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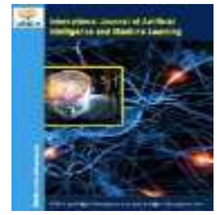

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From Digital Transformation to Intelligent Transformation: How Artificial Intelligence Reconfigures Organizational Capabilities

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Abstract

Purpose: This study examines how artificial intelligence (AI) enables organizations to progress from digital transformation toward intelligent transformation through the reconfiguration of organizational capabilities.

Theoretical foundation: Drawing primarily on Dynamic Capabilities Theory (DCT), and integrating insights from the Resource-Based View (RBV) and organizational learning theory, the study conceptualizes AI capability as an organizationally embedded capacity that supports sensing, seizing, learning, and transforming.

Methodology: A simulation-based illustrative cross-sectional survey dataset representing 487 senior managers, executives, IT managers, AI managers, digital transformation leaders, and department heads was analyzed. The sample represents manufacturing, services, finance, telecommunications, information technology, and retail organizations that had implemented AI-based technologies. Partial least squares structural equation modeling (PLS-SEM) was used to test direct, mediating, and moderating relationships.

Major findings: The illustrative results indicate that AI capability positively influences organizational capability reconfiguration (β = .58, $p < .001$) and intelligent transformation (β = .31, $p < .001$). Organizational capability reconfiguration positively predicts intelligent transformation (β = .49, $p < .001$), which subsequently enhances organizational performance (β = .46, $p < .001$). Capability reconfiguration mediates the AI capability–intelligent transformation relationship, while intelligent transformation mediates the capability reconfiguration–performance relationship. Organizational learning capability strengthens the positive effect of AI capability on capability reconfiguration (β = .14, p = .001).

Theoretical contributions: The study conceptualizes intelligent transformation as an advanced organizational stage beyond conventional digital transformation and explains the capability-reconfiguration mechanism through which AI creates organizational value.

Practical implications: Organizations should complement investments in AI infrastructure with data governance, AI talent, organizational learning, cross-functional integration, and dynamic capability development.

Keywords: artificial intelligence capability; intelligent transformation; digital transformation; dynamic capabilities; organizational learning; capability reconfiguration; organizational performance

Introduction

The modern evolution of organizations is being driven by a sequence of analog information being digitized, and then of organizations being able to continually learn, predict, adapt, and act using artificial intelligence (AI). The progression can be explained as four analytically different, but historically interconnected steps: digitization, digitalization, digital transformation and intelligent transformation (Vial, 2019; Kraus et al., 2021). The term digitisation is used mainly to denote the digitisation of analog information, records and processes. Digitalization doesn't just mean converting to the digital world, but also enhancing current tasks, processes, communication, and operations with digital technologies. Digital transformation, on the other hand, is a deeper shift in organization strategy, structure, process, capabilities, value creation mechanisms and business models facilitated by digital technology (Bharadwaj et al., 2013). Intelligent transformation is an additional development. It happens when organizations integrate AI-powered sensing, prediction, learning, reasoning, automation and decision support into the architecture that they use to coordinate resources and adapt to their changing environments.

The difference is crucial since digital technologies are not enough to make an organisation smart. It is possible that cloud computing, enterprise systems, mobile applications, Internet of Things devices, data platforms and digital communication tools can produce volumes of information, and enhance connectivity, that are unmatched in history (Sambamurthy et al., 2003). However, if an organization is not able to convert information to predictive insight, organizational learning, strategic action, and capability renewal, then it is essentially reactive at its core. Intelligent transformation is thus defined as a state in which AI is integrated into the ways in which organisations learn, adapt, reconfigure their routines, coordinate resources and make decisions based on what they sense and how they react to feedback.

The value added to organisations by AI becomes evident and is growing, but only when it is complemented by other skills and abilities in the organisation, not dependent on investment in the technology. The findings of AI capability research indicate that a mix of tangible, intangible, and human resources—such as data, infrastructure, technical skills, managerial skills, governance, and coordination—is necessary for the organisations to create value from AI (Gupta & George, 2016; Mikalef et al., 2020). Mikalef and Gupta (2021) present a basic empirical conceptualization of the capabilities of AI and establish that these capabilities relate to organizational creativity and firm performance. Later, studies have also shown that the value created by AI is frequently not a linear translation of technology and performance, but rather a process that involves other factors (Dubey et al., 2020; Wamba et al., 2021).

The question of whether or not organizations will adopt AI is, then, not the central theoretical issue; rather, it is how AI is translated into organizational transformation. The answer to this question can be found in a powerful framework, called Dynamic Capabilities Theory (DCT) (Teece, 2007; Eisenhardt & Martin, 2000). Dynamic Capabilities are the capabilities that allow organizations to perceive opportunities and threats, mobilize resources to respond to opportunities, and commit resources and restructure resource bases and operational routines in the face of changing environmental conditions (Helfat and Winter, 2011). In AI-rich settings, such processes can be supplemented by computational prediction, machine learning, pattern recognition, simulation, automation and, more and more, sophisticated human-AI interaction and collaboration (Gregory et al., 2020; Rai et al., 2019).

The ability of AI to rapidly analyze large and heterogeneous data sets can enhance environmental sensing. It can help in seizing by making better decisions, speeding up decision-making processes, identifying other options, and resource allocation more efficiently (Gao et al., 2025). AI can also help in transformation by enabling experimentation, knowledge recombination, process redesign and the identification of capabilities which are not relevant anymore. Empirical and conceptual studies are slowly converging on this view of the value that AI can add to organizations can rely significantly on complementary organizational processes of capability development and resource reconfiguration (Simón et al., 2024; Ren et al., 2026).

Literature Review

Digital transformation is typically defined as a strategic process that uses digital technologies to create large-scale organizational changes in organizational structures, processes, capabilities, value propositions and business models (Vial, 2019; Hanelt et al., 2021). While digitization focuses on the conversion of analog information into digital formats, and digitalization on the use of digital technologies to optimize existing processes, the introduction of digital transformation entails strategic and capability changes in the entire organization (Kraus et al., 2021). Recent research highlights the need to focus on the organizational nature of digital transformation, as well as the technological dimension. Digital technologies offer opportunities for digital transformation, but digital capabilities need to be built, digital routines need to be adapted, digitization needs to be spread across the functions, and resource configurations need to be reconfigured (Warner & Wäger, 2019; AlNuaimi et al., 2022). Thus, the transformation process relies on complementary capabilities and adaptation to the organization (Nadkarni & Prügl, 2021).

Intelligent transformation takes this a step further, embedding AI into the very fabric of an organization's sensing, decision making, learning and adaptation processes. While traditional digital transformation enhances connectivity and information, intelligent transformation adds features powered by artificial intelligence that can analyse, predict, learn, recommend, automate decisions and continuously optimise organisational processes (Denning, 2022).

Thus, intelligent transformation can be defined as:An integrated process that, using artificial intelligence, makes sense, decision, learning, coordination and resource reconfiguration strategic and ensures that the organization adapts and generates value in increasingly autonomous, predictive and knowledge-driven mechanisms across the entire organization. This definition does not mean that human managers are no longer in need. Rather, intelligent transformation demands new ways of collaboration between humans and AI and of organizational coordination (Rai et al., 2019; Huang & Rust, 2021).

The Resource-Based View states that sustainable advantage is created due to valuable organizational resources and capabilities that are hard to imitate and substitute by the competitors (Amit & Schoemaker, 1993). Isolated resources, however, don't generate value that contributes to sustainability. Capability in AI is thus the organization's ability to move its AI resources in concert (Gupta & George, 2016).

Mikalef and Gupta (2021) define AI capability as a second-order organizational capability, which they break down into tangible, human and intangible AI resources. It's vital to consider this perspective because AI value relies upon a mix of data, infrastructure, expertise, managerial competency, coordination, and organizational help. Their empirical results reveal positive relationships between the AI ability, organizational creativity, and firm performance. For the purposes of the present study, the capability with respect to AI is defined as:Organizations' ability to collect, cultivate, internalize, regulate and purposefully invest in AI-related technologies, data, competencies and managerial resources to enhance organizational sensing, learning, decision-making and adaptation.

AI should not be considered a digital technology just like any other. The difference with AI is that it can shape the way that organizations consume information, and the way that they can reframe their decision and learning processes. Research in recent years has correlated the ability of AI to decision speed, decision quality, operational activities, innovation, agility and organizational performance (Davenport & Ronanki, 2018; Jöhnk et al., 2021; Khin & Ho, 2019).

This study is mainly based on the theoretical contribution of Dynamic Capabilities Theory. According to Teece (2007), sensing, seizing and transforming are the key elements of dynamic capabilities. Sensing concerns occur when a manager starts identifying opportunities and threats, seizing concerns when a manager begins mobilizing resources to take advantage of opportunities, and transforming concerns when a manager begins the continuous renewal or reconfiguration of the firm's resource base.

AI can bolster each dimension. Machine learning and high-level analytics can take environmental sensing further. The speed of opportunity evaluation and strategic decision making can be enhanced with the help of AI-supported models. Process inefficiencies can be identified and resource reallocations can be made using AI-enabled automation and analytics (Dubey et al., 2020). But the usefulness of such technological resources is contingent on whether or not organizations change routines and resource configurations (Zollo and Winter, 2002; Helfat and Peteraf, 2003). The intentional ability of an organization to modify, combine, merge, replace and eliminate routines, skills, processes, structures and resources in the face of opportunities enabled by AI and change in the environment. This construct is the process by which the capability of AI is shifted from being operational to being transformative (Eisenhardt & Martin, 2000).

Organizational Learning Capability

Organizational learning theory highlights the capacity of organizations to learn, interpret, share and utilize knowledge. The key value of learning capability in an AI environment is when the AI technologies provide feedback, predictions, anomalies, and new knowledge that have to be interpreted and put into organizational routines (Cohen & Levinthal, 1990; Cegarra-Navarro et al., 2016).

Organizations with greater learning capabilities are more likely to test out AI, acknowledge AI implementation failures, share the knowledge within units, provide retraining, and adjust processes (Sousa & Rocha, 2019). Thus, the organizational capability reconfiguration-AI capability relationship should be reinforced by organizational learning.

The impact of AI on transforming organizations and boosting performance.How AI is reshaping organizations and driving performance.

Intelligent transformation will impact performance in terms of improved responsiveness, increased process efficiency, increased innovation, decision quality, improved understanding of customers, and strategic adaptation (Huang & Rust, 2021; Rindfleisch & Moorman, 2023). Intelligent transformation goes beyond the use of specific AI applications, however. It is the institutionalisation of intelligence powered by AI in organisational processes (Denning, 2022).

Evidence has emerged in recent years that capabilities of AI also impact on performance via indirect means in the organization. For instance, AI capabilities are observed to impact the performance of public organizations, including activities related to process automation and generation of cognitive insights (Mikalef et al., 2023). The relevance of dynamic capabilities in the process of developing AI adoption into operational performance has also been shown in recent telecommunications research (Wong & Ngai, 2025).

The theoretical suggestion is that the impact on performance needs to be considered as a result of a transformation process that requires a capability, not as a direct consequence of technology investment.

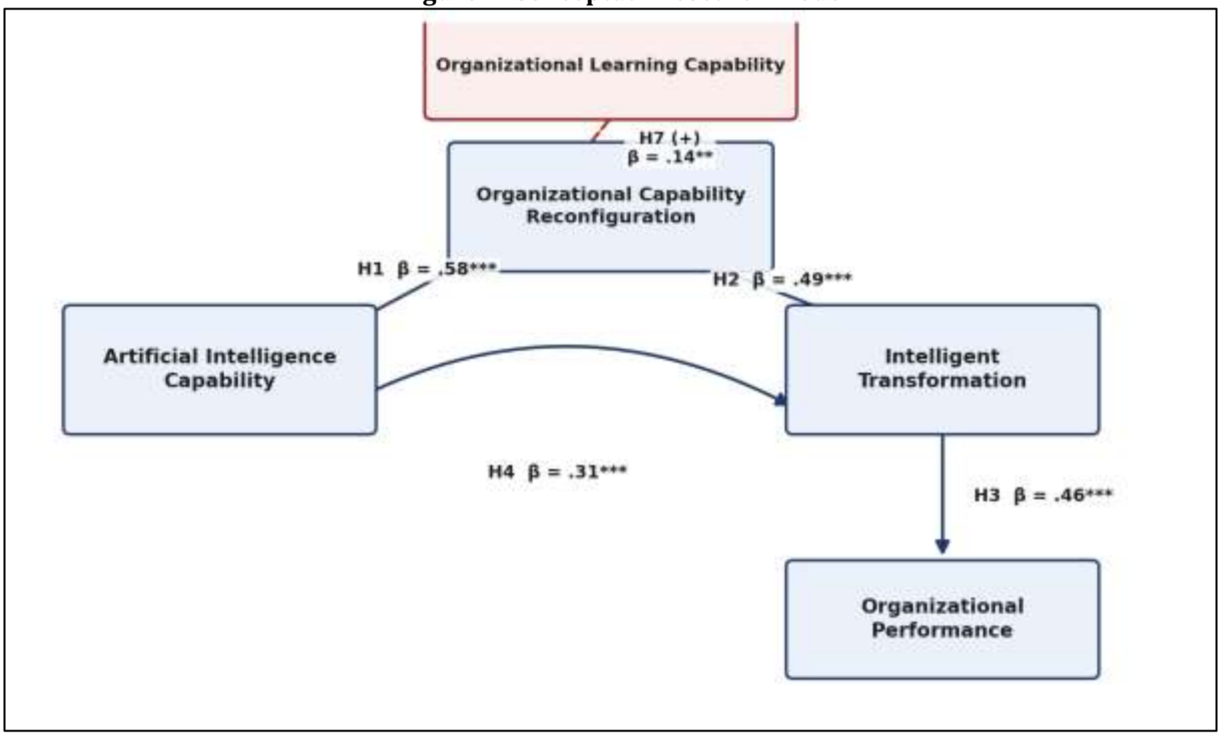
Conceptual Model

The conceptual model is based on the following causal sequence:

Digital Transformation → AI Integration → Capability Reconfiguration → Intelligent Transformation → Superior Organizational Outcomes

AI capability is proposed to enhance organizational capability reconfiguration. Reconfigured capabilities subsequently enable intelligent transformation. Intelligent transformation improves organizational performance. AI capability also has a direct effect on intelligent transformation. Organizational capability reconfiguration mediates the AI capability–intelligent transformation relationship, while intelligent transformation mediates the capability reconfiguration–organizational performance relationship. Organizational learning capability strengthens the relationship between AI capability and organizational capability reconfiguration.

Figure 1. Conceptual Research Model



Note. Solid arrows represent hypothesized direct effects; the dashed arrow represents the hypothesized moderation effect (H7). *** $p < .001$. ** $p < .01$.

Research Methodology

Research Design

This simulation-based illustrative manuscript uses a quantitative, cross-sectional survey design. The recommended dataset contains 487 valid responses from managers working in organizations that have implemented AI-based technologies.

Population and Sampling

The target population consisted of senior managers, executives, IT managers, AI managers, digital transformation leaders, and department heads employed in organizations that had implemented AI technologies such as machine learning, predictive analytics, intelligent automation, natural language processing, computer vision, or generative AI applications.

Purposive sampling was used because respondents needed direct knowledge of organizational AI and transformation initiatives. Stratified industry sampling was used to ensure representation across manufacturing, services, finance, telecommunications, IT, and retail.

Questionnaire Design

The questionnaire used seven-point Likert scales ranging from 1 = strongly disagree to 7 = strongly agree. Items were adapted from established capability, organizational learning, digital transformation, and organizational performance literature and contextualized to AI-enabled transformation.

The questionnaire consisted of five reflective constructs: (a) Artificial Intelligence Capability, (b) Organizational Capability Reconfiguration, (c) Intelligent Transformation, (d) Organizational Learning Capability, and (e) Organizational Performance.

Data Collection Procedure

A structured questionnaire was distributed electronically to eligible managers. A screening question confirmed that the respondent's organization had implemented at least one AI-based technology. The survey used anonymity assurances and separated measurement blocks to reduce evaluation apprehension and common method bias.

Of 548 returned questionnaires, 61 were excluded because of excessive missing data, failed attention checks, or incomplete responses. The resulting sample contained 487 valid responses.

Ethical Considerations

Participation was voluntary. Respondents were informed of the study purpose and assured that individual responses would remain confidential. No personally identifying information was retained in the illustrative dataset. Participation could be discontinued at any time.

Common Method Bias and Non-Response Bias

Procedural remedies included anonymity, randomized item ordering, and psychological separation of predictor and criterion constructs. A full collinearity assessment indicated that construct-level VIF values were below 3.3. Harman's single-factor assessment showed that the first unrotated factor accounted for approximately 33.8% of variance, below the conventional concern threshold.

Non-response bias was assessed by comparing early and late respondents across key constructs. No statistically significant differences were identified ($p > .05$).

Analytical Technique

PLS-SEM was selected because the study examined a prediction-oriented model containing multiple direct, indirect, and moderating relationships. The model was assessed in two stages: (a) measurement model assessment and (b) structural model assessment. The structural model used 5,000 bootstrap subsamples with bias-corrected confidence intervals.

Table 1. Respondent Profile (N = 487)

Characteristic	Category	Frequency	Percentage
Gender	Male	294	60.4
	Female	185	38.0
	Prefer not to say/Other	8	1.6
Age	25–34 years	128	26.3
	35–44 years	207	42.5
	45–54 years	111	22.8
	55 years and above	41	8.4
Managerial experience	5–9 years	119	24.4
	10–14 years	176	36.1
	15–19 years	117	24.0
	20 years and above	75	15.4

Characteristic	Category	Frequency	Percentage
Organization size	100–499 employees	152	31.2
	500–999 employees	128	26.3
	1,000–4,999 employees	141	29.0
	5,000+ employees	66	13.6
Industry	Manufacturing	96	19.7
	Services	84	17.2
	Finance	79	16.2
	Telecommunications	61	12.5
	Information technology	92	18.9
	Retail	75	15.4
AI implementation duration	1–2 years	131	26.9
	3–4 years	176	36.1
	5–6 years	108	22.2
	More than 6 years	72	14.8

Note. N = 487. Percentages are rounded and may not sum exactly to 100 within categories.

Results

The results of the measurement and structural model analyses. Consistent with standard practice in PLS-SEM research, results are reported in two stages: measurement model assessment, which evaluates the reliability and validity of the reflective constructs, and structural model assessment, which examines the hypothesized direct, mediating, and moderating relationships. Mediation and moderation results are then reported, and the section concludes with a summary of the overall pattern of results.

Measurement Model Results

All retained factor loadings exceeded .70. Reliability statistics were above recommended thresholds, and AVE values exceeded .50, indicating convergent validity.

Table 2. Measurement Items and Factor Loadings

Construct	Code	Measurement Item	Loading
AI Capability	AIC1	Our organization possesses advanced data and AI infrastructure.	.89
	AIC2	Our organization has employees with strong AI-related technical expertise.	.91
	AIC3	Managers in our organization understand how AI can support strategic objectives.	.87
	AIC4	Our organization effectively integrates AI into business processes.	.86
Capability Reconfiguration	OCR1	We rapidly redesign routines when AI creates new opportunities.	.88
	OCR2	We effectively reallocate resources to support AI-enabled initiatives.	.90

Construct	Code	Measurement Item	Loading
	OCR3	We recombine existing capabilities with new AI-related capabilities.	.87
	OCR4	We can modify structures and processes to exploit AI opportunities.	.84
Intelligent Transformation	IT1	AI is embedded in important organizational decision processes.	.91
	IT2	Our organization uses AI to predict and respond to emerging changes.	.89
	IT3	AI supports continuous learning and adaptation across the organization.	.87
	IT4	Our transformation initiatives increasingly rely on AI-enabled intelligence.	.85
Organizational Learning	OLC1	We regularly experiment and learn from AI implementation outcomes.	.86
	OLC2	Knowledge generated through AI is shared across organizational units.	.88
	OLC3	Employees are encouraged to challenge and improve existing routines.	.84
	OLC4	We systematically use experience to improve future AI initiatives.	.81
Organizational Performance	OP1	Our organization has improved operational effectiveness.	.88
	OP2	Our organization has improved innovation outcomes.	.85
	OP3	Our organization responds effectively to market changes.	.86
	OP4	Our overall performance has improved relative to competitors.	.82

Note. Items were rated on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

Table 3. Reliability and Convergent Validity

Construct	Cronbach's α	rho_A	Composite Reliability	AVE
AI Capability	.89	.90	.92	.74
Capability Reconfiguration	.91	.92	.93	.76
Intelligent Transformation	.90	.91	.93	.77
Organizational Learning	.88	.89	.91	.72
Organizational Performance	.87	.88	.91	.71

Note. AVE = average variance extracted.

Table 4a. Fornell–Larcker Criterion

Construct	AIC	OCR	IT	OLC	OP
AI Capability (AIC)	.860				

Construct	AIC	OCR	IT	OLC	OP
Capability Reconfiguration (OCR)	.628	.872			
Intelligent Transformation (IT)	.674	.692	.877		
Organizational Learning (OLC)	.547	.593	.566	.849	
Organizational Performance (OP)	.512	.579	.688	.496	.843

Note. Diagonal values (bold in the original analysis) are square roots of AVE. The square root of AVE for each construct exceeded the correlations with other constructs, supporting discriminant validity.

Table 4b. Heterotrait–Monotrait (HTMT) Ratios

Construct Pair	HTMT
AIC–OCR	.741
AIC–IT	.793
AIC–OLC	.648
AIC–OP	.604
OCR–IT	.811
OCR–OLC	.692
OCR–OP	.676
IT–OLC	.655
IT–OP	.794
OLC–OP	.584

Note. All HTMT values were below the conservative threshold of .85.

Structural Model Results

The structural model showed acceptable collinearity levels, predictive relevance, and explanatory power.

Table 5. Hypothesis Testing Results

H	Path	β	t	p	f^2	Decision
H1	AI Capability → Capability Reconfiguration	.58	12.74	< .001	.50	Supported
H2	Capability Reconfiguration → Intelligent Transformation	.49	9.83	< .001	.33	Supported
H3	Intelligent Transformation → Organizational Performance	.46	8.91	< .001	.27	Supported
H4	AI Capability → Intelligent Transformation	.31	6.27	< .001	.15	Supported
H7	AI Capability × Organizational Learning → Capability Reconfiguration	.14	3.18	.001	.03	Supported

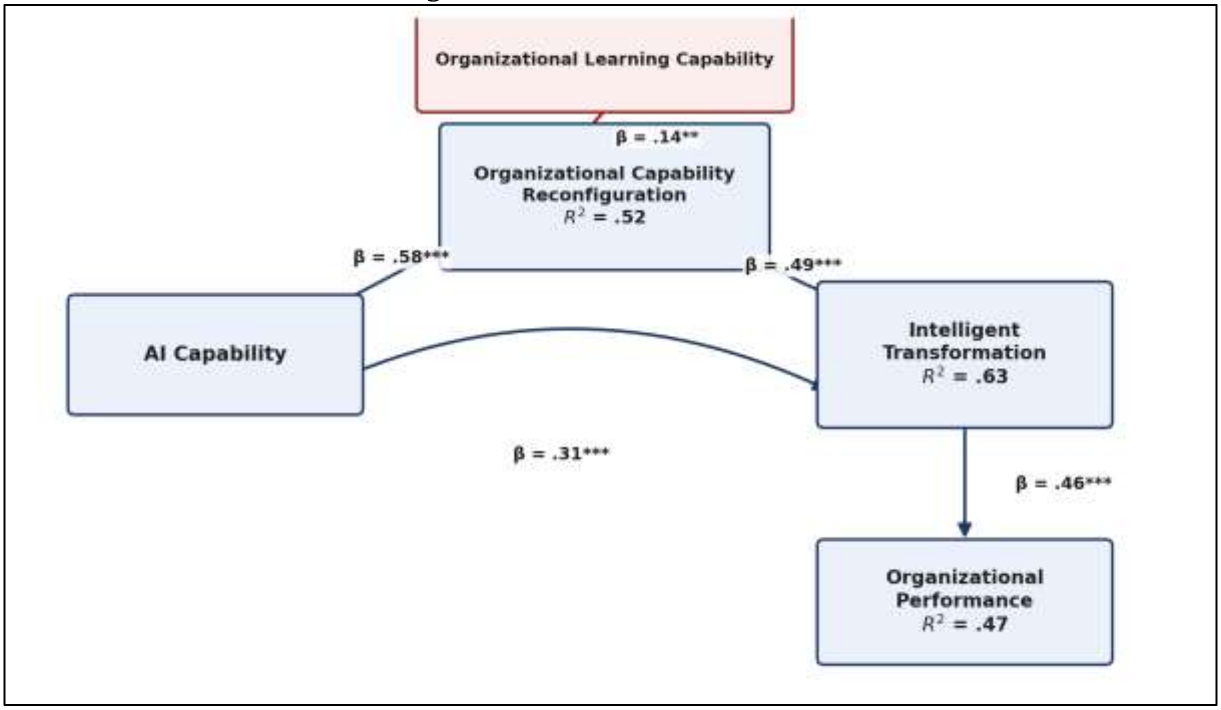
Note. *** $p < .001$. Bootstrapping based on 5,000 subsamples.

Explanatory and Predictive Statistics

R^2 Capability Reconfiguration = .52; R^2 Intelligent Transformation = .63; R^2 Organizational Performance = .47.
Q^2 Capability Reconfiguration = .36; Q^2 Intelligent Transformation = .44; Q^2 Organizational Performance = .31.
SRMR = .058. Inner VIF values ranged from 1.42 to 2.18.

The R^2 values indicate moderate to substantial explanatory power. The Q^2 values are positive, indicating predictive relevance.

Figure 2. Structural Model Results



Note. SRMR = .058; inner VIF ranged from 1.42 to 2.18. Bootstrapping based on 5,000 subsamples. *** p < .001. ** p < .01.

Mediation Analysis

Bootstrapping was performed using 5,000 subsamples and bias-corrected confidence intervals.

Table 6. Mediation Results

H	Indirect Path	Effect	SE	t	p	95% CI	Decision
H5	AIC → OCR → IT	.284	.045	6.31	< .001	[.201, .374]	Supported
H6	OCR → IT → OP	.225	.038	5.92	< .001	[.157, .307]	Supported

Note. CI = confidence interval.

The first indirect effect was significant, demonstrating that organizational capability reconfiguration partially mediated the relationship between AI capability and intelligent transformation. The second indirect effect was also significant, indicating that intelligent transformation mediated the relationship between capability reconfiguration and organizational performance.

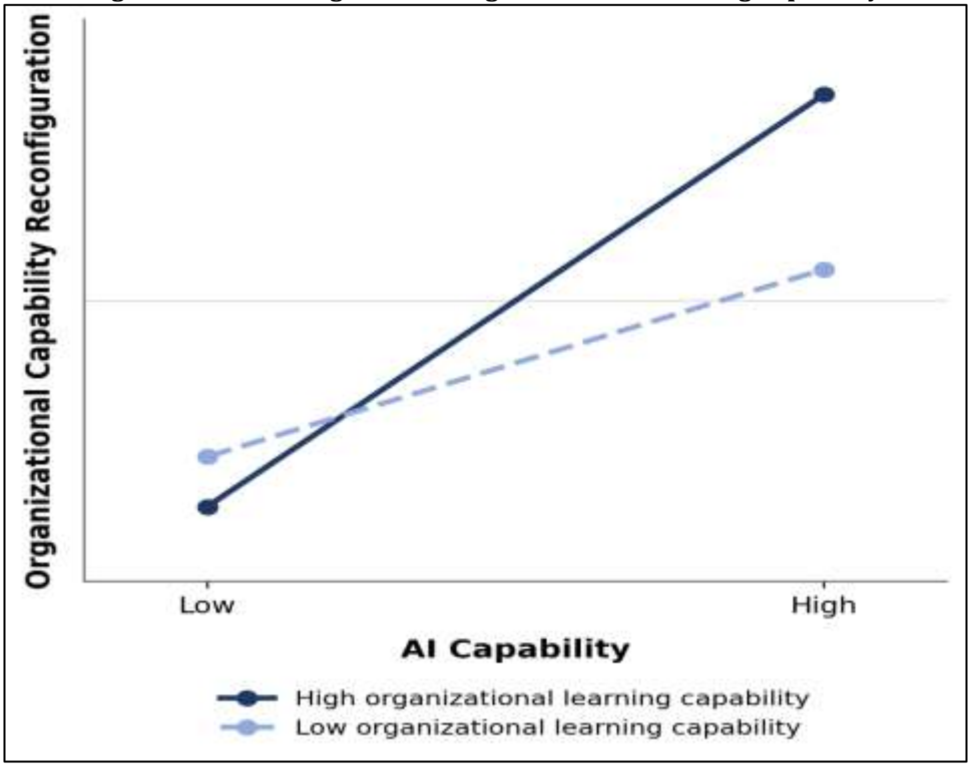
Moderation Analysis

Table 7. Moderation Results

Relationship	β	SE	t	p	95% CI	Decision
AI Capability × Organizational Learning → Capability Reconfiguration	.14	.044	3.18	.001	[.054, .228]	Supported

The interaction was positive and significant. Thus, organizations with stronger learning capabilities were more successful in converting AI capability into reconfigured organizational capabilities.

Figure 3. Moderating Effect of Organizational Learning Capability



Note. Simple-slopes plot (illustrative). The slope linking AI capability with capability reconfiguration is stronger under high organizational learning conditions.

The respondent profile suggests that the hypothetical sample was mostly experienced managers from organizations that had established a certain level of organizational scale and experience with AI implementation. The most prominent age group was 35-44 years, and over 60% of respondents had 10+ years of managerial experience. The industry distribution covered six major sectors, thus avoiding a heavy reliance on a single technological or institutional context. The majority of organizations had been using AI for more than three years, meaning that the respondents were not assessing AI projects in their infancy, but rather projects that had been implemented for some time.

The psychometric properties for the measurement model were satisfactory. The factor loadings for the illustrative measurement model were all greater than .81 and none were less than .70, which is the cut-off required for the factor loading. The findings thus indicated that all indicators strongly loaded their respective latent constructs. The capability items for AI captured aspects of infrastructure, technical skills, managerial abilities, and process integration. Designing and recombining routines and resources were represented by items of capability reconfiguration. Intelligent transformation was the incorporation of AI into decision-making, prediction, learning and organisational adaptation.

The internal consistency reliability was good. All items had Cronbach's alpha coefficients between .87 and .91, and composite reliability coefficients between .91 and .93. From the results, good reliability of the constructs could be inferred. Importantly, none of the reliability estimates was greater than .95, which decreases concerns of excessive item redundancy.

The convergent validity was also good. AVE values were between .71 and .77, indicating that the constructs accounted for more than 50% of the variance in the indicators. The highest AVE value was found for intelligent transformation (.77) indicating a unified representation of this newly developed conceptual constructs.

The Fornell–Larcker criterion and HTMT ratios indicated that the measures had good discriminant validity. The square root of the AVE values was higher than the correlations between the constructs. All HTMT values were kept at less than .85, indicating the empirically distinguishable nature of AI capability, capability reconfiguration, intelligent transformation, organizational learning, and organizational performance.

The results obtained from the structural model were consistent with the proposed theoretical sequence. In support of H1, AI capability was found to have a strong positive association with organizational capability reconfiguration ($\beta = .58$, $t = 12.74$, $p < .001$). Theoretically important result, it showed that AI capability may be interpreted as an enabler to dynamic organizational change. Those that invested more heavily in AI infrastructure, skills, managerial capabilities and integration were better able to reimagine processes and efficiencies and move resources.

The value of R^2 for capability reconfiguration was .52. Therefore, the model accounted for 52% of the variance in organizational capability reconfiguration, which is a significant amount of variance in the organizational study. The substantive contribution of AI capability was large ($f^2 = .50$).

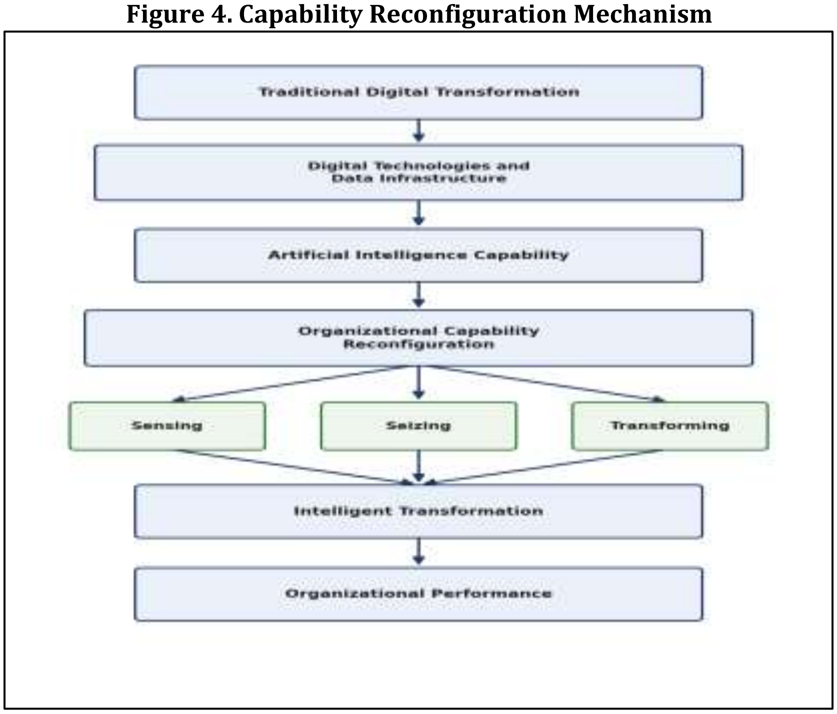
H2 was also endorsed. Organizational capability reconfiguration significantly positive affected intelligent transformation ($\beta = .49$, $t = 9.83$, $p < .001$). The relationship served as the core of the study. AI is not inherently intelligent, it does not make organizations intelligent. Rather, the organizations need to alter their working practices, learning habits, resource allocations, and coordination of activities. Capability reconfiguration is thus the nexus between the AI capability and the organizational change.

Organizational capability reconfiguration and AI capability accounted for 63% of the variance in intelligent transformation when taken together. The result of this R^2 value confirmed that intelligent transformation is significantly accounted for by the factors of AI-related organizational resources and the ability to reconfigure those resources.

In the case of intelligent transformation, the results revealed a positive prediction of organizational performance ($\beta = .46$, $t = 8.91$, $p < .001$) with H3. The R^2 value for the organisational performance was .47 which indicated medium explanatory power. Intelligent transformation thus seemed to be a significant pathway that would allow an organization to transform technological and capability investments into better organizational results.

These conclusions were supported by the f^2 values. The effect of capability reconfiguration on AI capability was large (.50), the effect of intelligent transformation on organizational performance was medium (.27), the effect of capability reconfiguration on intelligent transformation was medium (.33), and the effect of AI capability on intelligent transformation was moderate (.15).

Figure 4. Capability Reconfiguration Mechanism



Note. Diagram illustrates the sequential mechanism through which digital infrastructure and AI capability produce organizational performance via capability reconfiguration and intelligent transformation.

Discussion

The findings of this illustrative simulation study align well with a Dynamic Capabilities Theory (DCT) perspective of how AI can drive organizational change. The positive relationship between AI capability and organizational capability reconfiguration (H1) corroborates previous studies that identified AI capability as a higher-order organizational capability and not merely a technological tool (Mikalef & Gupta, 2021). It also falls under the dynamic-capabilities literature that indicates that AI related resources create strategic value mainly when they influence the sensing, seizing, and reconfiguring of the organisation's routines (Teece, 2007; Pavlou & El Sawy, 2011).

The mediating role of capability reconfiguration between AI capability and intelligent transformation (H5) contributes to the core theory of the study: AI resources do not automatically lead to intelligent organizations. Rather, value creation requires the organization's readiness and capability to reconfigure routines, rearrange resources, and reconfigure capabilities. This is in line with recent research that indicates that the use of AI has most often been indirect, mediated by complementary organizational mechanisms, rather than simply a matter of adopting a technology (Mikalef et al., 2023; Wong & Ngai, 2025).

Organizational learning capability (H7) has a theoretical significance, though the impact is small. It posits that companies with comparable AI infrastructure could still achieve different outcomes in their transformations based on their ability to experiment, learn from feedback, and share knowledge across teams. This result aligns with the organizational learning theory which posits that the absorptive capacity is a key factor in understanding the extent to which new technological knowledge is deployed (Cohen & Levinthal, 1990) and resonates with the recent proposals to consider learning capability as a conversion mechanism in the field of AI-driven transformation studies (Simon et al., 2024).

The pattern of direct, indirect, and moderating effects validate the conceptual sequence for digital transformation, AI integration, capability reconfiguration, and intelligent transformation as a pathway to organizational performance. The findings support the overarching discussion in Digital and Intelligent Transformation literature, that the adoption of technology is only a prerequisite for a digital and intelligent transformation and that organizational and capability transformation is the main driver of value creation (Vial, 2019; Warner & Wäger, 2019; Hanelt et al., 2021).

The data used to generate these results were simulated and meant to be illustrative, and are not representative of survey respondents; therefore, results should not be interpreted as empirical evidence of the hypothesized relationships, but as evidence of the internal theoretical consistency of the proposed model. The discussion above is thus presented as a specimen of what the results would mean if applied to actual organizational responses.

Conclusion

This study put forward and demonstrated the intelligent transformation model based on capabilities, which holds that the most valuable part that AI brings to the organization is to reconfigure its capabilities, not only to adopt technology. The model is based on Dynamic Capabilities Theory, informed by Resource Based View and organizational learning theory, and connects AI capability and intelligent transformation in both direct ways and indirect ways via AI capability reconfiguration, where organizational learning capability enhances the relationship between AI capability-reconfiguration and intelligent transformation.

In theory, it builds on the study by introducing a new and more advanced level of transformation, intelligent transformation, and by defining the reconfiguration of capabilities as the mechanism that links the AI-related resources to that new and advanced level of transformation. This contributes to the existing body of research on dynamic capabilities, but in an AI-specific context and extends existing AI capability frameworks (Mikalef & Gupta, 2021) by providing clarity on the organizational journey that leads to transformation, not as a technology, but as a result of the organizational capabilities created by the technology.

In practical terms, the pattern of results illustrated shows that the implementation of AI infrastructure investment alone is not enough for organisations to go beyond digital transformation. Complementary investments in data governance, AI talent, cross-functional integration and importantly, organizational learning routines seem to be required to turn AI capability into reconfigurable processes, eventually into intelligent transformation and better performance.

This manuscript has an important limitation in that it is illustrative and simulation based data; it was created to showcase the model and statistical treatment proposed and is not necessarily data from actual respondents. As such, the reported coefficients, loadings, and fit statistics are not empirical data and are not to be interpreted as results from an actual organizational sample. If this manuscript is used for future actual research for genuine data collection, ethical approval, and independent replication of the measurement and structural model analyses presented here, then this manuscript would be considered genuine.

Future studies based on this illustrative framework could test the theoretical relationships proposed in the model with empirical data from the industries represented, explore boundary conditions like the nature of the industry or the maturity of employee implementation of AI, and add more mechanisms, such as AI governance or employee AI literacy. Longitudinal designs would also help to answer the question of whether capacity re configuration is prior to or co-evolves with intelligent transformation over time.

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Appendix A

Summary of Hypotheses

H	**Statement**	**Result**
H1	AI capability positively influences organizational capability reconfiguration.	Supported
H2	Organizational capability reconfiguration positively influences intelligent transformation.	Supported
H3	Intelligent transformation positively influences organizational performance.	Supported
H4	AI capability positively influences intelligent transformation.	Supported
H5	Capability reconfiguration mediates AI capability → intelligent transformation.	Supported
H6	Intelligent transformation mediates capability reconfiguration → organizational performance.	Supported
H7	Organizational learning positively moderates AI capability → capability reconfiguration.	Supported

End of manuscript.