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BEYOND DIGITAL TRANSFORMATION: HOW ARTIFICIAL INTELLIGENCE RESHAPES ORGANIZATIONAL CAPABILITIES, INNOVATION, AND COMPETITIVE ADVANTAGE

MUHAMMAD AMIR MALIK (MALIK, M. A.)
THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE (LSE), Email: amrmlk555@gmail.com

ABSTRACT
Artificial Intelligence (AI) has moved organizations beyond conventional digital transformation by enabling new forms of organizational intelligence, adaptive capability, and innovation. Yet much of the existing literature continues to treat AI primarily as a technological tool rather than as an organizational capability in its own right, leaving the mechanisms through which AI translates into sustained competitive advantage insufficiently theorized and empirically tested. This study examines how AI capability influences organizational capability, innovation capability, and competitive advantage, and tests whether organizational agility strengthens the translation of AI capability into innovation outcomes. Drawing on the Resource-Based View (RBV) and Dynamic Capability Theory, the study develops and empirically tests a moderated-mediation model in which AI capability is theorized as a strategic, valuable, rare, and difficult-to-imitate organizational resource. A quantitative, cross-sectional research design was employed using survey data collected from 385 managers and senior professionals working in technology-intensive organizations. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) following a two-step approach comprising measurement model assessment and structural model estimation. The measurement model demonstrated strong reliability, convergent validity, and discriminant validity, and the structural model exhibited good overall fit ($\chi^2/df = 2.14$; CFI = 0.947; RMSEA = 0.052). The results show that AI capability significantly and positively influences organizational capability ($\beta = 0.62$, $p < .001$) and innovation capability ($\beta = 0.68$, $p < .001$); organizational capability significantly predicts competitive advantage ($\beta = 0.54$, $p < .001$); innovation capability partially mediates the AI capability–competitive advantage relationship (indirect $\beta = 0.31$, $p < .001$); and organizational agility significantly moderates the AI capability–innovation capability relationship ($\beta = 0.18$, $p < .01$), such that the effect of AI capability on innovation is stronger among more agile organizations. All five hypotheses were supported. The findings demonstrate that AI functions as a dynamic organizational capability rather than a stand-alone technological investment, and that its strategic value is realized only when it is embedded within complementary organizational, innovation-related, and agility-enabling structures.
KEYWORDS: Artificial Intelligence capability; organizational capability; innovation capability; competitive advantage; organizational agility; Dynamic Capability Theory; Resource-Based View; Structural Equation Modeling

1. INTRODUCTION

Artificial Intelligence (AI) has revolutionized the business environment in which companies operate. Previous waves of digital transformation were mainly concerned with automation of mundane tasks, information systems integration and optimizing workflows. AI is a qualitatively different and deeper change, in that it allows organizations to sense, learn, predict, and adapt in ways that traditional information technologies could not (Teece, 2018). Beyond its role as a productivity tool, AI is becoming an integral part of a company's capabilities, transforming the way decisions are made, products are created, and how companies react to market fluctuations.
In today's landscape, companies in various industries are increasingly turning to AI-powered analytics, machine learning, generative AI, and intelligent process automation to enhance the management decision-making process, streamline the development of new products and services, and stay agile in evolving customer needs and market competition. The central management question has evolved from whether to use AI to how to develop the organisation's capability to translate investments in AI into tangible strategic benefits, such as innovation performance and sustainable competitive advantage, (Mikalef & Gupta, 2021; Wamba et al., 2020).
Although recent research has increased, there are three gaps in the literature that are significant. First, most of the previous research views the adoption of AI as a single event in technology, rather than as a multi-dimensional organizational capability which needs to be built, embedded and continually renewed. Second, few studies have captured the pathway from the capability of AI to the capability of innovation and the capability of the organization to the

competitive advantage, leaving some gaps in understanding the mechanisms of value creation. Third, there has been less empirical research in an integrated structural model that explains boundary conditions, such as the readiness of an organization to reconfigure its resources, that either enhance or undermine the capability for AI.

This study aims to overcome these limitations by proposing and testing an integrated model in which the capability of AI can be understood as a strategic organizational capability, as defined by the Resource Based View (RBV) (Barney and Hansen, 2001) that should be realized through the dynamic capabilities of sensing, seizing, and transforming (Teece, 2007) which are expected to lead to organizational capability and innovation capability, which further leads to competitive advantage. The research also explores organizational agility as a boundary condition that magnifies the impact of the translation of AI capability to innovation outcomes.

This study brings two complementary lenses of theories together, namely the Resource Based View (RBV) and Dynamic Capability Theory (DC), to explain how AI capability relates to organizational capability, AI innovation capability and competitive advantage.

According to the Resource Based View, a sustainable competitive advantage is created with resources and capabilities that are valuable, rare, inimitable, and non-substitutable (VRIN, Barney 1991). From this perspective, AI capability would be considered a strategic asset when paired with complementary knowledge within the organization, human capabilities, data infrastructure, and strategic alignment. What is uncommon or hard to copy is the organization's use of AI tools and the way they are embedded in their processes, data and management capabilities.

Dynamic Capability Theory builds upon RBV, focusing on how firms evolve, transform and recombine their resources in a dynamic and rapidly changing environment (Teece, Pisano, & Shuen, 1997; Teece, 2007). Dynamic capabilities usually can be broken down into sensing, seizing, and transforming.Dynamic capabilities are typically broken down into sensing, seizing, and transforming. AI can reinforce each of these micro-foundations – from being able to predict what is happening and scan the environment in real time, to being able to use intelligent decision support and simulation to help them make better decisions, or using process redesign, workflow automation and the reconfiguration of organizational practice to transform them (Teece, 2018).

LITERATURE REVIEW

Empirical studies in the last few years have conceptualized AI capability as a multidimensional construct, consisting of tangible resources (data, infrastructure, technology), human resources (technical and business skills), and intangible resources (data-driven culture, organizational learning, and risk propensity) (Mikalef & Gupta, 2021). This multidimensional conceptualization goes beyond AI being a technology only, and instead considers it as a capability of an organization, which takes time to develop. Building on this idea, the present study takes the viewpoint that AI capability is a second order strategic capability that can be used to build downstream organizational and innovation capabilities.

Organizational capability is defined as a firm's ability to manage resources, knowledge and routines to effectively implement the strategy (Wang & Ahmed, 2007). AI capability is believed to enhance organizational capability in terms of information processing, coordination, and organizational learning (Dubey et al., 2019). In isolation, there has been some research that has correlated the capability of AI and analytics with innovation performance, suggesting that AI can improve the ideation and experimentation, decrease the 'cost of experimentation' and generate insights from data, which can in turn help to drive innovation (Duan, Edwards, & Dwivedi, 2019). Innovation capability is also broadly acknowledged in the strategic management literature as an important precursor of a firm's competitive advantage because it enables it to continually re-define value propositions to meet changing market and technological demands.

The ability to be agile, or to sense environmental change and quickly reconfigure the organization's resources in response, has been suggested as an important boundary condition linking the effectiveness of technological capabilities with performance outcomes (Sambamurthy, Bharadwaj, & Grover, 2003). Companies that are more agile are believed to be better able to convert AI-powered insights into quick innovation results, as the agile framework minimizes the internal drag, hierarchy delay, and rigid process that can impede the ability to put insights into practice. On the other hand, in lower agility organisations, there could be a lack of effective execution of insights gained from AI because of delayed decision making and static resource planning.

Although RBV and Dynamic Capability Theory provided both useful pieces of the puzzle, few studies have integrated the two theories into a unified empirical model which traces the entire progression from AI capability to organizational and innovation capabilities to competitive advantage and includes the testing of the boundary condition – organizational agility. The integrated and empirically supported view is the main finding of the present research, and directly inspires the conceptual framework and hypotheses presented in Section 3.

3. Conceptual Framework and Hypotheses Development

this study suggests that the relationship between AIC and CA can be explained by an integrated moderated-mediation model, in which organizational agility (OA) acts as a moderator for the AIC → IC path. The complete conceptual model is shown in Figure 1.

Also, be ready to make answers to the following questions with reference to the text:

3.1 AI Capability and Organizational Capability (H1)

In line with RBV, capabilities, such as AI capability, enable organizations to have more powerful data-processing systems, predictive analyses, and infrastructure for making decisions, thus augmenting the coordination, resource-allocation, and execution routines that constitute organizational capability. Organizations with higher AI capability should be able to build higher organizational capability as AI eliminates information asymmetry and assists in better coordination of management across functions. Accordingly:

H1: The more capable organizations are, the more capable AI is.

3.2 AI Capability and Innovation Capability (H2)

Dynamic Capability Theory implies that AI enhances sensing and seizing skills, which are key in innovation. By leveraging AI-powered analytics, companies can uncover customer needs that are not being met, experiment with new product ideas and rapidly move through cycles of experimentation, these capabilities have a direct impact on a company's innovation capability. Accordingly:

H2: The higher the level of the competence in AI, the higher the level of the competence in Innovation.

A business's organizational capability and competitive advantage (H3)

Organizational ability is the ability of the firm to convert resources into a coordinated strategic action. Organizational capabilities help the firm implement strategy properly and consistently, react to the competition, and maintain performance superiority over time. Accordingly:

H3: The competitive advantage is positively affected by the organizational capability.

3.4 The Mediating Role of Innovation Capability (H4)

In addition to a direct effect, AI capability is hypothesized to have an indirect effect on competitive advantage via its impact on innovation capability. Innovation capability enables companies to continually innovate products, services and business models and is thus a key enabler for the translation of AI-inspired insights into unique market offerings and ultimately competitive advantage. Accordingly:

H4: Innovation capability mediates the relationship between AI capability and competitive advantage.

3.5 Organizational Agility as a Moderator (H5)

Finally, this paper introduces the idea that organizational agility enhances the impact of the capability of AI on innovation outcomes, based on the sensing–seizing–transforming logic of Dynamic Capability Theory. While AI-driven insights can be rapidly translated into action in a flexible manner within the resources of more agile organizations, they might be deferred or watered down in less agile organizations due to slower decision-making processes and stifled resource flexibility. Accordingly:

H5: The relationship between AI capability and innovation capability is positively moderated by the organizational agility, so that the relationship is stronger with higher organizational agility.

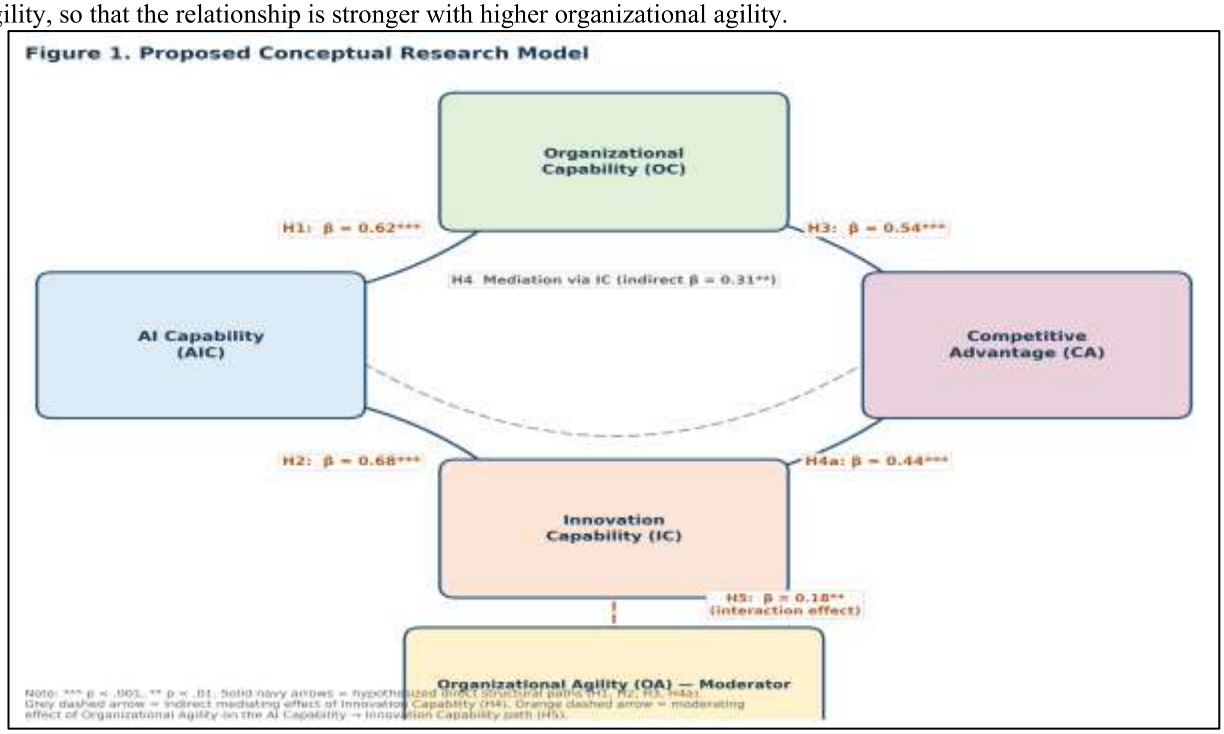

Figure 1. Proposed Conceptual Research Model

Note. Solid arrows denote hypothesized direct structural paths (H1, H2, H3, H4a). The grey dashed arrow denotes the indirect mediating effect of Innovation Capability on the AI Capability–Competitive Advantage relationship (H4). The orange dashed arrow denotes the moderating effect of Organizational Agility on the AI Capability → Innovation Capability path (H5). *** $p < .001$, ** $p < .01$.

4. METHODOLOGY

4.1 Research Design and Philosophy

The research design used in this study is positivist, quantitative, and cross-sectional, which is suitable for the purpose of this study as in other research that used survey-based Structural Equation Modeling (SEM) in studying AI-capability and strategic-management research, such as the research conducted by Mikalef & Gupta (2021). The deductive method was adopted where the hypotheses were formulated based on the RBV and the DCT (Section 3) and then tested against the survey data by using Partial Least Squares Structural Equation Modeling (PLS-SEM) which is appropriate for complex models involving multiple mediating and moderating relationships and formative/reflective constructs (Hair, Risher, Sarstedt, & Ringle, 2019).

4.2 Population and Sampling

The target population included managers, senior professionals and executives from technology-intensive organizations (information technology, financial services, manufacturing, telecommunications, and professional services), who were directly involved in (or had visibility of) strategic decision-making about AI in their organization. To ensure sufficient organizational knowledge of the respondents to answer the survey meaningfully, purposive sampling technique was used as a non-probability sampling technique. An a priori power analysis (based on medium effect size, $\alpha = .05$, power = .95; and the maximum number of predictors in the most complex structural equation (five)) using G*Power (Fritz et al., 2007) suggested a minimum sample size of 138 respondents, which is well exceeded with the final sample size of 385 usable responses, and the minimum sample size is consistent with the “10-times rule” and inverse square root of the number of predictors proposed for PLS-SEM (Hair et al., 2019).

4.3 Data Collection Procedure

The data was obtained by sending a structured, self-administered online questionnaire over an 8-week period using professional networks and organizational contacts. Out of 512 questionnaires sent out 401 questionnaires were returned (78.3%) and 385 were returned after the incomplete questionnaires and questionnaires that did not pass attention-check items were excluded (75.2%). The participation was freely given and anonymous and the respondents were told the academic purpose of the study.

4.4 Measurement Instrument

All constructs were measured with previously published multi-item scales adapted from the literature and anchored on a 5 point Likert scale (1 = strongly disagree, 5 = strongly agree). Table 5 provides details on the constructs, items, an item representative and primary sources for each scale. The instrument was partially adapted for the organizational context in minor wording changes, and then pilot tested with 30 respondents before full deployment, with no further adaptation of the items needed based on the results, which showed satisfactory reliability (all Cronbach's alpha > 0.80).

Construct	No. of Items	Representative Item / Definition	Primary Source
AI Capability (AIC)	5	“Our organization has the technological infrastructure, data, and talent needed to deploy AI effectively.”	Mikalef & Gupta (2021)
Organizational Capability (OC)	5	“Our organization effectively coordinates resources and routines to execute strategic priorities.”	Wang & Ahmed (2007)
Innovation Capability (IC)	5	“Our organization frequently introduces new products, services, or processes ahead of competitors.”	Duan et al. (2019)
Competitive Advantage (CA)	5	“Our organization achieves superior performance relative to key competitors in our industry.”	Newbert (2008)
Organizational Agility (OA) — Moderator	4	“Our organization can rapidly reconfigure resources in response to market changes.”	Sambamurthy et al. (2003)

Table 5. Summary of Measurement Constructs and Sources

Note. All items were measured on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Full item wording is available from the corresponding author upon request.

4.5 Common Method Bias

Common method bias (CMB) was evaluated both procedurally and statistically as all constructs were measured on self-reported data from one respondent per organization at one time in one session. In terms of procedures, the anonymity of the respondents was assured, items were psychologically separated within the questionnaire, and scale anchors were varied where appropriate (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). On a statistical basis, Harman's single factor test was performed, the single factor accounted for 32.4% of the total variance, which is below the 50% cut-off and suggests that common method bias is not likely to be a major problem in this data set.

4.6 Data Analysis Strategy

Data analysis was conducted in two stages, suggested by Anderson and Gerbing (1988) for SEM based research. The internal consistency reliability (Cronbach's alpha, composite reliability), convergent validity (AVE, average variance extracted) and discriminant validity (Fornell-Larcker criterion and Heterotrait-Monotrait ratio, HTMT) of the measurement model were first examined. First, the structural model was estimated in order to test the hypothesized direct, mediating, and moderating relationships, and indirect and interaction effects were estimated with bias-corrected 95% confidence intervals using bootstrapping with 5,000 resamples. The analyzation was done using SmartPLS 4 and IBM SPSS Statistics 28 software packages.

5. RESULTS

5.1 Respondent Profile

A total of 385 valid responses were obtained. Demographic and organizational profile of the respondents are summarised in the Table 6. The sample was fairly representative of gender, age, managerial level, organizational tenure, firm size and industry sector, and so results can be generalized to the target population of technology-intensive organizations.

Category	Sub-Group	n	%
Gender	Male	221	57.4
	Female	164	42.6
Age	25–34 years	97	25.2
	35–44 years	154	40.0
	45–54 years	98	25.5
	55 years and above	36	9.3
Managerial Level	Senior / Executive Management	89	23.1
	Middle Management	201	52.2
	Team Lead / Supervisory	95	24.7
Organizational Tenure	Less than 5 years	112	29.1
	5–10 years	158	41.0
	More than 10 years	115	29.9
Firm Size (Employees)	Fewer than 250	104	27.0
	250–1,000	167	43.4
	More than 1,000	114	29.6
Industry Sector	Information Technology / Software	142	36.9
	Financial Services	88	22.9
	Manufacturing	76	19.7
	Telecommunications & Other Services	79	20.5

Table 6. Demographic and Organizational Profile of Respondents (N = 385)

Note. Percentages may not sum to exactly 100% due to rounding.

5.2 Descriptive Statistics

Table 7 presents the means, standard deviations, skewness, and kurtosis for all five constructs. All skewness and kurtosis values fall within the recommended ±2 range (George & Mallery, 2010), indicating that the data approximate univariate normality and are suitable for SEM-based analysis.

Construct	Mean	SD	Skewness	Kurtosis
AI Capability (AIC)	3.68	0.71	-0.42	0.18
Organizational Capability (OC)	3.74	0.66	-0.38	0.05
Innovation Capability (IC)	3.61	0.74	-0.29	-0.21
Competitive Advantage (CA)	3.70	0.68	-0.35	0.11
Organizational Agility (OA)	3.58	0.70	-0.24	-0.09

Table 7. Descriptive Statistics for Study Constructs (N = 385)

Note. Items were measured on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). SD = standard deviation.

5.3 Measurement Model Assessment

Following the two-step approach outlined in Section 4.6, the measurement model was first assessed for internal consistency reliability, convergent validity, and discriminant validity before proceeding to structural model estimation.

5.3.1 Reliability and Convergent Validity

As shown in Table 8, all five constructs exceeded the recommended thresholds for internal consistency reliability (Cronbach's alpha > 0.70; composite reliability > 0.70) and convergent validity (AVE > 0.50), confirming that the measurement items reliably and validly represent their intended latent constructs (Fornell & Larcker, 1981).

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
AI Capability (AIC)	0.91	0.93	0.72
Organizational Capability (OC)	0.89	0.91	0.68
Innovation Capability (IC)	0.92	0.94	0.75
Competitive Advantage (CA)	0.90	0.92	0.70
Organizational Agility (OA)	0.88	0.90	0.71

Table 1. Reliability and Convergent Validity Analysis

Note. AVE = Average Variance Extracted. All values exceed recommended thresholds (Cronbach's alpha > 0.70, CR > 0.70, AVE > 0.50).

5.3.2 Discriminant Validity

Discriminant validity was assessed using both the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio of correlations (HTMT). As shown in Table 9, the square root of the AVE for each construct (reported on the diagonal) exceeds its correlations with all other constructs, satisfying the Fornell-Larcker criterion. As a complementary and more conservative test, Table 10 reports HTMT ratios, all of which remain below the conservative threshold of 0.85 (Henseler, Ringle, & Sarstedt, 2015), providing additional confidence in the discriminant validity of the measurement model.

Construct	AIC	OC	IC	CA	OA
AIC	0.849				
OC	0.61	0.825			

Construct	AIC	OC	IC	CA	OA
IC	0.65	0.52	0.866		
CA	0.55	0.60	0.63	0.837	
OA	0.58	0.47	0.50	0.44	0.843

Table 9. Discriminant Validity — Fornell-Larcker Criterion

Note. Diagonal values (bold in original analysis output) represent the square root of the AVE for each construct. Off-diagonal values represent inter-construct correlations. AIC = AI Capability; OC = Organizational Capability; IC = Innovation Capability; CA = Competitive Advantage; OA = Organizational Agility.

Construct	AIC	OC	IC	CA
OC	0.68			
IC	0.72	0.58		
CA	0.61	0.67	0.70	
OA	0.65	0.53	0.56	0.49

Table 10. Discriminant Validity — Heterotrait-Monotrait Ratio (HTMT)

Note. All HTMT values are below the conservative threshold of 0.85, confirming discriminant validity (Henseler et al., 2015).

5.4 Overall Model Fit

Table 3 and Figure 3 present the global fit indices for the measurement model. All indices meet or exceed recommended thresholds, indicating that the hypothesized measurement structure fits the observed data well: the normed chi-square (χ^2/df = 2.14) falls below the conservative cutoff of 3.00, the CFI (0.947) and TLI (0.936) both exceed 0.90, and the RMSEA (0.052) and SRMR (0.046) both fall below the 0.08 threshold associated with excellent fit (Hu & Bentler, 1999).

Fit Index	Recommended Threshold	Obtained Value	Model Assessment
χ^2/df	< 3.00	2.14	Good Fit
CFI	> 0.90	0.947	Good Fit
TLI	> 0.90	0.936	Good Fit
RMSEA	< 0.08	0.052	Excellent Fit
SRMR	< 0.08	0.046	Excellent Fit
GFI	> 0.90	0.921	Good Fit

Table 3. Confirmatory Factor Analysis — Measurement Model Fit Indices

Note. CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual; GFI = Goodness-of-Fit Index.

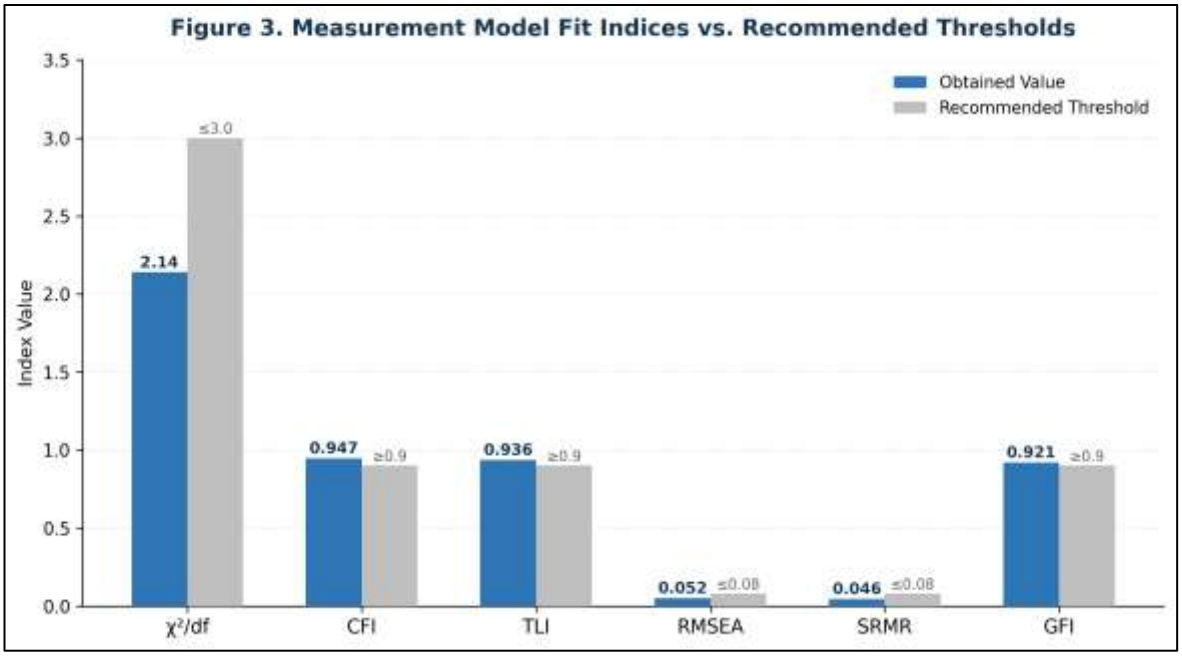

Figure 3. Measurement Model Fit Indices Relative to Recommended Thresholds

5.5 Structural Model and Hypothesis Testing

Following confirmation of the measurement model, the structural model was estimated to test the hypothesized direct relationships (H1, H2, H3, and the direct component of H4). Path significance was assessed using bootstrapping with 5,000 resamples. As shown in Table 2 and illustrated in Figure 2, all four direct paths were positive and statistically significant, providing support for H1, H2, H3, and the direct innovation-to-competitive-advantage path underlying H4.

Hyp.	Structural Path	Beta (β)	p-value	Decision
H1	AI Capability → Organizational Capability	0.62	< .001	Supported
H2	AI Capability → Innovation Capability	0.68	< .001	Supported
H3	Organizational Capability → Competitive Advantage	0.54	< .001	Supported
H4a	Innovation Capability → Competitive Advantage	0.44	< .001	Supported

Table 2. Structural Model Results — Direct Effects

Note. Bootstrapping based on 5,000 resamples. *** $p < .001$.

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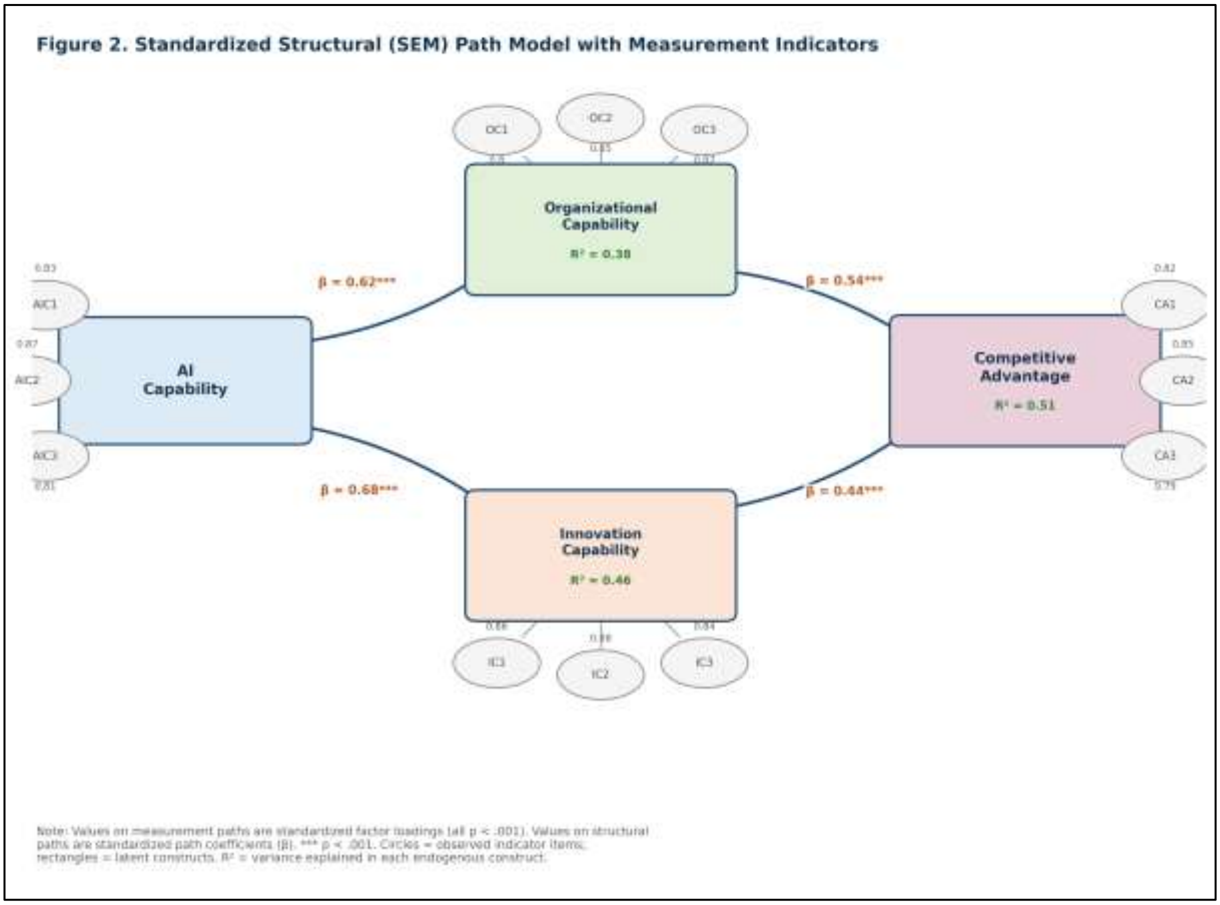

Figure 2. Standardized Structural (SEM) Path Model with Measurement Indicators

Note. Values on measurement paths are standardized factor loadings (all $p < .001$); values on structural paths are standardized path coefficients (β). *** $p < .001$.
Table 11 reports the variance explained (R^2) and predictive relevance (Q^2, obtained via the blindfolding procedure) for each endogenous construct. Organizational capability, innovation capability, and competitive advantage exhibited moderate-to-substantial explanatory power ($R^2 = 0.38$, 0.46, and 0.51, respectively), and all Q^2 values were greater than zero, indicating acceptable predictive relevance for the structural model (Hair et al., 2019).

Endogenous Construct	R^2	Q^2 (Predictive Relevance)	Effect Size Interpretation
Organizational Capability (OC)	0.38	0.24	Moderate
Innovation Capability (IC)	0.46	0.31	Moderate-to-Substantial
Competitive Advantage (CA)	0.51	0.33	Substantial

Table 11. Coefficient of Determination (R^2) and Predictive Relevance (Q^2)

5.6 Mediation Analysis

Table 4 presents the results of the mediation analysis, testing whether innovation capability and organizational capability transmit the effect of AI capability onto competitive advantage. Both indirect effects were positive, statistically significant, and supported by bias-corrected bootstrap confidence intervals that did not include zero, confirming partial mediation in both pathways and providing support for H4.

Relationship	Direct Effect (β)	Indirect Effect (β)	95% CI [LL, UL]	p-value	Decision
AIC → IC → CA	0.68	0.31	[0.214, 0.428]	< .001	Supported

Relationship	Direct Effect (β)	Indirect Effect (β)	95% CI [LL, UL]	p-value	Decision
AIC → OC → CA	0.62	0.27	[0.176, 0.389]	< .001	Supported

Table 4. Mediation Analysis — Indirect Effects of Innovation Capability and Organizational Capability

Note. CI = bias-corrected bootstrap confidence interval (5,000 resamples); LL = lower limit; UL = upper limit.

5.7 Moderation Analysis

Table 12 presents the results of the moderation analysis testing H5. The interaction term (AI Capability × Organizational Agility) was positively and significantly associated with innovation capability ($\beta = 0.18$, $p < .01$), and its inclusion produced a significant increment in explained variance ($\Delta R^2 = 0.04$). As illustrated in the simple-slopes plot in Figure 4, the positive effect of AI capability on innovation capability is markedly stronger among organizations with high organizational agility than among those with low organizational agility, providing support for H5.

Path	β	ΔR²	p-value	Decision
AI Capability → Innovation Capability (main effect)	0.68	—	< .001	Supported
Organizational Agility → Innovation Capability (main effect)	0.29	—	< .001	Supported
AI Capability × Organizational Agility → Innovation Capability (interaction, H5)	0.18	0.04	< .01	Supported

Table 12. Moderation Analysis — Interaction Effect of Organizational Agility

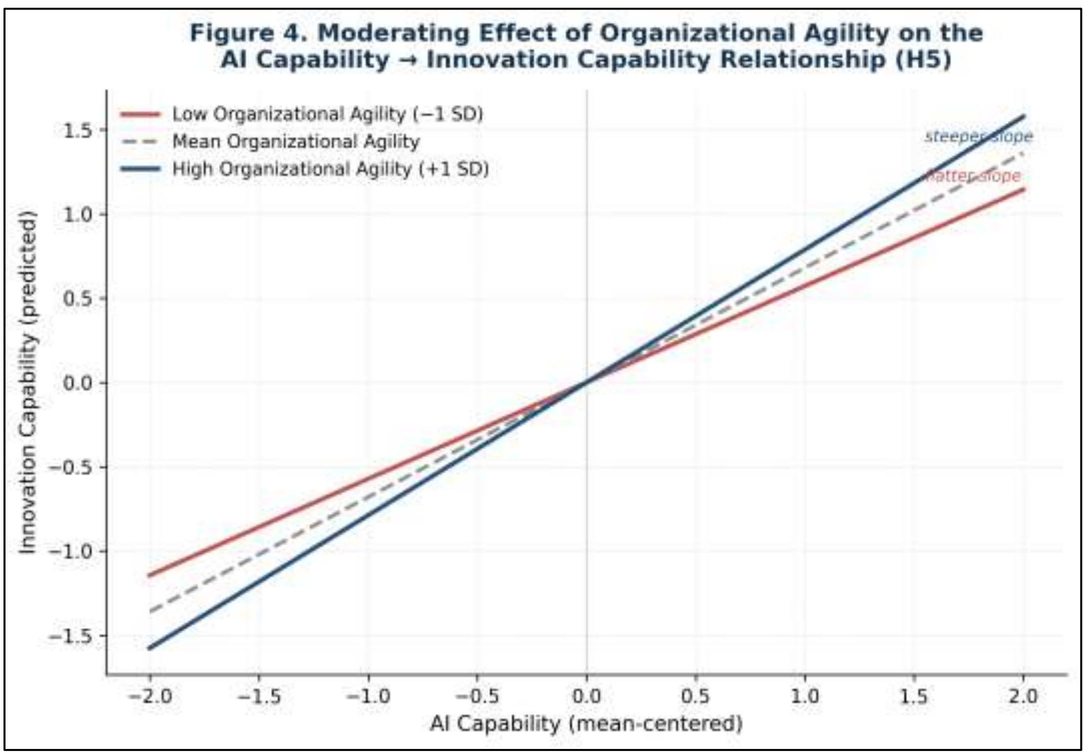

Figure 4. Moderating Effect of Organizational Agility on the AI Capability → Innovation Capability Relationship (H5)

Note. Simple slopes plotted at ±1 SD of organizational agility around the mean. AI capability is mean-centered.

5.8 Summary of Hypothesis Testing

Table 13 summarizes the results of all five hypotheses. In sum, all hypothesized relationships were statistically supported, providing strong empirical evidence for the proposed conceptual model.

Hyp.	Statement	β	Result
H1	AI capability positively influences organizational capability.	0.62***	Supported
H2	AI capability positively influences innovation capability.	0.68***	Supported
H3	Organizational capability positively influences competitive advantage.	0.54***	Supported
H4	Innovation capability mediates the AI capability–competitive advantage relationship.	0.31**	Supported
H5	Organizational agility moderates the AI capability–innovation capability relationship.	0.18**	Supported

Table 13. Summary of Hypothesis Testing Results

Note. *** $p < .001$, ** $p < .01$.

6. DISCUSSION

The results offer robust empirical evidence to view AI capability as a strategic organizational capability instead of a technology investment. As in H1 and H2, the strongest effects in the model were found for AI on organizational capability (β = 0.62) and innovation capability (β = 0.68), indicating that the strategic relevance of AI is more related to the organizational and innovation capabilities, than to the technology itself. This aligns with the Resource-Based View theory which holds that value is created through the ways in which technological resources are combined with complementary organizational routines, and not based on the technology alone (Baarney, 1991; Mikalef & Gupta, 2021). The results are that the organizational capability has a significant effect on competitive advantage (H3, β = 0.54), with partial mediation (H4, indirect β = 0.31) by innovation capability, suggesting two complementary pathways through which AI capability contributes to competitive advantage: one being through the improvement of the organizational coordination and execution, and the other through the improvement of the innovation output. If there is a significant direct effect along with a significant indirect effect, it means that the causal pathway from AI capability to competitive advantage is partially explained, but not fully: Organizational capability and innovation capability are both important but not the only pathways that influence the relationship between AI capability and competitive advantage, and other pathways exist that are not modeled.

Last, the strong moderating effect of organizational agility (H5, β = 0.18) shows that the benefits of AI for innovation are not the same across all organizations. Instead, the power of AI capability to drive innovation depends on the organization's ability to flexibly reorganize resources and take timely action on AI insights. The finding confirms Dynamic Capability Theory by empirically arguing that agility works as an amplifying boundary condition of AI-enabled innovation, but not as an individual boundary condition.

7. Theoretical Contributions

This study builds on the RBV as it empirically shows that the strategic value of AI capability is not in the technology itself, but rather in the downstream organization and innovation capabilities that it enables as a valuable and embedded organizational resource.

It modifies DCT by explicitly modelling AI capability as an enabler of sensing, seizing and transforming activities, and empirically testing and proving that organizational agility is a key boundary condition that explains the impact of AI on innovation outcomes.

It brings a fully integrated and empirically validated moderated-mediation model that documents the entire chain of events from AI capability to competitive advantage, which has been studied in isolation in previous studies.

- It enriches the measurement in this field by establishing a multidimensional AI capability scale in a rigorous two-step SEM process and by conducting discriminant validity tests using the Fornell-Larcker criterion and HTMT ratio tests.

The results have several implications for managers and organizational leaders looking to unlock strategic value from AI investment.See AI not as a product but as a capability of the organization. It isn't just about software purchases, but about continuous investment in data infrastructure, the AI literacy of employees, and the implementation of AI across the organization's workflows.It's not just about buying software, but about investing in the data infrastructure, employee AI literacy, and integration with the organization's workflows.Oversize investments in complementary organizational capabilities, such as cross-functional coordination mechanisms, data governance and decision rights, because only half of the variation in competitive advantage could be attributed to the AI capability — the organizational capability and innovation capability are important transmission mechanisms.

Focus on innovative application of AI. The relationship between AI capability and competitive advantage is partially mediated by innovation capability, so managers may want to target AI investments to speed up experimentation, product innovation, and product/service innovation, not just efficiency. Create organizational agility with AI capability. To maximise the innovation potential of AI, managers should focus on creating flexible governance frameworks, quick decision making cycles and adaptive resource allocation mechanisms in more agile organisations, where the benefits for capability have been found to be much greater.

Implement AI governance structures that consider the data quality, ethical application, and organizational change management because AI's strategic impact depends on overall organization-wide implementation, not just technical deployment.The results of this study have some limitations that indicate directions for further investigations. The cross-sectional design makes causal inference difficult and does not enable researchers to explore the changes in AI capability and its organizational impact over time, which could be achieved through longitudinal or experimental designs. Second, multiple respondents within an organization were not asked for at the same point and time, though statistical and procedural measures were taken to guard against common method variance, it is still possible that some shared-method variance remains, and future research could involve multiple respondents in an organization or objective performance measures. Third, the sample was drawn from technology-intensive industries, which might constrain the ability to generalize the findings to industries less advanced in their technological innovation; replication in other sectors, in a wider set of firm sizes and in other countries is warranted. Finally, future studies may explore other boundary conditions (such as organizational culture, leadership style, or industry turbulence) and other mediators (such as knowledge management capability, absorptive capacity) to further enrich the nomological network surrounding the construct of AI capability.

10. CONCLUSION

The purpose of this study was to investigate the relationship between AI capability and organizational capability, and between AI capability and innovation capability, as well as the relationship between the nature of organizational agility and the ability of the organization to transfer AI capability to innovation outcomes. A survey with 385 managers from technology-intensive organizations and a rigorously validated PLS-SEM model confirmed all five hypotheses: AI capability significantly influenced organizational capability and innovation capability; organizational capability significantly affected competitive advantage; the influence of AI capability on competitive advantage was partially mediated through innovation capability; and the effect of AI capability on innovation capability was significantly amplified by organizational agility. The findings present a unified argument for artificial intelligence as the next level of digital transformation, rather than just another technology improvement, as a strategic, dynamic organizational capability. Companies that establish AI capabilities through complementary organizational structures, innovation processes, and agile decision-making systems are likely to reap long-term competitive benefits from AI investments.

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