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HOW INSTITUTIONAL AI READINESS SHAPES ACADEMIC RESEARCH PERFORMANCE: EVIDENCE FROM PUBLIC UNIVERSITIES IN VIETNAM

Nguyen Thi Bich Thuy[1], Nguyen Minh Tuan[2*]

[1]*Ho Chi Minh City University of Industry and Trade*

[2]*Ho Chi Minh City University of Banking*

*Email: *tuannm@hub.edu.vn*

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ABSTRACT

The rapid diffusion of artificial intelligence (AI) technologies is reshaping academic research practices in higher education worldwide. However, empirical evidence explaining how institutional and individual AI-related factors influence lecturers' research work performance remains limited, particularly in emerging economies. This study investigates the determinants of research performance among university lecturers by examining the roles of AI application policy, AI support conditions, AI usage skills, AI trends, and digital technology infrastructure. It further proposes that these factors enhance research performance indirectly through the mediating mechanism of AI experience. Drawing on the technology - organization - environment (TOE) framework and experiential learning theory, the study conceptualizes AI experience as a critical capability that transforms institutional readiness and individual competencies into effective research outcomes. A quantitative survey design will be employed to collect data from lecturers working at public universities in Ho Chi Minh City, Vietnam. Structural equation modeling (SEM) was used the hypothesized relationships. The study contributes to literature in three ways. First, it integrates institutional AI readiness and individual digital competencies into a unified research performance framework. Second, it highlights AI experience as a key mediating construct linking technological readiness to research productivity. Third, it provides empirical evidence from a developing higher education context, offering practical implications for university leaders seeking to enhance research performance through AI adoption strategies. The findings are expected to support policy makers and university administrators in designing AI-driven research ecosystems that foster innovation, productivity, and academic competitiveness.

Keywords: Artificial intelligence, AI experience, higher education, research performance.

1. INTRODUCTION

In recent years, artificial intelligence (AI) has emerged as a transformative force in higher education, significantly reshaping teaching, learning, and research activities. AI applications are increasingly being explored across teaching, learning, assessment, and other academic activities in higher education [1]. In particular, AI tools such as data analytics, machine learning, and automated writing assistants have become essential resources for supporting academic research processes.

Despite the growing importance of AI, the effectiveness of AI adoption in higher education depends not only on the availability of technology but also on institutional readiness and individual capability. Prior studies emphasize that organizational factors such as policies, technological infrastructure, and support mechanisms play a critical role in facilitating technology adoption [2], [3]. At the same time, the Resource-Based View suggests that organizational resources can only create value when transformed into capabilities that enhance performance outcomes [4].

In the context of developing countries such as Vietnam, public universities are undergoing rapid digital transformation, yet the integration of AI into research activities remains uneven. While many institutions have introduced AI-related policies and invested in digital infrastructure, lecturers often lack the necessary skills and support to effectively utilize AI in their research. This gap highlights the importance of understanding how institutional AI readiness translates into individual competence and research performance.

Therefore, this study aims to examine the impact of institutional AI readiness on academic research performance, with a particular focus on the mediating role of AI research competence. By integrating the TOE framework, Resource-Based View, and Social Cognitive Theory, this study contributes to the literature by proposing a capability-driven perspective on AI adoption in higher education.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. Literature review

2.1.1. Resource-Based View (RBV)

The Resource-Based View (RBV) provides a fundamental theoretical lens for explaining how organizational resources contribute to performance outcomes. According to RBV, sustainable competitive advantage arises from resources that are valuable, rare, inimitable, and non-substitutable [4]. In the context of higher education, institutional AI readiness can be conceptualized as a strategic resource that enables universities to enhance research capabilities and academic productivity.

AI-related resources, including digital infrastructure, AI policies, and technical support systems, represent critical organizational assets that facilitate the adoption of advanced technologies. However, RBV emphasizes that resources alone may not generate performance benefits unless organizations develop the capabilities required to mobilize and use them effectively [3], [4]. In this study, lecturers' AI research competence is viewed as a key capability that transforms institutional AI readiness into improved research performance.

Thus, RBV provides a strong theoretical foundation for examining how institutional resources are converted into individual-level capabilities that ultimately drive academic outcomes.

2.1.2. Technology–Organization–Environment (TOE) Framework

The Technology–Organization–Environment (TOE) framework posits that organizational adoption of technological innovations is shaped by technological, organizational, and environmental contexts [16].

In this study, institutional AI readiness is conceptualized as a multidimensional construct aligned with the TOE framework. The technological context includes digital infrastructure and AI tools, while the organizational context encompasses policies, support mechanisms, and human resource capabilities. These factors collectively determine the extent to which AI technologies are effectively integrated into academic research. In higher education, these factors are critical in shaping lecturers' ability to utilize AI in research activities. Therefore, the TOE framework supports the argument that institutional readiness not only drives AI adoption but also influences individual competence and performance outcomes.

2.1.3. Social Cognitive Theory (SCT)

Social Cognitive Theory (SCT) [6] explains how individual behavior and performance are shaped by the interaction between personal factors, environmental conditions, and learning processes. A key concept in SCT is self-efficacy, which reflects an individual's belief in their ability to perform tasks successfully.

In the context of AI adoption, lecturers' competence in using AI tools is influenced by institutional support, training, and access to technological resources. These environmental factors facilitate learning through experience and interaction, thereby enhancing individual capability. As lecturers develop higher levels of AI competence, they are more likely to effectively apply AI tools in research activities, leading to improved performance outcomes. Accordingly, SCT provides a theoretical basis for understanding the mediating role of AI competence in translating institutional readiness into research performance.

2.2. Research Hypotheses Development

Building upon the theoretical foundations of the Resource-Based View (RBV), the Technology–Organization–Environment (TOE) framework, and Social Cognitive Theory (SCT), this study develops a set of hypotheses to explain how institutional AI readiness influences academic research performance through AI-related competence and under the moderating role of digital mindset.

H1: AI application policy positively influences lecturers' AI research competence. Formal institutional policies provide direction and incentives for technology adoption and capability development [2].

H2: AI support conditions positively influence lecturers' AI research competence. Supportive organizational environments enhance learning and capability formation [6].

H3: AI usage skills positively influence lecturers' AI research competence. Individual skills are essential for effective technology utilization [1].

H4: Perceived AI trends positively influence lecturers' AI research competence. Awareness of technological trends motivates individuals to adopt and learn new technologies [2].

H5: Digital technology infrastructure positively influences lecturers' AI research competence.
Technological resources provide the foundation for capability development [7].

H6: AI application policy positively influences lecturers' research performance. Institutional policies can provide strategic direction, governance principles, and enabling conditions for organizational AI adoption [2], [10]. Therefore, this study proposes that AI application policy may also contribute directly to lecturers' research performance

H7: Digital technology infrastructure positively influences lecturers' research performance. Digital infrastructure is a key driver of performance in technology-enabled environments [9].

H8: AI research competence positively influences lecturers' research performance. Capabilities are critical determinants of performance outcomes [4].

H9: From an RBV perspective, organizational resources contribute to performance through the development and deployment of capabilities [3], [4]. Accordingly, AI research competence is proposed as a mediating mechanism through which institutional AI readiness may influence research performance.

2.3. Proposed Research Model

Based on the Resource-Based View (RBV), the Technology–Organization–Environment (TOE) framework, and Social Cognitive Theory (SCT), this study proposes a research model to explain how institutional AI readiness shapes tutors' research performance in public universities in Vietnam. The model assumes that institutional AI readiness is reflected through five key dimensions, namely AI application policy, AI support conditions, AI usage skills, perceived AI trends, and digital technology infrastructure.

Research Model

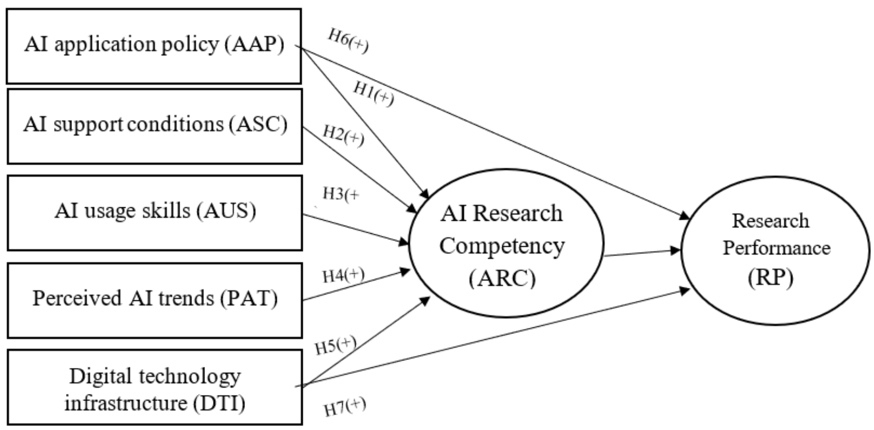

*Figure 1. P*roposed research model

(Source: Author's suggestion.)

3. METHODOLOGY

This article uses a combination of computational and quantitative research methods. Qualitative research methods were used to design the measurement scale and construct the survey. Survey data was collected from 280 lecturers currently teaching officially and with more than 3 years of teaching experience of teaching experience at several public universities such as the University of Banking Ho Chi Minh City, University of Industry and Trade Ho Chi Minh City, University of Foreign Trade Ho Chi Minh City, University of Economics Ho Chi Minh City, and University of Industry Ho Chi Minh City through an online survey from October 20, 2025 to February 25, 2026. The filtered results were ready, with 250 valid responses remaining to be processed using SMART PLS software.

This study employed a structured questionnaire adapted from validated scales in prior research to ensure content validity and reliability [11]. The measurement items were refined through expert consultation and a pilot test to enhance clarity and contextual relevance. A convenience sampling method was adopted due to accessibility constraints and the exploratory nature of AI adoption research in Vietnamese public universities, which is consistent with prior studies in emerging contexts [12]. Data were collected through online and offline surveys targeting lecturers across multiple institutions. To minimize common method bias, procedural remedies were applied, including ensuring respondent anonymity, varying scale formats, and separating measurement of independent and dependent variables [13]. Additionally, statistical checks such as collinearity assessment were conducted to further validate the robustness of the data.

4. RESULTS AND DISCUSSION

4.1. Measurement Model Assessment (Validity)

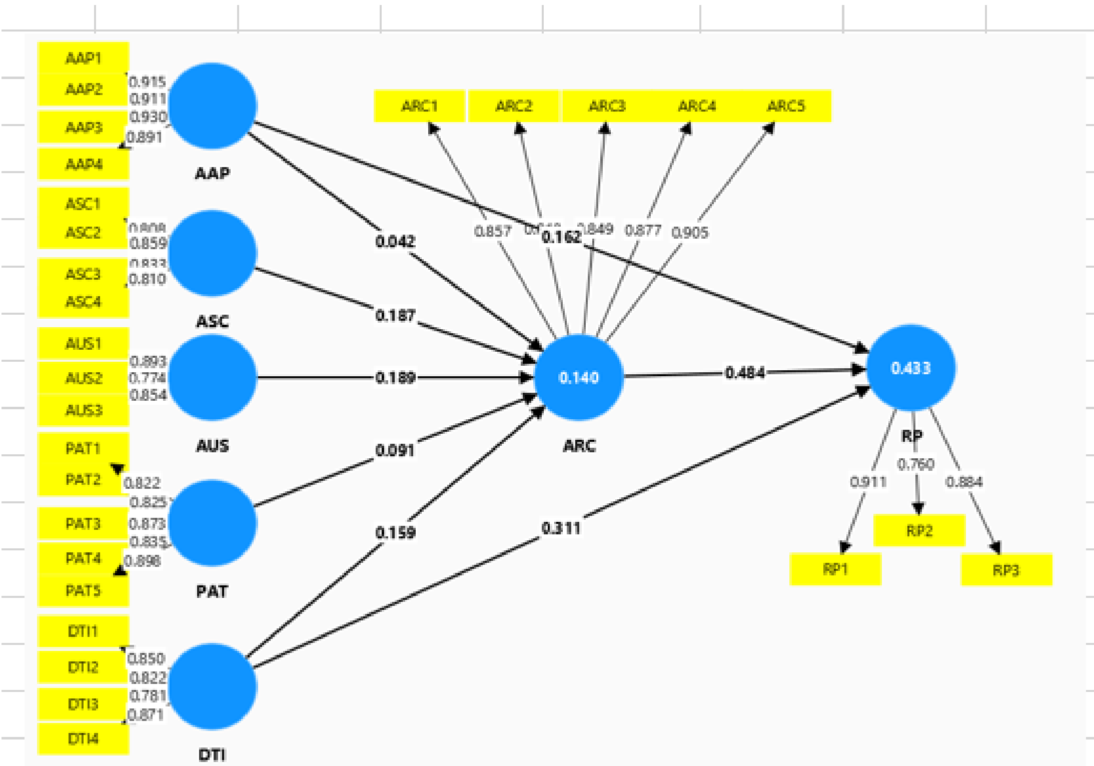

Figure 2. Research Model (PLS, SEM)

Source: Extracted from SMART.PLS results

4.1.1. Outer Loadings

The outer loadings of all measurement items were examined to assess indicator reliability. All factor loadings exceed the recommended threshold of 0.70 [11], ranging from 0.760 to 0.930. Specifically:

- AI application policy (AAP): 0.891 – 0.930
- AI research competence (ARC): 0.810 – 0.905
- AI support conditions (ASC): 0.808 – 0.859
- AI usage skills (AUS): 0.774 – 0.893
- Digital technology infrastructure (DTI): 0.781 – 0.871
- Perceived AI trends (PAT): 0.822 – 0.898
- Research performance (RP): 0.760 – 0.911

These results indicate strong indicator reliability and confirm that all observed variables adequately represent their respective latent constructs.

4.1.2. Convergent Validity

Table 1. Construct reliability and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)

AAP	0.933	0.952	0.952	0.832
ARC	0.912	0.923	0.934	0.74
ASC	0.847	0.849	0.897	0.685
AUS	0.803	0.87	0.879	0.709
DTI	0.851	0.858	0.899	0.691
PAT	0.906	0.928	0.929	0.724
RP	0.817	0.868	0.889	0.73

Source: Extracted from SMART.PLS results

Convergent validity was assessed using Cronbach's alpha, Composite reliability and Average Variance Extracted (AVE). The results indicate that all constructs meet the recommended thresholds. Specifically:

- Cronbach's alpha values range from 0.803 to 0.933, exceeding the minimum threshold of 0.70 [11].
- Composite reliability (ρc) values range from 0.879 to 0.952, indicating high internal consistency.
- Composite reliability (ρa) values range from 0.849 to 0.952, further confirming construct reliability.

Regarding convergent validity, AVE values range from 0.685 to 0.832, all above the recommended threshold of 0.50 [5]. These results confirm that all constructs exhibit strong convergent validity, as each construct explains more than 50% of the variance in its indicators. Furthermore, the consistently high composite reliability values indicate that the measurement scales are both reliable and internally consistent.

4.1.3. Discriminant Validity

Heterotrait - monotrait ratio (HTMT) Criterion

Discriminant validity was first assessed using the Heterotrait–Monotrait ratio (HTMT). As shown in the results:

- HTMT values range from 0.043 to 0.614
- Highest value: ARC → RP = 0.614
- Other notable values: DTI → RP = 0.495; ASC → RP = 0.431; AUS → RP = 0.423

All HTMT values are well below the conservative threshold of 0.85 [14], indicating strong discriminant validity. The HTMT results confirm that all constructs are empirically distinct and do not suffer from multicollinearity or construct overlap.

Fornell–Larcker Criterion

Discriminant validity was further evaluated using the Fornell-Larcker criterion [5]. The square root of AVE for each construct is presented on the diagonal of the matrix: AAP = 0.912; ARC = 0.860; ASC = 0.828; AUS = 0.842; DTI = 0.831; PAT = 0.851; RP = 0.854

These values are all higher than their corresponding inter-construct correlations. For example:

- ARC → RP correlation = 0.558 < 0.860
- DTI → RP correlation = 0.416 < 0.831
- ASC → RP correlation = 0.365 < 0.828

The Fornell–Larcker [5] criterion is fully satisfied, confirming that each construct shares more variance with its own indicators than with other constructs. Overall, both HTMT and Fornell–Larcker results consistently demonstrate that the measurement model achieves strong discriminant validity. Combined with the satisfactory convergent validity, these findings indicate that the measurement model is reliable and valid, providing a solid foundation for subsequent structural model analysis.

4.1.4. Multicollinearity (VIF)

The VIF values (from previous analysis) range from 1.695 to 4.457, all below the threshold of 5.0 [11]. This indicates that multicollinearity is not a concern, and the structural relationships can be interpreted reliably.

4.2. Structural Model Assessment

4.2.1. Path Coefficients

The structural model results reveal that all hypothesized relationships are positive, with varying magnitudes.

Effects on AI Research Competence (ARC)

- AAP → ARC: $\beta = 0.042$
- ASC → ARC: $\beta = 0.187$
- AUS → ARC: $\beta = 0.189$
- DTI → ARC: $\beta = 0.159$
- PAT → ARC: $\beta = 0.091$

Among these factors, AI usage skills ($\beta = 0.189$) and AI support conditions ($\beta = 0.187$) exert the strongest influence on AI research competence, followed by digital infrastructure ($\beta = 0.159$). In contrast, AI application policy ($\beta = 0.042$) shows a relatively weak effect, suggesting that formal policies alone are insufficient without practical support and skills development.

Effects on Research Performance (RP)

- ARC → RP: $\beta = 0.484$
- AAP → RP: $\beta = 0.162$
- DTI → RP: $\beta = 0.311$

The strongest predictor of research performance is AI research competence ($\beta = 0.484$), confirming its central role in translating institutional readiness into performance outcomes. Additionally, digital infrastructure ($\beta = 0.311$) shows a substantial direct effect, while AI policy ($\beta = 0.162$) has a moderate impact.

4.2.2. Coefficient of Determination (R^2)

The explanatory power of the structural model was assessed using the coefficient of determination (R^2).

Table 2. R - square

	R-square	R-square adjusted
ARC	0.14	0.123
RP	0.433	0.426

Source: Extracted from SMART.PLS results

The results show:

- AI research competence (ARC): $R^2 = 0.140$; Adjusted $R^2 = 0.123$
- Research performance (RP): $R^2 = 0.433$; Adjusted $R^2 = 0.426$

R^2 of AI Research Competence (ARC)

The R^2 value of 0.140 indicates that institutional AI readiness explains approximately 14.0% of the variance in AI research competence. According to [15], this level can be considered weak to moderate, suggesting that although institutional factors contribute to AI competence, other factors (e.g., individual motivation, prior experience) may also play an important role. This finding implies that AI competence is not solely determined by organizational readiness but also depends on individual-level characteristics, aligning with Social Cognitive Theory [6].

R^2 of Research Performance (RP)

The R^2 value of 0.433 indicates that the model explains approximately 43.3% of the variance in academic research performance. This level is considered moderate according to [15], demonstrating that the model has substantial explanatory power. This result confirms that the combination of institutional AI readiness and AI research competence provides a meaningful explanation of lecturers' research performance.

4.3. Interpretation of Total Effects

The total effects analysis provides a comprehensive understanding of the overall influence of institutional AI readiness factors on academic research performance, incorporating both direct and indirect effects through AI research competence.

4.3.1. Total Effects on AI Research Competence (ARC)

The results indicate that all dimensions of institutional AI readiness positively influence AI research competence, with varying magnitudes:

- AI usage skills (AUS → ARC): $\beta = 0.189$
- AI support conditions (ASC → ARC): $\beta = 0.187$
- Digital technology infrastructure (DTI → ARC): $\beta = 0.159$
- Perceived AI trends (PAT → ARC): $\beta = 0.091$
- AI application policy (AAP → ARC): $\beta = 0.042$

Among these factors, AI usage skills ($\beta = 0.189$) and AI support conditions ($\beta = 0.187$) exert the strongest total effects on AI research competence. This finding suggests that capability-building mechanisms (skills and support) are more influential than structural or strategic elements such as policy. In contrast, AI application policy shows the weakest effect ($\beta = 0.042$), indicating that formal institutional regulations alone are insufficient to enhance lecturers' AI-related capabilities. This result reinforces the assumptions of Social Cognitive Theory, which emphasizes that individual competence is primarily shaped by learning, experience, and environmental support rather than formal rules [6].

4.3.2. Total Effects on Academic Research Performance (RP)

The total effects on research performance reveal the relative importance of different factors:

- AI research competence (ARC → RP): $\beta = 0.484$
- Digital technology infrastructure (DTI → RP): $\beta = 0.388$
- AI application policy (AAP → RP): $\beta = 0.182$

- AI usage skills (AUS → RP): β = 0.092
- AI support conditions (ASC → RP): β = 0.091
- Perceived AI trends (PAT → RP): β = 0.044

The strongest total effect is observed for AI research competence (β = 0.484), indicating that it is the most critical determinant of academic research performance. This finding confirms the Resource-Based View, which posits that organizational resources only generate performance outcomes when transformed into capabilities [4].

The second strongest effect is digital infrastructure (β = 0.388), suggesting that infrastructure plays both: A direct role in supporting research activities and an indirect role through enhancing AI competence. Infrastructure is a dual-impact factor, making it a strategic investment for universities.

AI application policy shows a moderate total effect (β = 0.182), indicating that while policy is important, its influence is significantly weaker than infrastructure and competence. Policies may guide behavior but do not automatically translate into performance unless supported by skills and resources. Although AI usage skills (β = 0.092) and support conditions (β = 0.091) have relatively small total effects on performance, they play a crucial indirect role through AI competence. This indicates that these factors function as enablers rather than direct drivers, aligning with the TOE framework [16]. Perceived AI trends show the weakest total effect (β = 0.044), suggesting that awareness alone is insufficient to improve research performance.

4.4. Mediation Analysis (Specific Indirect Effects)

Although indirect coefficients are not explicitly shown, mediation can be inferred:

Table 3. Results of Specific indirect effects

	Specific indirect effects
AAP -> ARC -> RP	0.021
ASC -> ARC -> RP	0.091
AUS -> ARC -> RP	0.092
DTI -> ARC -> RP	0.077
PAT -> ARC -> RP	0.044

Source: Extracted from SMART.PLS results

Strong mediation:

- AUS → ARC → RP: β = 0.092; $p = 0.003 < 0.05$
- ASC → ARC → RP: β = 0.091; $p = 0.003 < 0.05$

Moderate meditation:

- DTI → ARC → RP: β = 0.077; $p = 0.00 < 0.05$

Weak mediation:

- AAP → ARC → RP: β = 0.021; $p = 0.00 < 0.05$

AI research competence plays a partial mediating role, especially for Skills and Support. This finding supports Social Cognitive Theory [6], emphasizing that competence is the key mechanism linking environment to performance. The findings extend the Resource-Based View by demonstrating that institutional AI readiness alone does not guarantee performance improvement. Instead, AI research competence (β = 0.484) acts as a critical capability that transforms resources into outcomes. Moreover, the TOE framework is validated, as technological (DTI) and organizational (ASC, AUS) factors significantly influence competence development. Importantly, the weak effect of policy suggests that formal structures are less effective than operational capabilities, contributing new insights to digital transformation literature.

4.5. Discussion of Bootstrap Results

4.5.1. Bootstrap Results for Outer Loadings

The bootstrapping results confirm that all measurement items are statistically significant, with all outer loadings exceeding the recommended threshold of 0.70 [11]. Specifically, the loadings range from 0.760 to 0.930, and all corresponding t-values are substantially higher than 1.96 ($p < 0.001$), indicating strong indicator reliability.

- AI application policy (AAP): 0.891 – 0.930 (t = 28.923 – 47.573)
- AI research competence (ARC): 0.810 – 0.905 (t = 23.838 – 57.720)
- AI support conditions (ASC): 0.808 – 0.859 (t = 17.463 – 20.713)
- AI usage skills (AUS): 0.774 – 0.893 (t = 8.893 – 22.066)
- Digital technology infrastructure (DTI): 0.781 – 0.871 (t = 17.538 – 28.839)
- Perceived AI trends (PAT): 0.822 – 0.898 (t = 12.195 – 17.557)
- Research performance (RP): 0.760 – 0.911 (t = 18.854 – 86.546)

These results demonstrate excellent measurement reliability and confirm that all indicators significantly contribute to their respective constructs. The very high t-values (e.g., RP1 = 86.546; ARC5 = 57.720) further indicate the robustness and stability of the measurement model. This finding is consistent with PLS-SEM measurement theory, which emphasizes that strong outer loadings enhance construct validity and reduce measurement error [11].

4.5.2. Bootstrap Results for Path Coefficients

Effects on AI Research Competence (ARC)

The results reveal that several institutional AI readiness factors significantly influence AI research competence:

- AUS → ARC: $\beta = 0.189$, $t = 3.267$, $p = 0.001$
- ASC → ARC: $\beta = 0.187$, $t = 2.995$, $p = 0.003$
- DTI → ARC: $\beta = 0.159$, $t = 2.581$, $p = 0.010$

AI usage skills and support conditions are the strongest determinants of AI competence, suggesting that hands-on capability development and institutional support are more critical than structural factors. This finding supports the Technology-Organization-Environment framework, which emphasizes that technological and organizational conditions jointly shape capability development [16].

Non-significant effects

- AAP → ARC: $\beta = 0.042$, $t = 0.717$, $p = 0.473 > 0.05$
- PAT → ARC: $\beta = 0.091$, $t = 1.529$, $p = 0.126 > 0.05$
- PAT → RP: $\beta = 0.044$, $t = 1.475$, $p = 0.14 > 0.05$

AI policy and perceived AI trends do not significantly influence AI competence.

- Formal policies do not translate into capability
- Awareness does not guarantee competence

Effects on Research Performance (RP)

The results indicate strong and significant relationships:

- ARC → RP: $\beta = 0.484$, $t = 11.393$, $p = 0.00 < 0.001$
- DTI → RP: $\beta = 0.311$, $t = 7.215$, $p = 0.00 < 0.001$
- AAP → RP: $\beta = 0.162$, $t = 3.532$, $p = 0.00 < 0.001$

AI research competence has the strongest effect on research performance, confirming its central role as the key driver. This finding strongly supports the Resource-Based View, which posits that capabilities are the primary mechanism transforming resources into performance outcomes [4].

4.6. Advanced Discussion

4.6.1. The central role of AI competence in research performance

The findings of this study reveal that AI research competence exerts the strongest effect on academic research performance ($\beta = 0.484$, $p < 0.001$). This result is consistent with recent studies emphasizing the importance of digital and AI-related competencies in enhancing research productivity.

For instance, [1] argue that AI technologies only generate value when users possess the necessary capabilities to integrate them into work processes. Similarly, [17] highlights that digital transformation outcomes depend more on capability development than on technology availability.

Recent evidence from higher education further shows that digital competence can enhance research and innovation performance among faculty members and research scholars [8]. This study extends prior research by empirically demonstrating that AI competence is not merely a supporting factor but the primary driver of research performance in AI-enabled academic environments.

4.6.2. The dominant role of infrastructure in digital transformation

The results show that digital technology infrastructure has a strong and significant impact on research performance ($\beta = 0.311$, $p < 0.001$), making it the second most influential factor.

This finding aligns with prior studies emphasizing the importance of digital infrastructure in enabling innovation and performance. For example, [7] argue that digital infrastructure is a foundational element of digital transformation strategies. Similarly, [9] highlight that technological readiness significantly influences organizational performance in AI contexts.

This study provides empirical evidence from an emerging economy context, demonstrating that infrastructure plays a dual role—both directly enhancing research performance and indirectly through competence development.

4.6.3. The critical role of skills and organizational support

The results indicate that AI usage skills ($\beta = 0.189$, $p = 0.001$) and AI support conditions ($\beta = 0.187$, $p = 0.003$) significantly influence AI research competence and indirectly affect research performance. This study confirms that skills and support are not direct performance drivers but essential enablers that operate through capability development, thereby extending the TOE framework in the context of AI in academia.

4.6.4. The limited role of AI policy in capability development

One of the most notable findings is the non-significant effect of AI application policy on AI competence ($\beta = 0.042$, $p = 0.473$), although it has a moderate direct effect on research performance ($\beta = 0.162$, $p < 0.001$).

This result contrasts with some prior studies that emphasize the importance of institutional policies in technology adoption. For example, studies by [8] suggest that policy frameworks can facilitate technology implementation. However, more recent research indicates that policy alone is insufficient. [18] argue that organizational performance depends more on capability development than on formal governance structures. Similarly, studies in digital transformation [17] suggest that policies must be complemented by operational capabilities.

This study provides new evidence that in AI-driven academic environments, formal policies do not directly translate into individual capabilities, highlighting the gap between policy design and practical implementation.

4.6.5. The negligible effect of perceived AI trends

The results show that perceived AI trends do not significantly influence AI competence ($\beta = 0.091$, $p = 0.126$) or research performance ($\beta = 0.044$, $p = 0.140$).

This finding is consistent with studies suggesting that awareness of technology trends does not necessarily lead to effective adoption. For example, [2] note that organizations often recognize the importance of digital technologies but fail to translate this awareness into actual capabilities. Similarly, research by [10] indicates that cognitive awareness must be complemented by skill development and organizational support to produce meaningful outcomes.

This study highlights that perception of AI trends alone is insufficient to drive performance, emphasizing the importance of actionable capabilities over passive awareness.

4.6.6. Integrated insight: A capability-driven transformation model

This model is consistent with the Resource-Based View and Social Cognitive Theory, while extending the TOE framework into the AI context. AI-driven transformation in higher education is not policy-driven but capability-driven, where practical factors such as skills, support, and infrastructure play a more critical role than formal institutional policies.

5. CONCLUSION AND MANAGERIAL IMPLICATIONS

5.1. Conclusion

This study examines how institutional AI readiness influences academic research performance through the mediating role of AI research competence in the context of public universities in Vietnam. The findings provide robust empirical evidence that institutional AI readiness significantly enhances research performance, primarily through the development of individual-level AI competence.

The results reveal that AI research competence is the most influential determinant of academic research performance ($\beta = 0.484$, $p < 0.001$), confirming its central role in transforming institutional resources into tangible outcomes. In addition, digital technology infrastructure ($\beta = 0.311$, $p < 0.001$) and AI application policy ($\beta = 0.162$, $p < 0.001$) also exert significant direct effects on research performance.

At the same time, the study finds that AI usage skills ($\beta = 0.189$, $p = 0.001$), AI support conditions ($\beta = 0.187$, $p = 0.003$), and digital infrastructure ($\beta = 0.159$, $p = 0.010$) significantly contribute to the development of AI research competence. In contrast, AI application policy ($\beta = 0.042$, $p = 0.473$) and perceived AI trends ($\beta = 0.091$, $p = 0.126$) do not significantly influence AI competence, highlighting a gap between formal institutional structures and practical capability development.

Overall, the findings support the Resource-Based View and Social Cognitive Theory by demonstrating that organizational resources only generate performance outcomes when transformed into individual capabilities. Importantly, the study contributes to the literature by proposing that AI-driven transformation in higher education is capability-driven rather than policy-driven.

5.2. Managerial Implications

Based on the empirical findings, this study offers several important managerial implications for university leaders and policymakers, particularly in the context of digital transformation in higher education.

5.2.1. Prioritize the development of AI research competence

Given that AI research competence has the strongest impact on research performance ($\beta = 0.484$), universities should place primary emphasis on developing lecturers' AI-related capabilities. Specifically, universities should:

- Design structured AI training programs focused on research applications (e.g., data analysis, academic writing, systematic review)
- Organize hands-on workshops to enhance practical AI usage
- Encourage continuous learning and experimentation with AI tools

This approach aligns with Social Cognitive Theory, which emphasizes that competence is developed through learning and experience.

5.2.2. Strengthen AI usage skills and institutional support systems

The significant effects of AI usage skills ($\beta = 0.189$) and AI support conditions ($\beta = 0.187$) on AI competence suggest that universities should invest in both individual and organizational capability-building mechanisms. Recommended actions include:

- Establishing AI support centers or digital labs
- Providing technical assistance and mentoring programs
- Promoting peer learning communities among lecturers

These measures can accelerate the development of AI competence and indirectly enhance research performance.

5.2.3. Invest strategically in digital technology infrastructure

Digital infrastructure has both direct ($\beta = 0.311$) and indirect effects on research performance, making it a critical strategic resource. Universities should:

- Invest in AI-powered research tools (e.g., data analytics software, AI writing assistants)
- Improve access to international academic databases (Scopus, WoS)
- Develop integrated digital research platforms

This finding supports the Resource-Based View, which highlights the importance of technological resources in achieving competitive advantage [4].

5.2.4. Rethink the role of AI policies

Although AI application policy significantly influences research performance ($\beta = 0.162$), it does not significantly impact AI competence ($\beta = 0.042$, $p = 0.473$). This suggests that policies alone are insufficient, and implementation mechanisms are more important. Therefore, universities should:

- Link policies with practical training and support

- Introduce incentive systems (e.g., rewards for AI-based research outputs)
- Ensure policy–practice alignment

5.2.5. Move beyond awareness toward actionable capability

The non-significant effect of perceived AI trends ($\beta = 0.044$, $p = 0.140$) indicates that awareness alone does not improve research performance. Thus, universities should:

- Focus less on promoting awareness
- Focus more on developing actionable skills and capabilities

5.2.6. Strategic implication for Vietnamese public universities

In the context of Vietnam, where digital transformation in higher education is still evolving, the findings highlight a critical shift. Universities should transition from a policy-driven approach to a capability-driven approach in AI adoption. This means prioritizing: Human capital development, Practical AI integration, and Institutional support systems rather than relying solely on formal regulations.

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