023). The significant positive impact of AI adoption (AI) on operational performance (OPF) also provided empirical evidence that technology adoption led to measurable improvements in efficiency, decision-making, and competitive advantage, as suggested by prior research (Badghish & Soomro, 2024; Duan et al., 2019). These insights were crucial for understanding how behavioral shifts toward AI could enhance organizational performance. Furthermore, the study suggested that behavioral interventions, such as training programs and change management strategies, could further enhance AI adoption and utilization, contributing to long-term organizational success and performance improvements (Rahman et al., 2022).

Conclusion

This study examined the factors driving AI adoption in Thai technology enterprises and its impact on operational performance. The findings highlight that competitive pressure, top management commitment, and organizational readiness significantly influence AI adoption, while external support and employee adaptability were not significant predictors. A strong positive relationship between AI adoption and operational performance suggests that effective AI integration enhances organizational efficiency. Organizations should prioritize leadership commitment, strategic planning, and internal capability-building to facilitate AI adoption. While external support was not a key factor, engaging with stakeholders and enhancing employee adaptability through training remains beneficial. Future research should explore these relationships across different industries and regions to deepen the understanding of AI adoption dynamics.

Declarations

Conflicts of Interest: The author declares no conflicts of interest.

Ethical Approval Statement*:* "The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and was approved by the Institutional Review Board (IRB) of Assumption University of Thailand (protocol code 31/2023, approved on 10 January 2024). All participants provided informed consent prior to participation."

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