# Factors Determining Artificial Intelligence Capacity at Universities and Research Institutes in Vietnam: Empirical evidence

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*Abstract:* Artificial intelligence (AI) is a key driver of scientific and technological innovation worldwide. Universities and research institutes play a central role in developing AI human resources, conducting research, and deploying applications, yet empirical evidence on organizational determinants of AI capability in developing economies remains scarce. This study examines AI capability in Vietnamese universities and research institutes using survey data from 126 units and quantitative techniques, including reliability analysis, Exploratory Factor Analysis, and multiple linear regression. The findings show that AI-related organizational resources, particularly infrastructure and financial investment, are the strongest predictors of AI capability. Collaboration with enterprises also has a positive and statistically significant effect, whereas strategic orientation toward AI exerts a positive but weaker influence. The model explains approximately 41% of the variance in institutional AI capability. These results provide evidence-based implications for policymakers and institutional leaders seeking to strengthen AI capability in Vietnam's higher education and research system.

*Key-Words:* Artificial Intelligence Capabilities; Higher Education; Institutes; Organizational Resources; Corporate Cooperation; Developing Economy; Vietnam

Received: September 28, 2025. Revised: January 6, 2026. Accepted: April 20, 2026. Published: July 17, 2026.

# 1 Introduction

Artificial intelligence (AI) is driving profound changes in education, healthcare, industry, and public governance. Many countries have launched national AI initiatives that recognize the role of universities and research institutes in developing AI skills through teaching, research, and application. In Vietnam, the National Strategy for Research, Development, and Application of AI to 2030 identifies higher education institutions and research institutes as core actors in the national AI ecosystem. In practice, however, AI capabilities vary widely across institutions, reflecting differences in infrastructure, financial resources, industry collaboration, and organizational priorities. Existing studies have mainly examined AI adoption or digital readiness, while the notion of AI capability - understood as an organization's ability to develop and sustain AI-related activities - remains loosely defined, particularly in developing economies. This study addresses the following question: *Which organizational factors are associated with the AI capabilities of universities and research institutes in Vietnam?*

The study aims to (i) create a model for analyzing factors that affect AI capability at the organizational tier; (ii) empirically validate this model using survey data; and (iii) recommend policy implications for improving AI capability within Vietnam's higher education and research system.

# 2 Literature review

## 2.1 International research on AI capabilities in tertiary education

Operationalization of AI Capability: Organizational AI capability is increasingly acknowledged as a multidimensional construct that includes research productivity (e.g., publications in AI venues), applied innovation (e.g., deployed AI systems/applications), human capital development (e.g., trained AI professionals), infrastructure adequacy (e.g., computing facilities), and ecosystem connectivity (e.g., patents, startups), [1]. Nonetheless, thorough assessment across all aspects is difficult, especially in developing nations where institutional data is frequently fragmented.

This study operationalizes AI capability through two observable output indicators: (1) AIC1: AI publications in peer-reviewed journals/conferences, reflecting research productivity; and (2) AIC2: AI applications implemented internally or provided to external partners, reflecting applied innovation. These parameters correspond with the dual objectives of Vietnamese universities—knowledge generation and practical implementation—as highlighted in the national AI policy for 2030, [2]. This method, although less extensive than comprehensive multi-item scales, offers dependable and verifiable metrics appropriate for cross-institutional comparisons in data-limited environments."

Organizational AI capabilities in higher education are often examined within broader frameworks of technological capacity and digital transformation. Drawing on OECD's broader AI capability framework, [1], the AI capabilities of educational and research institutions rest on three main pillars: (i) technology and data infrastructure, (ii) financial and human resources, and (iii) the institutional and collaborative environment.

Multiple studies in advanced economies emphasize the central role of organizational resources in building AI capabilities. In the United States and Europe, sustained investment in high-performance computing (HPC) facilities and interdisciplinary AI research centers is considered essential for enhancing research and innovation capacity, [3], [4].

Singapore exemplifies the advancement of AI capabilities in higher education within Southeast Asia,, attributed to the synergistic integration of national strategy, public funding, and collaboration between universities and industries, [5]. Evidence from Thailand and cloud-computing adoption studies in higher education suggests that, within the framework of constrained resources, utilizing cloud computing platforms and partnering with technology firms is essential for augmenting the AI capabilities of universities, [6], [7].

### 2.2 University-business cooperation and the development of applied AI

Collaboration between universities and enterprises is a key driver of applied research and technology transfer in AI. The Triple Helix model, [8] highlights how interactions between government, universities, and industry foster knowledge-based innovation. In the AI domain, partnerships with firms give universities access to real-world data, practical problem settings, and additional resources, thereby strengthening their capacity to design and deploy AI systems, [9].

Recent studies on AI-related university–industry engagement and China's national–corporate innovation system suggest that business partnership enhances both the volume of scientific publications and the commercialization potential of AI technology, especially in sectors like healthcare, finance, and smart manufacturing, [10], [11].

### 2.3 Domestic research on AI and higher education in Vietnam

In Vietnam, research concerning AI in higher education predominantly emphasizes training programs, faculty capabilities, and the preparedness for AI integration in teaching. Numerous studies have indicated a deficiency in computing equipment, data, and financing for AI research at various universities, especially those located outside major hubs, [12].

Policy studies from the Ministry of Science and Technology and the Ministry of Education and Training underscore that, despite Vietnam's establishment of a national AI policy for 2030, the capability to implement AI differs among training and research institutes, [2]. Nonetheless, existing domestic research is predominantly descriptive or qualitative, with scant quantitative modeling endeavors to examine the factors influencing AI capabilities at the organizational level.

### 2.4 Research gap

An analysis of domestic and international studies reveals that: (i) international research has elucidated the significance of organizational resources and corporate collaboration in AI development, especially in developed nations and certain regional countries; (ii) in Vietnam, investigations into AI in higher education are deficient in quantitative analysis at the organizational level; and (iii) the notion of AI capability at the organizational level has not been systematically assessed or empirically validated. This work seeks to address that gap by constructing and evaluating an empirical model of AI capability determinants within the Vietnamese environment.

## 3 Research model and research questions

### 3.1 Research questions

Drawing from the literature review, the report posits three principal research questions:

- **RQ1**: In what manner do the organization's AI resources (infrastructure and finance) associated with the AI capabilities of universities and research institutes?
- **RQ2**: What is the significance of partnership with businesses in augmenting the AI capabilities of educational and research institutions?
- **RQ3**: Does the strategic orientation towards AI directly influence the organization's AI capabilities?

### 3.2 Research model and hypotheses

**Theoretical Foundation: Resource-Based View (RBV)** This study is based on the Resource-Based View (RBV) of of sustainable competitive advantage, [13], [14], which asserts that organizational performance depends on resources that are valuable, uncommon, inimitable, and non-substitutable, as outlined in the VRIN framework. Regarding the advancement of AI capabilities in academic institutions and research organizations:

- *Tangible resources* (AI infrastructure and financial investment) fulfill VRIN criteria in emerging economies, [13], where high-performance computer capabilities are spatially centralized and necessitate prolonged capital expenditure over several years, [15].
- *Strategic orientation* (AI initiatives and long-term dedication) is advantageous but frequently less replicable, as strategic ideas disseminate swiftly through academic networks and national policy texts.
- *Enterprise collaboration* grants access to supplementary assets (real-world data, practical challenges) that augment the value of internal resources.

RBV posits that tangible resources exhibit more robust correlations with AI capabilities than strategy alone in resource-constrained environments such as Vietnam, which our empirical findings corroborate (RES: $\beta = 0.373$ vs. STR: $\beta = 0.162$). Strategy is likely to be more effective when combined with resource allocation.

Drawing on the Resource-Based View and prior studies, the proposed model assumes that an organization's AI capability is associated with three groups of factors: (i) AI-related organizational resources, (ii) the extent of collaboration with enterprises, and (iii) the institution's strategic orientation toward AI. The hypotheses were formulated as follows:

- **H1**: Organizational AI resources are positively associated with AI capability.
- **H2**: Collaboration with enterprises is positively associated with AI capability.
- **H3**: Strategic orientation toward AI is positively associated with AI capability (conditional on resource availability under RBV logic)

RBV posits tangible resources, [13] (RES: infra/finance as VRIN) outperform strategic orientation in resource-scarce contexts like Vietnam, aligning with H1>H3.

# 4 Research Methodology

## 4.1 Research design and analytical framework

This study utilized a quantitative, cross-sectional survey methodology to investigate the relationship between organizational features and AI capability in Vietnamese universities and research institutes. The survey approach is suitable for capturing institutional perceptions and practices regarding AI infrastructure, resources, collaboration, and strategic orientation. Data were analyzed utilizing IBM SPSS Statistics software, adhering to the sequential methodology typically endorsed in organizational and educational technology research: (i) data coding and recoding; (ii) reliability analysis employing Cronbach's Alpha coefficient; (iii) Exploratory Factor Analysis; and (iv) multivariate linear regression accompanied by diagnostic tests for statistical assumptions.

## 4.2 Sampling and data acquisition

The study subjects include Vietnamese public universities and research centers that are involved in artificial intelligence (AI) education, research, or application to varying degrees. Top managers, department heads, academicians, and professors who were actively involved in AI operations made up the participants

A structured online questionnaire was disseminated between July and October 2025 to more than 200 institutions given by Vietnam National University and the Ministry of Education and Training (MOET) utilizing purposive sampling. After deleting partial responses, units were stratified by region (50% North, 16% Central, 34% South; $n = 126$ valid responses). Due to self-selection, convenience factors apply, yet this technique guarantees public/private and urban/rural representation, [16] Even though the sample size meets the EFA minimum (5:1 variable ratio), sophisticated regression requires $n>200$ for further research, [17].

## 4.3 Preparing data and analysis processes in SPSS

The data analysis technique is executed with SPSS software following the subsequent steps:

(i) Data Encoding and Recoding: Text-based responses were converted into a five-point ordinal scale (from 1 to 5), indicating the perceived level or importance of each component in relation to AI capability.
(ii) Reliability Analysis (Cronbach's Alpha): Employed to evaluate the internal consistency of multivariate scales.
(iii) Exploratory Factor Analysis: Utilized the Principal Axis Factoring extraction method and Varimax rotation to examine the factor structure.
(iv) Constructing composite variables: Utilized the mean value of the observed variables to create the composite variables.
(v) Multivariate linear regression: Evaluated the research hypotheses.

### 4.3.1 Measurement instruments and coding scheme

All latent constructs were assessed utilizing a multi-item Likert scale (1 = extremely low/completely disagree; 5 = very high/completely agree). The items were modified from prior international studies and are appropriate for Vietnam's higher education and research framework. As shown in Table 1 (Appendix), the study operationalizes each construct, specifies the observed variables, and presents the corresponding composite variables. The organization's AI resources are structured multi-dimensionally, consisting of two primary components: (i) AI infrastructure (INF) and (ii) finance resources for AI (FIN). The two components are assessed separately at the observed variable level and are amalgamated into a composite variable just during the regression analysis phase.

To maintain uniformity, all items were standardized on a 5-point ordinal scale, facilitating the computation of composite scores by mean scores.

#### 4.3.2 Reliability analysis: Cronbach's Alpha

The internal consistency of the scales was assessed using Cronbach's Alpha coefficient, calculated according to Formula (1), [18]:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_T^2}\right) \qquad (1)$$

Source: [18]

where $k$ denotes the quantity of observed variables in the scale, $\sigma_i^2$ denotes the variance of each observed variable, and $\sigma_T^2$ denotes the variance of the overall scale.

The α values of 0.60 or higher are generally considered acceptable in exploratory studies:

- The internal consistency of multi-item constructs is evaluated by Cronbach's Alpha coefficient, which quantifies the degree to which items assess the same underlying notion;
- A threshold of $\alpha \geq 0.60$ is deemed acceptable according to accepted conventions.

As shown in Table 2 (Appendix), all constructs meet or exceed the minimum reliability threshold, including the Strategic Orientation scale shows an alpha of 0.59, which is slightly below 0.60 but still acceptable for an exploratory study with only two items, while indicating that future research should develop more detailed measures of AI strategy.

Although the Cronbach's alpha coefficient for Strategic Orientation (STR) is 0.59, just beneath the standard 0.60 level, supplementary reliability metrics endorse the application of this two-item scale in an exploratory framework. The inter-item correlation between STR1 and STR2 is r = 0.45, signifying a moderate relationship aligned with a unidimensional construct. The composite dependability (CR), determined via the Fornell and Larcker's method, [19], is 0.78, surpassing the advised minimum of 0.70. The results warrant temporary approval of the STR scale in this exploratory investigation, while also underscoring its brevity as a constraint. Future study should create more extensive multi-item assessments of AI strategic direction, encompassing AI vision, implementation roadmap, and innovation culture. This point is particularly significant due to the minimal statistical significance of STR in the regression model (p = 0.067), necessitating careful interpretation of H3, [20], [21].

#### 4.3.3 Exploratory Factor Analysis

Exploratory factor analysis was performed at the observed variable level, including all items from STR, INF, FIN, COL, and AIC, to test the measurement structure before constructing composite variables.

As shown in Table 3, the rotated factor matrix indicates that the INF and FIN variables load strongly on the same factor, supporting the decision to combine them into the RES construct. EFA is performed based on a linear model, according to Formula (2):

$$\mathbf{X} = \mathbf{\Lambda F} + \varepsilon \qquad (2)$$

Source: [22]

where **X** specifies the vector of observed variables, **Λ** signifies the factor loading matrix, **F** represents the latent factor vector, and $\varepsilon$ indicates the measurement error vector.

An observed variable is retained when the factor loading coefficient $|\lambda| \geq 0.50$, [23].

*a. Suitability tests*

The appropriateness of the data for factor analysis was assessed utilizing the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity.

- KMO measure: 0.771
- Bartlett's Test of Sphericity: $\chi^2$ = significant, $p < 0.001$
- The results suggest that the data are appropriate for factor analysis.

Exploratory Factor Analysis (EFA) was utilized instead of Confirmatory Factor Analysis (CFA) for three primary reasons. The sample size (n = 126) meets exploratory factor analysis (EFA) minimum criteria, such as at least five observations per item, but it is marginal for CFA and structural equation modeling, which require 200 or more observations to guarantee stable parameter estimations. Despite the prior theoretical specification of the factor structure, this study is the first empirical validation of these constructs in Vietnamese higher education and research, so an exploratory approach was appropriate to determine if the items worked as expected. Third, exploratory factor analysis (EFA) at the observed variable level before creating composite variables confirmed that infrastructure (INF) and financial resources (FIN) significantly converged into a singular resources factor (RES), minimizing measurement error in the regression analysis. Future research with larger samples (n ≥ 250) should use CFA in a structural equation modeling framework to strengthen construct validity and investigate alternative measuring methods.

*b. Extraction and rotation*

The extraction method used is Principal Axis Factoring, combined with the rotation method Varimax with Kaiser normalization. Factors were retained based on the criteria of eigenvalues > 1 and factor loadings ≥ 0.50. The EFA results show that the INF and FIN variables strongly converge into a single common factor, reflecting the organization's AI resources. This provides an empirical basis for constructing the RES composite variable in the next analysis step.

Table 3. Rotated EFA matrix

| Variables | F1 (RES) | F2 (COL) | F3 (STR) | F4 (AIC) |
|---|---|---|---|---|
| INF1 | 0.81 | – | – | – |
| INF2 | 0.77 | – | – | – |
| INF3 | 0.73 | – | – | – |
| FIN1 | 0.69 | – | – | – |
| FIN2 | 0.72 | – | – | – |
| FIN3 | 0.68 | – | – | – |
| COL1 | – | 0.81 | – | – |
| COL2 | – | 0.76 | – | – |
| STR1 | – | – | 0.72 | – |
| STR2 | – | – | 0.67 | – |
| AIC1 | – | – | – | 0.74 |
| AIC2 | – | – | – | 0.71 |

Source: created by the authors.

#### 4.3.4 Construction of composite variables

According to the reliability results and exploratory factor analysis, the composite variables, derived from the average scores of items within each construct, were verified by the following formulas:

$$INF_{\text{mean}} = \frac{1}{3}\sum_{i=1}^{3} INF_i \tag{3}$$

$$FIN_{\text{mean}} = \frac{1}{3}\sum_{i=1}^{3} FIN_i \tag{4}$$

$$RES_{\text{mean}} = \frac{INF_{mean} + FIN_{mean}}{2} \tag{5}$$

Source: created by the authors.

This approach helps reduce measurement noise, ensures conceptual consistency between the measurement model and regression analysis, and preserves the ordinal properties of items in the Likert scale, [20].

#### 4.3.5 Regression analysis and model specification

To test the research hypothesis, the multivariate linear regression method was used and calculated according to Formula (6). As shown in Table 4 (Appendix), organizational AI resources exert the strongest positive effect on AI capability, followed by corporate collaboration, while strategic orientation shows a weaker and marginal effect.

$$AIC = \beta_0 + \beta_1 RES + \beta_2 COL + \beta_3 STR + \varepsilon \tag{6}$$

Source: created by the authors.

where $\beta_i$ represents the regression coefficients obtained by the ordinary least squares (OLS) method, and $\varepsilon$ is the random error term.

Coefficient of determination $R^2$ reflecting the percentage of variance in AI capability elucidated by the model was computed with Formula (7):

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \tag{7}$$

Source: [24]

Model fit statistics:

- $R^2 = 0.408$
- $F = 28.263$
- $p < 0.001$

The model explains approximately 41% of the variance in AI capability scores across institutions.

### 4.4 Diagnostic tests and regression assumptions

A variety of diagnostic tests were performed to confirm the reliability of the regression outcomes.

- Multicollinearity: The Variance Inflation Factor (VIF) values span from 1.21 to 1.38, much below the threshold of 5.

- Normality of residuals: The frequency histogram and P-P plot indicate an approximately normal distribution.
- Homogeneity of variance: The scatter plot of standardized residuals exhibits no pattern.
- Independence of errors: The Durbin-Watson statistic is approximately 1.9, signifying the absence of autocorrelation.
- The diagnosis confirms that the assumptions of multivariate linear regression are adequate.

### 4.5 Methodological rigor and limitations

The study technique adheres to recognized best practices in organizational technology and educational research, encompassing sequential exploratory factor analysis, composite variable construction, and multivariate regression with thorough diagnostic testing. However, the study has several important limitations that should be considered when interpreting the results.

Cross-sectional designs impede causal inference because they assess independent variables (RES, COL, STR) concurrently with the dependent variable (AIC). This design removes the chronological precedent required to demonstrate causation, indicating that rather than resources driving performance, higher-performing institutions may attract greater resources and collaborations. Consequently, the results should be seen as robust statistical correlations pertinent to Vietnamese higher education at a specific moment, rather than universally applicable causal mechanisms. Moreover, self-reported questionnaires employed for data gathering may induce biases. Despite attempts to guarantee anonymity and the application of stringent scientific procedures, such as Harman's test and meticulous question formulation, dependence on single-source data may nevertheless result in.

The model overlooks significant control variables such as institutional size, urban or rural location, academic composition, faculty specialty, and government affiliation. These metrics exhibit weak to moderate correlations with AI performance ($r = 0.12$-$0.21$), functioning as additive factors rather than confounding variables, although their incorporation may enhance explanatory power.

The implementation of AI capacity is constrained to two output indicators: publications and applications. While these include implemented research and application efforts, they omit other aspects such as patents, AI training programs, infrastructure quality, or the corporate culture related to AI. This measurement method is suitable for cross-institutional survey comparisons but limits comprehensiveness; future studies employing more extensive institutional data should develop multi-dimensional scales.

These limitations are substantially alleviated with stringent scale validation, thorough regression diagnostics (VIF<2, normal residuals, absence of heteroscedasticity or autocorrelation), and straightforward reporting. This initial organizational-level investigation of AI capability in Vietnam validates the current methodology and indicates clear pathways for future confirmatory and longitudinal studies.

### 4.6 Robustness check: Disaggregated resource dimensions

Table 5. Robustness check regression results

| Independent variable | Standardized $\beta$ | $p$-value |
|---|---|---|
| INF_mean | 0.261 | 0.004 |
| FIN_mean | 0.289 | 0.002 |
| COL_mean | 0.232 | 0.005 |
| STR_mean | 0.148 | 0.081 |

Source: created by the authors.

As shown in Table 5, both infrastructure and finance have an independent and statistically significant impact on AI capability, confirming the robustness of the research model.

### 4.7 Common Method Bias: Harman's Single-Factor Test

Common method variance (CMV) may threaten validity since all data were acquired from single respondents using the same questionnaire. We addressed this concern using complementing statistical and procedural methods indicated in current methodological literature, [25].

*Statistical Tests*:

- Harman's single-factor test: Principal axis factoring was used to unrotate EFA all model variables (STR, INF, FIN, COL, AIC). Multiple factors with eigenvalues >1 were found, with the greatest component accounting for <40% of total variance, below the 50% criterion for significant CMV, [25].
- We included a theoretically unrelated "marker" item in the questionnaire, "Institutional readiness for general digital transformation" (excluded from the main model), to strengthen the test. There were no significant correlations (all r<0.10) between this marker and focal constructs, indicating that CMV does not significantly impact observed relationships.

Procedural remedies implemented ex ante included (1) anonymity guarantee, (2) no rightwrong answers instructions, (3) thematically.

These methods significantly minimize CMV risk, but the single-source, cross-sectional design cannot remove it. Interpret results as robust within-method connections. Further research using administrative records, third-party audits, or objective indicators would provide greater proof.

# 5 Ethical considerations

The study adhered to ethical guidelines for social scientific inquiry, emphasizing voluntary participation and informing respondents of its purpose. No personally identifiable information was collected, ensuring anonymity before analysis. Data is used solely for academic research purposes.

# 6 Research Results

## 6.1 Descriptive statistics

As shown in Table 6, the descriptive statistics for the primary variables in the research model, encompassing the mean (Mean), standard deviation (SD), minimum (Min), and maximum (Max) values.

Table 6. Descriptive statistics of the research variables ($N = 126$)

| Variables | Mean | SD | Min | Max |
|---|---|---|---|---|
| STR_mean | 3.21 | 0.86 | 1.50 | 5.00 |
| INF_mean | 2.94 | 0.91 | 1.00 | 5.00 |
| FIN_mean | 2.78 | 0.88 | 1.00 | 5.00 |
| RES | 2.86 | 0.84 | 1.00 | 5.00 |
| COL_mean | 3.02 | 0.83 | 1.00 | 5.00 |
| AIC_mean | 2.67 | 0.79 | 1.00 | 5.00 |

Source: created by the authors.

The findings indicate considerable variations in AI development across universities and research institutes in Vietnam, especially concerning infrastructure (INF) and financial resources (FIN). The average AI capacity (AIC) score of low-medium indicates that AI is in the nascent phases of development across numerous organizations.

## 6.2 Regression analysis

The findings of the multiple linear regression analysis reveal that the model is statistically significant ($R^2 = 0.408$, $F = 28.263$, $p < 0.001$). Organizational AI resources have the strongest positive association with AI capability ($\beta = 0.373, p < 0.001$). Collaboration with enterprises is also positively and significantly associated with AI capability ($\beta = 0.241, p = 0.003$). Strategic orientation toward AI has a positive but only marginally significant association ($\beta = 0.162$, $p = 0.067$).

The model explains 41% of AI capacity score variance ($R^2$ = 0.408), leaving 59% of volatility unexplained. This residual variance may be explained by institutional age (years since establishment), geographic location (urban versus non-urban), discipline composition (the relative emphasis on STEM-related programs), faculty size and specialization (number of academic staff with AI-related expertise), and government affiliation or status. AI competency is weakly correlated with institutional age, geographic proxy, discipline composition, faculty size, and government affiliation (r = 0.12, ns; r = 0.15, ns; r = 0.18, ns; r = 0.21, $p < 0.05$; r = 0.14, ns). These findings show that these traits may cumulatively improve AI capability rather than complicate the linkages explored here.

To improve explanatory power and institutional AI understanding, future research with larger samples and multi-level designs must explicitly integrate these contextual factors.

# 7 Discussion

The findings underscore the central role of organizational resources in developing AI capability in Vietnamese universities and research institutes. Institutions with stronger AI infrastructure and more stable AI-related funding tend to report higher levels of AI publications and applications. Collaboration with enterprises provides an important complementary mechanism, while strategic orientation appears to matter mainly when it is linked to concrete investments and implementation. This indicates that in emerging economies, essential elements like infrastructure and financing remain prerequisites for the implementation of AI policies.

The marginal statistical significance of the strategic orientation variable (STR) may indicate that numerous teaching and research institutes in Vietnam have formulated AI plans; however, these strategies have not been adequately converted into concrete investments and quantifiable outcomes.

# 8 Policy Implications

## 8.1 Policy ramifications concerning the organization’s AI assets (RQ1)

The findings indicate that organizational AI resources, including infrastructure and financial support, are the strongest determinants of AI capability. Therefore, several policy implications can be proposed.

*Initially*, a national framework for assessing institutional AI capability should be developed, covering core areas such as AI infrastructure, data resources, research capacity, teaching capability, and applied AI outputs. This framework can support resource allocation and institutional performance monitoring.

*Secondly*, a dedicated academic AI research fund should be established to support small but innovative research groups, especially in universities and research institutes outside major urban centers.

*Third*, regional academic AI centers should be developed to share computing infrastructure, datasets, GPU resources, and technical expertise, thereby reducing capability gaps among institutions.

*Fourth*, systematic AI training and certification programs should be implemented for lecturers and researchers, in cooperation with domestic and international partners, to strengthen long-term teaching and research capacity.

### 8.2 Policy Implications Concerning Academic and Business Collaboration (RQ2)

The study findings further validate the beneficial impact of collaboration on augmenting AI capabilities.

*Consequently*, it is imperative to: First, augment domestic academic exchange through thematic workshops, seminars, and inter-university collaborations to facilitate the dissemination of knowledge, research methodologies, and experiences in AI deployment.

*Secondly*, enhance international academic collaboration through joint doctoral programs, cooperative laboratories, and transnational research initiatives within the context of ASEAN or other global frameworks. This bolsters the standing of Vietnamese AI research throughout the area.

### 8.3 Policy Implications Concerning Strategic Direction (RQ3)

While strategic focus on AI yields marginal benefits, research indicates strategy becomes significant only when associated with specific objectives and resources. A roadmap for AI development in higher education and research should include explicit quantitative indicators, such as the number of training programs, research groups, and AI application products. An annual report on academic AI in Vietnam would monitor developmental advancements and support evidence-based policymaking. AI development policies should also incorporate ethical and responsible principles into AI research and training to ensure sustainable and accountable advancement.

## 9 Conclusion

This study examines factors influencing AI capabilities at Vietnamese universities and research institutes, emphasizing a systematic framework in which organizational resources are essential. It enhances literature by (i) presenting a framework for evaluating organizational-level AI proficiency in developing economies, (ii) supplying evidence on organizational resources for AI advancement in higher education, and (iii) elucidating connection between corporate collaboration and strategic orientation in augmenting AI capabilities. Future research may use panel data or worldwide comparisons to evaluate AI growth patterns and training obstacles for policy recommendations.

*Acknowledgment:*
This study was funded by the research project QG.24.82 of Vietnam National University, Hanoi, Vietnam.

*References:*

[1] Organisation for Economic Co-operation and Development, Artificial intelligence in society, ISBN: 978-9264582545, *OECD Publishing*, 2019, `https://doi.org/10.1787/eedfee77-en`.

[2] (Text in Vietnamese) Prime Minister of Vietnam, Decision No. 127/QĐ-TTg dated 26 January 2021 on promulgating the National Strategy for Research, Development and Application of Artificial Intelligence until 2030, (Quyết định số 127/QĐ-TTg ngày 26/01/2021 về việc ban hành Chiến lược quốc gia về nghiên cứu, phát triển và ứng dụng Trí tuệ nhân tạo đến năm 2030), *Government of Vietnam*, 2021, `https://vanban.chinhphu.vn/default.aspx?pageid=27160&docid=202565` (Accessed Date: February 11, 2026.)

[3] McAfee A., & Brynjolfsson E., Machine, platform, crowd: Harnessing our digital future, ISBN-13: 978-0393254297, *W.W. Norton & Company*, 2017, `https://wwnorton.co.uk/books/9780393254297-machine-platform-crowd`.

[4] Cockburn I. M., Henderson R., & Stern S., The impact of artificial intelligence on innovation: An exploratory analysis. In The economics of artificial intelligence: An agenda, ISBN-13:

978-0226613338, *University of Chicago Press*, 2018, pp.115-146, https://doi.org/10.3386/w24449.

[5] Smart Nation Singapore, National AI Strategy 2.0, *Government of Singapore*, 2023, https://go.gov.sg/nais2023 (Accessed Date: February 12, 2026.)

[6] Laorach C., & Tuamsuk K., Factors Influencing the Digital Transformation of Universities in Thailand, *International Journal of Innovative Research and Scientific Studies*, Vol.5, No.3, 2022, pp.211-219, https://doi.org/10.53894/ijirss.v5i3.646.

[7] Qasem Y. A., Abdullah R., Jusoh Y. Y., Atan R., & Asadi S., Cloud computing adoption in higher education institutions: A systematic review, *IEEE Access*, Vol.7, 2019, 63722-63744, https://doi.org/10.1109/ACCESS.2019.2916234.

[8] Etzkowitz H., Leydesdorff L., The dynamics of innovation: From national systems and "Mode 2" to a Triple Helix of university-industry-government relations, *Research Policy*, Vol.29, No.2, 2000, pp.109-123, https://doi.org/10.1016/S0048-7333(99)00055-4.

[9] Perkmann M., Tartari V., McKelvey M., Autio E., Broström A., D'este P., Fini R., Geuna A., Grimaldi R., Hughes A., Krabel S., Kitson M., Llerena P., Lissoni F., Salter A. & Sobrero M., Academic engagement and commercialization: A review of the literature on university-industry relations, *Research Policy*, Vol.42, No.2, 2013, pp.423-442, https://doi.org/10.1016/j.respol.2012.09.007.

[10] Arya V., Saraf A., Chichkanov N., Papa A., & Romano M., AI-enhanced competency transfer hubs: a conceptual framework for university-industry engagement and knowledge sharing, *The Journal of Technology Transfer*, 2025, pp.1-31, https://doi.org/10.1007/s10961-025-10233-7.

[11] Lundvall B. Å., & Rikap C., China's catching-up in artificial intelligence seen as a co-evolution of corporate and national innovation systems, *Research Policy*, Vol.51, No.1, 2022, 104395, https://doi.org/10.1016/j.respol.2021.104395.

[12] Le H. V. P., Luu T. L., Giang G. B., Vu H. L., & Nguyen T. N. N., AI Integration in Teaching and Learning: Faculty Training for the use of Artificial Intelligence in Higher Education in Vietnam, *Thu Dau Mot University Journal of Science*, Vol.7, No.4, 2025, https://doi.org/10.37550/tdmu.EJS/2025.04.687.

[13] Barney J., Firm resources and sustained competitive advantage, *Journal of management*, Vol.17, No.1, 1991, pp.99-120, https://doi.org/10.1177/014920639101700108.

[14] Wernerfelt B., A resource-based view of the firm, *Strategic management journal*, Vol.5, No.2, 1984, pp.171-180, https://doi.org/10.1002/smj.4250050207.

[15] OECD, A blueprint for building national compute capacity for artificial intelligence", OECD Digital Economy Papers, No. 350, 2023, OECD Publishing, Paris, https://doi.org/10.1787/876367e3-en.

[16] Andrade, C., The Inconvenient Truth About Convenience and Purposive Samples, Indian Journal of Psychological Medicine, Vol.43, No.1, 2021, pp.86–88, https://doi.org/10.1177/0253717620977000.

[17] VanVoorhis, C. R. W., & Morgan, B. L., Understanding Power and Rules of Thumb for Determining Sample Sizes, Tutorials in Quantitative Methods for Psychology, Vol.3, pp.43-50, 2007, https://doi.org/10.20982/tqmp.03.2.p043.

[18] Cronbach L. J., Coefficient alpha and the internal structure of tests, *Psychometrika*, Vol.16, No.3, 1951, pp.297-334, https://doi.org/10.1007/BF02310555.

[19] Fornell C., & Larcker D. F., Structural equation models with unobservable variables and measurement error: Algebra and statistics, *SAGE Publications, Inc.*, Vol.18, No.3, 1981, pp.382-388, https://doi.org/10.2307/3150980.

[20] Boateng, G. O., Neilands, T. B., Frongillo, E. A., Melgar-Quiñonez, H. R., & Young, S. L., Best practices for developing and validating scales for health, social, and behavioral research: a primer, Frontiers in public health, Vol.6, 2018, pp.149, http://doi.org/10.3389/fpubh.2018.00149.

[21] Wasserstein, R. L., & Lazar, N. A., The ASA statement on p-values: context, process, and purpose, The American Statistician, Vol.70, No.2, 2016, pp.129-133, https://doi.org/10.1080/00031305.2016.1154108.

[22] R Core Team, Factor Analysis, R Documentation: factanal function, R Foundation for Statistical Computing, https://stat.ethz.ch/R-manual/R-devel/library/stats/html/factanal.html (Access Date May, 24, 2026)

[23] Yong, A. G., & Pearce, S., A beginner's guide to factor analysis: Focusing on exploratory factor analysis, Tutorials in quantitative methods for psychology, Vol.9, No.2, 2013, pp.79-94, https://doi.org/10.20982/tqmp.09.2.p079

[24] Holmes, A., Illowsky, B., & Dean, S., Introductory business statistics 2e, ISBN-13: 978-1-711472-59-1, OpenStax, 2023, https://openstax.org/details/books/introductory-business-statistics-2e (Accessed Date: May 25, 2026).

[25] Podsakoff P. M., MacKenzie S. B., Lee J. Y., & Podsakoff N. P., Common method biases in behavioral research: A critical review of the literature and recommended remedies, *Journal of Applied Psychology*, Vol.88, No.5, 2003, pp.879-903, https://doi.org/10.1037/0021-9010.88.5.879.

**Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)** Toan Tran Tuan: conceptualization, data collection, methodology, and drafting. Huan Phung The: data analysis, statistical validation, and interpretation. Khanh Duong Quang: supervision, research design, and final revision. Son Le Hoang: literature review, policy analysis, and editing.

**Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself** This study was funded by the research project QG.24.82 of Vietnam National University, Hanoi, Vietnam

**Conflicts of Interest** The authors declare no conflicts of interest relevant to this article.

# Appendix

Table 1. Coding scheme and variable recoding

| Variable group | Variable code | Description of observed variables | Scale | Composite variable |
|---|---|---|---|---|
| Strategic direction | STR1<br>STR2 | There is an AI strategy at the organizational level<br>Long-term commitment to AI development | Likert 1–5<br>Likert 1–5 | STR_mean = MEAN(STR1, STR2) |
| AI infrastructure | INF1<br>INF2<br>INF3 | GPU/HPC infrastructure<br>AI/Cloud platform<br>Data for AI | Likert 1–5<br>Likert 1–5<br>Likert 1–5 | INF_mean = MEAN(INF1, INF2, INF3) |
| AI Finance | FIN1<br>FIN2<br>FIN3 | Budget for AI<br>AI financial stability<br>External funding | Likert 1–5<br>Likert 1–5<br>Likert 1–5 | FIN_mean = MEAN(FIN1, FIN2, FIN3) |
| AI Resources | - | High-level structure | - | RES = MEAN(INF_mean, FIN_mean) |
| Corporate Collaboration | COL1<br>COL2 | AI research with businesses<br>AI applications with business support | Likert 1–5<br>Likert 1–5 | COL_mean = MEAN(COL1, COL2) |
| AI capabilities | AIC1<br>AIC2 | AI publications<br>AI applications | Recode 1–5<br>Recode 1–5 | AIC_mean = MEAN(AIC1, AIC2) |

Source: created by the authors.

Table 2. Results of the reliability analysis

| Construct | Items | Cronbach's $\alpha$ | Composite Reliability | Status |
|---|---|---|---|---|
| AI capacity (AIC) | 2 | 0.71 | 0.82 | Acceptable |
| Organizational AI resources (RES) | 2 | 0.76 | 0.85 | Strong |
| Industry collaboration (COL) | 2 | 0.68 | 0.79 | Acceptable |
| Strategic orientation (STR) | 2 | 0.59 | 0.78 | Exploratory* |

**acceptable with caution*

Source: created by the authors.

Table 4. Regression results

| Predictor | Standardized $\beta$ | $t$-value | $p$-value | 95% CI Lower | 95% CI Upper | Interpretation |
|---|---|---|---|---|---|---|
| RES | 0.373 | 4.21 | $< 0.001$ | 0.25 | 0.49 | Highly significant |
| COL | 0.241 | 3.12 | 0.003 | 0.12 | 0.36 | Significant |
| STR | 0.162 | 1.85 | 0.067 | -0.01 | 0.33 | Marginally significant |
| Model fit | | | | | | |
| $R^2$ | 0.408 | | | | | |
| Adjusted $R^2$ | 0.394 | | | | | |
| $F$-statistic | 28.263 | | $< 0.001$ | | | Overall model significant |
| N | 126 | | | | | |

*$R^2$=0.408 implies 59% unexplained variance; potential omitted variables include institutional age (corr=0.12), location (urban/rural, corr=0.15), size (faculty n, corr=0.18), per robustness tests.*

Source: created by the authors.