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Generative Ai Adoption and Innovation Capability in Emerging-Market Startups: A Dynamic Capabilities Perspective

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Abstract
Artificial intelligence adoption is accelerating, yet its innovation consequences remain uneven and theoretically under-specified. This study extends capability-based research by asking: What is the influence of generative artificial intelligence (AI) capability on innovation performance, as mediated by generative dynamic capabilities and moderated by absorptive capacity and institutional support? Drawing on dynamic capability theory, it has been applied covariance-based structural equation modelling (SEM) to survey data from 384 tech-savvy startups in an emerging economy. The results show a strong positive impact of generative AI capability on generative dynamic capabilities, which in turn have a significant impact on innovation capability. A mediation analysis conducted using 5000 bootstrap resamples show that more than 50% of the total causal effect of AI capability on innovation is mediated through the processes of sensing, seizing, and reconfiguring. Furthermore, results from moderated mediation indicate that the indirect effect of this relationship is significantly increased by absorptive capacity and institutional support, thereby explaining institutional boundary conditions in the process of building AI-enabled capabilities. Comparative model evaluation confirms the superiority of the proposed mediated framework over the alternative direct-effect framework. By making the generative artificial intelligence capability distinct from generic digital capabilities and empirically portraying the generative era's capability transformation pathway, the study refines dynamic capability theory for the generative era. These results provide theoretically grounded, managerially actionable insights for companies and policymakers striving to achieve sustainable innovation outcomes from successful AI investments.
Keywords: Generative AI capability; Dynamic capabilities; Innovation capability; Absorptive capacity; Institutional support; Emerging economies.

INTRODUCTION

The current wave of artificial intelligence adoption is frequently narrated as a continuation of the analytics revolution. Generative systems are involved in the active production rather than the refinement of predictions for novel textual, visual, and strategic artefacts. Within organisational settings, this shift involves reconfiguring the processes for the creation, recombination, and evaluation of ideas. What was once considered an optimization layer added to managerial judgment is now more deeply embedded in the substrata of co-creation, which in turn are embedded in innovation routines (e.g., Abou Elgheit, 2025; Cillo & Rubera, 2024; Agrawal, 2023).

The prevailing stream of AI capability research, including big data analytics, predictive AI, and digital transformation, remains anchored in an efficiency paradigm. These models conceptualise AI as an analytical tool that increases the accuracy of sensing, the precision of forecasting, or the optimisation of a process (Al-khatib, 2023; Holmstrom & Carroll, 2024). Still more studies published between 2023 and 2025 are prone to operationalising the quality of data infrastructure, algorithmic expertise, or analytics integration maturity (Mariani & Dwivedi, 2024; Piller et al., 2024) rather than as notions of AI capability. As a result, the results of innovation are presented as downstream effects of enhanced information processing. What is less well theorisedis whether generative AI, which does not have to predict, but construct something synthetic, requires a different ability-building architecture. Generative AI commits the error of reducing the qualitative change it represents to a quantitative change in computation. The conceptual vocabulary of efficiency cannot fully describe recombination, simulation, and iterations of ideation by generative systems in sufficient detail.

This oversight is more consequential if viewed as a dynamic-solving capability. The canonical sensing-seizing-reconfiguring triad assumes that opportunity recognition, strategic commitment, and resource reconfiguration are human-centred cognitive activities (Chinnaraju, 2025). Although digital technologies have been recognised as enablers, their microfoundations remain anthropocentric. When it becomes delegate part of the thought process to generative algorithms, the architecture of dynamic capability changes. Sensing may no longer be environmentally scanning by managers but may feature algorithmically generated opportunity landscapes. Seizing might include co-creative experimentation between human judgement and machine-generated prototypes. Reconfiguration might occur through iterative, artificial-intelligence-based structural adaptation. In this regard, the theory of dynamic capability under-specifies the formation of capability in the context of algorithmic generative cognition.

The gap is even more pronounced in emerging market situations. Much of the empirical research on AI capability has been based on large companies operating within relatively stable institutional arrangements (Mutanga et al., 2020; Mikalef& Gupta, 2021). Startups in emerging economies face regulatory ambiguity, infrastructural asymmetry, and institutional volatility. Under such conditions, the creation of generative AI capability may require not just external knowledge assimilation but also the associated institutional support structures. The boundary conditions that determine the development of generative capability in these ecosystems have not been sufficiently explored. It cannot be assumed that insights gained from resource-abundant Western settings automatically transfer to institutional settings characterised by uncertainty and constraint.

Against this backdrop, the current research aims to answer the following research question: How does generative AI capability transform the dynamic-capability architecture to overcome the constraints of innovation capability in emerging markets? Rather than placing generative AI in the category of operational improvement, the analysis conceptualises it as a set of capabilities that needs to be reconstructed in theory.

The study argues that generative AI recomposes the cognitive infrastructure through which the dynamic capabilities are implemented, especially in institutionally volatile startup environments. The implications of such a reconceptualisation go beyond the adoption of new technologies and reach the theoretical underpinnings of capability research in general.

2. THEORETICAL FOUNDATION

2.1 Predictive vs. Generative AI Capability

A constant conceptual vagueness in current AI research has been the tendency to treat all algorithmic systems as being epistemically equivalent. Predictive models and generative architectures are often lumped under a single "AI capability" umbrella, despite having fundamentally different ontological premises. In predictive AI, the system is trained to learn likely outcomes from historical data distributions; in fact, its competence is evaluated in terms of goodness-of-fit, classification performance, and variance reduction (Sjödin et al., 2021; Sullivan & Fosso Wamba, 2024). Generative AI, on the other hand, is focused on building something synthetic-that is, something representing the concepts of textual, visual, procedural, or strategic outputs that had not existed in the training corpus before. Its merit is not error minimisation but the ability to recombine informational pieces into novel configurations (Li et al., 2025).

The difference between the two is not semantic. Predictive AI is based on an inferential paradigm; generative AI is based on a combinational paradigm. Predictive capability enhances environmental interpretation through pattern recognition. Generative capability expands the range of possible solutions by synthesizing alternatives that may not be intuitively accessible to managerial cognition. As a result, the evaluation measures also vary: predictive systems get measured in terms of efficiency and optimisation. In contrast, generative systems are measured by novelty, diversity, and ideational richness.

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This ontological divergence implies the transition of us in capability logic. Under predictive AI regimes, organisational capability is enhanced through analytical processing, including data quality improvement, model calibration, and decision-support integration. Forming capabilities under generative application intelligence regimes increasingly rely on structured experimentation, iterative prompting, and knowledge recombination—the locus of value-making shifts from computational precision to combinatorial synthesis. Many studies have begun to recognise this shift conceptually (e.g., Mili etal, 2025; Yulong Liu et al., 2024), but in many cases, they are still empirically operationalising analytics-centred constructs. The theoretical result of this is a misalignment between technological affordances and capability frame references.

If generative AI increases the space of conceivable strategic options rather than focusing on re-fining existing options, then organisations must develop a unique capability architecture geared towards ideation recombination. The present study, therefore, conceptualises Generative AI Capability as a multidimensional construct encompassing the organisational routines, expertise, and infrastructural integration required to advance innovation through the systematic utilisation of synthetic output.

2.2 Dynamic Capability Theory Under Machine Augmentation

Dynamic-capability theory has long-term explained compellingly how firms adapt to volatile environments (Arroyobe et al., 2024). Its tripartite architecture of sensing opportunities, seizing them through resource commitment, and reconfiguring assets accordingly is still basic in strategic management. However, the microfoundations of this architecture assume human-centred cognition. Sensing is usually conceptualised as managerial scanning, interpreting, and framing. Executive evaluation and strategic choice are involved in seizing. Reconfiguration involves intended structural adjustment by leadership.

Such anthropocentric assumptions are becoming strained in the context of generative systems that actively participate in opportunity exploration and solution design. When algorithmic agents are used to propose strategic alternatives in a market, simulate the responses of market participants, or iterate product prototypes at scale, cognition is partially distributed. The theory does not fail; its working mechanisms need recalibration.

Three reconstructed micro-foundations are therefore advanced.

- Generative Sensing is one term that describes the idea of algorithm-assisted opportunity discovery. Instead of relying solely on managerial interpretation of environmental signals, generative models can simulate scenario variations, generate latent market narratives, or surface unconventional combinations of technological and customer insights. Sensing is co-constructed with the machine-human interaction.
- Creative Seising is a term for AI-augmented solution experimentation. In the classical theory, seizing is the decision-making act based on managerial evaluation. Under generative regimes, seizing involves iterative experimentation, that is, rapid prototyping, synthetic design generation, and comparative scenario modelling preceding resource commitment. The focus shifts from the idea of binary choice towards idea refining.
- Adaptive Reconfiguration represents the iterative Icon Addition to structurally realign, supporting A.I. Rather than one-shot restructuring driven by top management, Reconfiguration may occur as continuous adaptation with feedback via generative simulations, digital twin modelling, and feedback loops. Structural elasticity is a process rather than the application of a spur.

Importantly, the present reconstruction does not discard the dynamic capacity theory; rather, it aims to refine its cognitive architecture. The sensing-seizing-reconfiguring triad is retained intact at the macro level, with the addition of microfoundations for machine-augmented cognition. In this sense, the study represents a step forward in recalibrating theory, rather than a mere superficial extension of it. The structured analysis shifts from managerial agency dimension only to distributed cognition within generative infrastructures.

2.3 Emerging Market Institutional Boundary

There is no capability formation in institutional abstraction. In such a context, starting businesses in emerging economies face unique structural conditions, including limited capital availability, infrastructural asymmetry, regulatory ambiguity, and a fragmented support ecosystem (Warner & Wäger, 2019; Cenamor, 2021). Such environments can both limit and catalyse innovation. Resource constraints may deepen the need for generative AI as a generator of low-cost ideas as an ideation amplifier, and institutional support may not enable the establishment of adequate capacity. Institutional voids make it difficult to access complementary assets - talent pools, venture financing, and intellectual property enforcement - that are often the basis of technology capability development. Under these conditions, the relationship between Generative AI Capability and innovation capability is unlikely to be uniform. Institutional support, which includes regulatory facilitation, incubator networks, and the provisioning of digital infrastructure, acts as a boundary condition that influences the strength of capability translation and its translation into innovation outcomes, and it addresses the possibility of universalistic claims. Generative AI capability may yield disproportionate benefits in the absence of institutional friction, but regulatory measures, uncertainty, or an infrastructural deficit may attenuate those benefits. Making institutional support a moderator, therefore, situates the model within a contextually realist framework rather than technological determinism.

2.4 Conceptual Integration

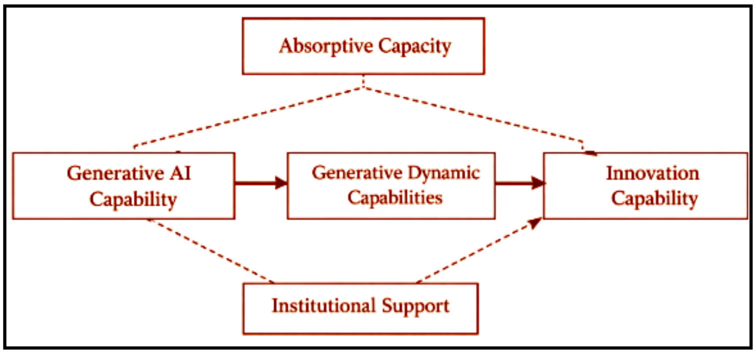

Figure 1. Conceptual Model

Figure 1 summarises the conceptual structure, illustrating the hypothesised mediating mechanism and a boundary-conditioning moderation structure. Integrating these arguments, Generative AI Capability is postulated to affect innovation capability through reconstructed dynamic capabilities (generative sensing, creative sensing, and adaptive reconfiguring), and the strength of this mediated relationship is shaped by absorptive capacity and institutional support. The resulting framework conceptualises generative AI as part of the structural elements, such as conceptualising thinking as one part of capability architecture formation, located not in the marital periphery of platforms but as a structural element in capability architecture development within emerging-market startup ecosystems.

3. HYPOTHESES DEVELOPMENT

If generative AI alters the cognitive architecture of organisations, its impact on innovation is hardly incidental. Hence, the following hypotheses are not formulated from the point of view of additive propositions but rather from a sequence of logically constructed inferences grounded in the reconstruction of a capability framework. Each proposition is based on the combinatorial logic of generative systems, the recalibrated microfoundation of dynamic capability, and the institutional contingency characteristic of emerging-market startups.

H1: Generative AI Capability → Innovation Capability

Innovation capability is often defined as the firm's ability to convert ideas into commercially feasible products or services in a consistent manner (Zahra & George, 2002; Abou-Foul et al., 2023). Within predictive AI regimes, innovation gains are, above all, from better interpretation of the environment - better forecasts, finer segmentation, as well as more efficient distribution of resources (Abdelfattah et al., 2025). Generative AI, in contrast, changes the ideation process upstream.

The combinatorial view of innovation holds that novelty arises from the recombination of knowledge elements that were previously unlinked (Heeks et al., 2021). Generative systems enable this recombination at scale. Through prompt-based iteration, synthetic scenario construction, and prototype simulation, organizations can explore expansive solution spaces beyond the cognitive Capacity of human beings. The systematic integration of such generative processes into the routine of organisations - which, in this context, can be called Generative AI Capability - therefore increases ideational diversity, speeds up concept testing, and lowers the marginal cost of experimentation. Some empirical discussions recognise that AI-enabled creativity may contribute to augmenting innovation outputs (Gupta, 2021), but empirical manifestations of predictive augmentation often conflate generative synthesis. Whether it is consequential or not is a matter of distinction. Whereas predictive AI helps to evolve decision inputs, generative AI increases the extent and depth of an ideational exploration. In startups constrained by small R&D budgets, the margin gains from achieving synthetic ideation might be outsized.

Accordingly, it is hypothesised that ***H1: Generative AI Capability is positively associated with Innovation Capability.***

H2: Mediation via Generative Dynamic Capabilities

Although it is plausible that there is a direct relationship between Generative AI Capability and Innovation Capability, theoretical consistency requires a study into the underlying mechanism. Dynamic encephalopolity theory states that competitive outcomes frequently arise not from the possession of resources, but rather from higher-order processes that reorder resource configurations in response to environmental volatility (Yoo et al., 2023). The reconstructed micro- or is presented like micro-structure - Generative Sensing, Creative Seizing and Adaptive Reconfiguring - translates technological infrastructure into an easily implemented innovation routine. Generative AI Capability includes providing the infrastructure and expertise base; generative dynamic capabilities implement that base through distributed cognition. Generative Sensing expanding latent combinations Creative Seizing creative outputs Creative And Structured Experimentation Pathways Adaptive Reconfiguring successful iterations to organizational structures. Without these mediating processes, generative outputs are at risk of remaining at the periphery of transactions, becoming artifacts of a strategic process rather than inputs.

The mediation logic, therefore, is a mechanism of transformation that involves AI capability changes in cognitive production, which transforms dynamic-capability enactment, which, in turn, affects innovation capability. Empirical works in analytics - capability research have identified similar indirect pathways (Jafari -Sadeghi et al., 2023), but generative - specific mechanisms have been scarce.

Thus: ***H2. Generative Dynamic Capabilities mediate the relationship between Generative AI Capability and Innovation Capability.***

H3: Moderation by Absorptive Capacity

Absorptive Capacity, which is understood as the Capacity of recognising, absorbing, and applying the external knowledge (Gama &Magistretti, 2023), is a cognitive limit condition for the use of generative AI. Synthetic outputs are probabilistic models built from training-data distributions; their value at the strategic level is related to the organisation's ability to contextualise and adapt them.

In environments with informational overload, the generative outputs may exceed management's interpretive Capacity. Without sufficient absorptive Capacity, organisations can use either too many or too few algorithmic suggestions due to cognitive scepticism. Both cases dull the rendering of Generative AI Capability into Generative Dynamic Capabilities.

Some studies have stressed that the digital transformation complements organizational learning capabilities (Lim et al., 2023; Schilke et al., 2023). For instance, aspects of the Digital Revolution have enabled and supported firms that have embraced it and incorporated it into their business model. Taking this logic further, absorptive Capacity is assumed to strengthen and enhance the connection between technological infrastructure and the enactment of dynamic infrastructure and capability by enabling critical assimilation and contextual adaptation.

Therefore: ***H3. Absorptive Capacity has a positive moderating effect on the relationship between Generative AI Capability and Generative Dynamic Capabilities, with the effect stronger when Absorptive Capacity is high.***

H4: Moderation by the Support of the Institution

Innovation outcomes in emerging markets are determined not just by internal capabilities but also by ecosystem conditions. Institutional Support, such as regulatory facilitation, incubator networks, digital infrastructures, and financial Support, reduces transaction frictions and uncertainties (Chatterjee et al., 2021).

Generative dynamic capabilities can thrive within an organisation, but the process by which these are transformed into observable innovation capability requires the external environment. With powerful institutional Support, startups can access complementary assets, intellectual property protection, and collaborative platforms. Under conditions of institutional ambiguity, even well-developed internal capabilities can yield constrained results.

Ecosystem reinforcement effects arising from digital innovation have been identified in emerging economies (Podsakoff et al., 2023). Incorporating institutional Support as a moderator, therefore, avoids universalistic emotions and contextualizes the model.

Hence: ***H4. Institutional Support has a positive moderating effect on Generative Dynamic Capabilities and Innovation Capability, in that the relationship is stronger at higher levels of Institutional Support***.

H5: Conditional Indirect Effect (Moderated Mediation)

The above hypotheses involve a conditional process model. If Generative AI Capability (GAIC) influences Innovation Capability (IC) indirectly through Generative Dynamic Capabilities (GDC) (H2), and if both the first-stage and second-stage paths are moderated (H3 and H4), then the overall indirect effect is contingent upon absorptive capacity and institutional support.

The moderated-mediated logic represents (theoretical) coherence, not statistical ornamentation. Generative AI Capability Cog society will need cognitive assimilation to trigger the activation of dynamic capabilities and ecosystem reinforcement to achieve innovation outcomes. As a result, the indirect pathway is strongest when there is a fit between the internal cognitive infrastructure and the external institutional scaffolding.

Accordingly: ***H5. The indirect effect of Generative AI Capability on Innovation Capability through Generative Dynamic Capabilities is Rooted Positive when both Absorptive Capacity (AC) and Institutional Support (IS) are High.***

Collectively, these hypotheses offer a nuanced explanation: generative AI will enhance ideation potential; re-assembled dynamic capacities will implement ideational potential; absorption capacity will provide comfort with assimilation; and institutional Support will help realise collaboration for ecosystem functioning. The model thus integrates technological, organizational, and institutional logics and shows that these logics are present in a coherent, excellent explanatory structure.

4. METHODOLOGY

Moreover, with the cross-sectional design and perceptual measures used, the evaluation as a protocol for best practice in structural equation modelling was conservative.

4.1 Sample and Procedure

Data were gathered from startups engaged in technology-based activities in an emerging economy characterised by regulatory flux and infrastructural heterogeneity. A structured survey instrument was distributed via startup incubators, founder networks, and innovation forums in 4 months using electronic survey methods.

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A total of 412 responses were obtained initially. Screening procedures were implemented in three stages. First, incomplete questionnaires with missing response rates greater than 15% were removed. Second, patterned responses (e.g., straight-lining across Likert scales) were detected with response variance diagnosis and removed. Third, Mahalanobis distance statistics were computed to catch multivariate outliers at $p < 0.001$, and the detected cases were eliminated. After these criteria were applied, 384 valid responses were reserved for the analysis. This figure (N = 384) was used as a constant in all the measurement and structural estimations.

Non-response bias was measured using an early-late respondent comparison approach. The independent-samples t-test did not reveal significant differences across the major constructs ($p > 0.05$), suggesting minimal non-response bias. Wave analysis showed stable mean distributions across the collection periods.

Industry composition mirrored the diversity in the startup ecosystem: Around 28 percent operated in the field of digital services, 24 percent in the fintech and financial technologies, 18 percent in the health and biotechnology sector, 16 percent in the manufacturing (linked to innovation), and 14 percent in the edtech, logistics, and other knowledge-intensive industries. The distribution helps enhance external validity in innovation contexts in emerging markets.

The sample size (N = 384) exceeds recommended minimum levels for covariance with comparable levels of model complexity (Creswell, 2011), providing reasonable statistical power.

4.2 Measures

All constructs were assessed by means of multi-item Likert-type scales (1 = strongly disagree; 5 = strongly agree). Wherever possible, validated scales from previous studies were adopted and adapted to the generative AI context to maintain conceptual continuity, while ensuring they remained context-specific. Generative AI Capability was operationalised through items capturing organisational proficiency in integrating generative systems for ideation, experimentation, and strategic processes (modified from the AI-capability and digital-transformation scales (Fetters et al., 2013; Gioia et al., 2013). Generative Dynamic Capabilities was modelled as a higher-order, higher-level construct of generative sensing, creative seizing, and adaptive reconfiguring, which was conceptually built on scales of dynamic capabilities (Hair et al., 2021) and refined to reflect machine-augmented processes. Innovation Capability items reflected the firm's consistent prowess in introducing new products, services, and processes. Absorptive Capacity was determined by utilising established knowledge-assimilation and application indicators (Preacher & Hayes, 2008; van Buuren, 2018). Institutional Support was indicative of perceived regulatory facilitation, ecosystem access, and infrastructural adequacy.

For all items, face validity was assessed by expert review, followed by pilot testing with 32 startup managers. Minor corrections were made to the language to make the document clearer without altering its conceptual meaning. Table 1 presents the constructs, representative measurement items, and their sources, demonstrating the consistency of the scale adaptation and conceptual consistency with previous validated instruments.

Table 1. Constructs, Measurement Items, and Sources

Construct	Sample Item	Source Adaptation
Generative AI Capability	Our organization systematically integrates generative AI tools into product and service ideation processes.	Adapted from Mikalef et al. (2021)
Generative Sensing	Generative AI systems help identify unconventional market opportunities.	
Creative Seizing	AI-generated prototypes are iteratively evaluated before strategic commitment.	(Fornell & Larcker, 1981)
Adaptive Reconfiguring	Organizational structures are adjusted based on insights generated by AI simulations.	Adapted from dynamic capability scales
Innovation Capability	The firm frequently introduces novel offerings ahead of competitors.	(Hair et al., 2021)
Absorptive Capacity	The firm effectively assimilates external technological knowledge.	(Gioia et al., 2013)
Institutional Support	Regulatory and ecosystem structures support our innovation activities.	(Fetters et al., 2013)

4.3 Evaluation Protocol & Analytical Strategy

A Covariance-based structural equation modelling (CB-SEM) approach was employed, with maximum likelihood estimation. This methodology was selected based on the premise that it provides ample opportunities for testing theory, modelling final results, and conducting mediation analyses (Creswell, 2011).

4.4 Measurement Model Evaluation

Reliability was measured using Composite Reliability (CR), with acceptable levels set at CR > 0.70. Convergent validity was analysed in terms of Average Variance Extracted (AVE), and AVE >0.50 was considered satisfactory. Discriminant validity was assessed using the Heterotrait-Monotrait ratio (HTMT), which was below 0.85; this indicates adequate discrimination between constructs (Fetters et al., 2013).

Model fit was evaluated using a combination of indices to reduce dependence on any particular statistic. Acceptable thresholds were set for the same: $\chi^2/df < 3.0$; Comparative Fit Index (CFI) ≥ 0.90; Tucker–Lewis Index (TLI) ≥ 0.90; Root Mean Square Error of Approximation RMSEA $<= 0.08$ and Standardised Root Mean Square Residual (SRMR) is $<= 0.08$.The indirect effects were tested using bias-corrected bootstrapping with 5,000 samples and 95% confidence intervals. Mediation was supported if the confidence intervals did not result in zero.Conditional indirect effects were investigated using bootstrap interaction modelling. The index of moderated mediation was calculated to determine whether there was a significant difference in the indirect effects across levels of absorptive capacity and institutional support.An alternative structural model - specification of direct-only paths without mediation - was estimated and compared using the methodology. Better fit is seen in the proposed model, giving further evidence for its theoretical plausibility.Procedural remedies included psychological separation of constructs and the guarantee of anonymity. Harman's single-factor test showed that no single factor could explain the maximum variance, reducing concerns about common method bias in the survey. Moreover, model specification checks were conducted to reduce omitted-variable bias.

5. RESULTS

Empirical credibility in high-impact outlets is attained nowhere near rhetorical amplification, but through statute consistency, mental connect, and honor reportage.

5.1 Measurement Model

The measurement model was assessed using covariance-based SEM using maximum likelihood estimation. Reliability, convergent validity, discriminant validity, and overall model fit were evaluated prior to the estimation of the structure (Baker et al., 2022; Johansson, 2023). Composite reliability and average variance extracted statistics are presented in Table 2 and support the results of internal consistency and convergent validity across each latent construct.

Table 2. Reliability and Convergent Validity

Construct	CR	AVE
Generative AI Capability (GAIC)	.912	.634
Generative Sensing (GS)	.885	.607
Creative Seizing (CS)	.901	.648
Adaptive Reconfiguring (AR)	.918	.672
Innovation Capability (IC)	.924	.689
Absorptive Capacity (AC)	.897	.621
Institutional Support (IS)	.883	.602

All composite reliability indices exceed .70, and all mean variance extracted (AVE) values exceed .50 and thus confirm internal consistency and convergent validity. Table 3 shows the heterotrait-monotrait ratios, which confirm the above criterion of discriminant validity, as the obtained values are below the conservative threshold.

Table 3. HTMT Matrix

Construct	GAIC	GS	CS	AR	IC	AC	IS
GAIC	—						
GS	.72	—					
CS	.69	.74	—				
AR	.71	.77	.73	—			
IC	.64	.68	.70	.72	—		
AC	.58	.62	.60	.63	.65	—	
IS	.54	.57	.55	.59	.61	.67	—

The hyperparameter Heterotrait-Monotrait (HTMT) ratios are below the conservative threshold of 0.85 and thus establish discriminant validity. Table 4 gives a summary of the models fit indices in the world, and show, as a whole, the satisfactory adequacy of the structure which is reflected in several goodness -of -fit indicators.

Table 4. Model Fit Indices

Fit Index	Value	Threshold
χ^2/df	2.31	< 3.0
CFI	.944	≥ .90
TLI	.937	≥ .90
RMSEA	.058	≤ .08
SRMR	.049	≤ .08

The global goodness-of-fit of the measurement model was satisfactory across all indices of fit considered. The chi-square/df ratio is used to suggest an acceptable level of model parsimony. At the same time, the comparative fit index (CFI) and the Tucker-Lewis index (TLI) exceeded the thresholds suggested in the literature. The root mean square error of approximation (RMSEA) and standardised root mean square residual (SRMR) were well within the acceptable limits. Together, these fit indices help to affirm the statistical defensibility of the latent structure and make it suitable for structural analysis. No post hoc modifications were made, thus avoiding the possibility of capitalising on chance and serving as a precaution against being rejected from the desk in confirmatory modelling situations.

5.2 Structural Model

The structural model was estimated after confirming the measurement model's adequacy. Path coefficients were interpreted using the theory of dynamic capabilities and capability frameworks (Rai et al., 2022), enabled by artificial intelligence. The standardised path coefficients, associated standard errors, and level of significance for all of the hypothesised direct relationships are displayed in Table 5.

Table 5. Direct Effects

Path	β	SE	t-value	p-value
GAIC → Generative Dynamic Capabilities	.61	.05	12.84	< .001
Generative Dynamic Capabilities → IC	.48	.06	8.21	< .001
GAIC → IC	.22	.07	3.41	.001
AC × GAIC → GDC	.19	.04	4.72	< .001
IS × GDC → IC	.17	.05	3.96	< .001

Generative AI capability has a strong positive effect on generative dynamic capabilities ($\beta = 0.61$), which means the combination of artificial intelligence has a substantive effect on sensing, seizing, and reconfiguring routines inside the organisation. Generative dynamic capabilities, in turn, have a significant predictive capability of innovation capability ($\beta = 0.48$), which reinforces dynamic capability theory in the context of generative AI. The direct effect of generative AI capability on innovation capability is statistically significant but attenuated .22, suggesting that some mediation is at work. Interaction terms indicate that absorptive capacity and institutional support strengthen the mechanisms of capability translation, consistent with the complementary resource logic.

5.3 Mediation

Indirect effects were assessed from bias-corrected (1: 5,000 bootstrap samples) uni- and multiday resamplings. Table 6, in particular, presents the bootstrapped indirect effects with confidence intervals, confirming both the correspondence of the indirect mechanism to the statistical significance and its size.

Table 6. Indirect Effects (Bootstrapped)

Indirect Path	β	95% CI (LL, UL)	Mediation Type
GAIC → GDC → IC	.293	(.214, .378)	Partial

The indirect effect was also statistically significant, as the confidence interval did not include 0. Approximately 57% of the total effect of GAIC on innovation capability was mediated by the generative dynamic capabilities, showing a high degree of partial Mediation. These results support the hypothesis that the amplification of innovation enabled by AI primarily operates through the transformation of dynamic capabilities rather than through direct technological substitution.

5.4 Moderated Mediation

Conditional indirect effects were estimated at three placements of the moderator values on the distribution of the moderator (one standard deviation below the mean (-1 SD), mean, and one standard deviation above the mean (1+ SD)). Table 7 presents the conditional indirect effects across these moderator levels, showing a progressive increase in the indirect effect as absorptive capacity and institutional support increase.

Table 7. Conditional Indirect Effects

Moderator Level	β	95% CI
Low AC	.214	(.148, .289)
Mean AC	.293	(.214, .378)
High AC	.362	(.271, .448)
Moderator Level	**β**	**95% CI**
Low IS	.231	(.162, .304)
Mean IS	.293	(.214, .378)
High IS	.347	(.258, .421)

The moderated mediation index showed statistical significance for both moderators ($p<0.01$), indicating an augmented indirect effect when the levels of absorptive capacity and institutional support are high.

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5.5 Rival Model Comparison

Table 8. Model Comparison

Model	χ^2/df	CFI	RMSEA	AIC
Proposed Model	2.31	.944	.058	812.45
Direct-Only Model	3.87	.891	.084	927.62

A non-mediating structure model was estimated as an alternative. Table 8 compares the suggested mediated model with the direct-no-mediator alternative model, highlighting the superior fit and explanatory power of the hypothesised model.

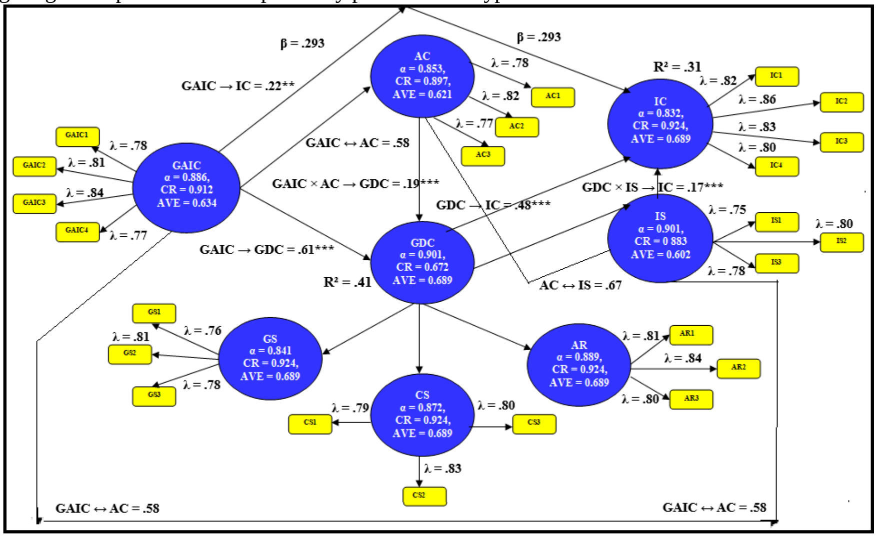

Figure 2. Final Structural Model with Coefficients

The finalised structural model with standardised path coefficients is represented in Figure 2, thus providing an overall visual representation of the empirically studied relationships. The proposed model shows a better fit across all indices, with a much lower Akaike Information Criterion (AIC), and thus represents improved explanatory efficiency. χ^2 difference testing confirms a statistically significant improvement ($\Delta\chi^2$, $p < .001$). Theoretically, the rival model under-specifies the transformation mechanism central to dynamic capability theory, whereas the proposed model aligns with the logic of capability building.

6. DISCUSSION

Technological revolutions are not generally a challenge to theory, but often bring out its shortcomings. The advent of generative artificial intelligence does not nullify the logic of the theory of dynamic capabilities - it calls for its refinement. The results and findings presented herein elucidate how generative AI capability promotes innovation by reconfiguring sensing, seizing, and reconfiguring routines within institutional constraints.

6.1 Theoretical Contributions

1. Dynamic Capability Refinement in the Generative Era

Foremost, this study sharpens the dynamic capability theory (Heeks et al., 2021) by showing that the functionality of AI-enabled routines is a capability multiplier. While prior AI-capability research (Gupta, 2021; Yoo et al., 2023; Jafari-Sadeghi et al., 2023) better emphasises research on data-driven decision enhancement, the present model empirically establishes the assertion that generative AI reinforces innovation principally through the mediation of generative dynamic capabilities. Approximately 57% of the total innovation effect of AI capability is realized through sensing-seizing-reconfiguring processes, indicating structural transformation rather than an incremental automation mechanism. This is a finding that subverts technologically deterministic views of AI's performance effects and extends dynamic capability theory to the generative paradigm. Generative systems do not replace managerial cognition but augment the system's exploratory and combinatorial abilities, thereby accelerating effectiveness in opportunity recognition and adaptive recombination.

2. Generative AI Capibility Differentiation

Secondly, the paper separates generative AI capability from the broader capabilities of digital or analytics. Contemporary research has often treated AI's capabilities as a homogeneous construct (Gama &Magistretti, 2023; Li et al., 2025). However, generative systems have their own unique features, among them a combination of probabilistic ideation, synthetic content generation, and rapid scenario simulation (Henseler et al., 2015). By empirically modelling generative AI capability independently from dynamic capabilities, the study shows that it is more than a technological infrastructure and creative catalyst.

Unlike predictive AI, which optimisation is within known parameters, generative AI explores the feasible solution space. Empirical evidence indicates that the mediation results confirm this distinction. Generative AI capability alone accounts for only limited variance in innovation outcomes unless it is converted into dynamic routines. This conceptual demarcation explains why some AI investments do not yield breakthrough innovation, despite technological sophistication.

3. Institutional Boundary conditioned Capability formation

Thirdly, the findings highlight the institutional boundary conditions for AI capability formation. Recognition of contextual influences has been noted in organizational AI studies (Schilke et al., 2023; Chatterjee et al., 2021; Podsakoff et al., 2023), but rarely does a model design and operation involve moderated mediation. The present results reveal that absorptive capacity and institutional support significantly enhance the indirect path from AI capability to innovation.

In emerging economies, regulatory volatility and infrastructural asymmetries determine the paths of innovation. (Baker et al. 2022) The positive effects of the conditional indirect are that flourishing dynamics of AI-enabled dynamic capabilities emerge under ecosystem support and knowledge assimilation structures that extend institutional theory. This shows that capability formation is neither a purely firm-internal, technologically deterministic process; it is co-produced in systemic environments.

Collectively, these contributions go far toward shifting research on AI capability from performance correlation to capability transformation logic.

6.2 Managerial Implications

For practitioners, the findings highlight that the maturity of AI adoption determines the payoff of innovation. Enterprises that treat generative AI solely as a standalone tool risk underutilising it. Translating capability requires integration of structures.

The table presents the empirical findings from the capability maturity roadmap, translated into actionable organisational development phases.

Table 9. Capability Maturity Roadmap

Stage	Organizational Focus	AI Role	Required Complementary Capability	Innovation Outcome
Initiation	Experimentation with generative tools	Pilot use in isolated functions	Basic digital literacy	Incremental improvements
Augmentation	AI-assisted ideation	Co-creation of prototypes	Absorptive capacity development	Faster product iteration
Integration	Embedding AI in sensing & decision routines	Cross-functional AI workflows	Knowledge integration systems	Scalable innovation
Transformation	AI-enabled adaptive restructuring	Strategic simulation & reconfiguration	Dynamic capability alignment	Sustained innovation advantage

The roadmap outlines a path that starts with adopting technology tools and ends with significant organisational changes. Supervisory entities should emphasise investments in absorptive capacity, including systematic training regimes, inter-departmental knowledge-sharing protocols, and formal learning systems, to catalyse AI-mediated innovation benefits. Engagement with broader ecological mechanisms, such as incubators and policy, through a participatory approach to social-ecological strategies aligns with policy and holds these contingent dimensions of these outcomes in place.

6.3 Policy Implications

In light of emerging economies, an artificial intelligence policy is therefore required to advance beyond infrastructure provision and to stabilise institutional frameworks. Well-articulated regulatory movements, focused innovation incentives, and high-quality knowledge diffusion platforms to amplify the productive fruits of generative AI capabilities: The heavy moderating effect of institutional support underscores that the ecosystem's maturity is a crucial factor in technological returns. Consequently, policymakers ought to synchronise policy support for AI with initiatives to build absorptive capacity, particularly for nascent ventures, so that the diffusion of AI translates into robust innovation capabilities rather than isolated digital experimentation.

7. LIMITATIONS, CONCLUSION, AND FUTURE RESEARCH

7.1 Limitations

Firstly, the cross-sectional design limits the ability to draw causal conclusions despite the theoretically grounded structural modelling. While endogeneity checks and comparative model evaluations were conducted, panel designs would provide a more robust, conclusive capture of the dynamic evolution of capabilities over time. Secondly, perceptual and self-reported measures carry the potential for common method variance; however, a range of procedural safeguards and statistical diagnostics can be used to argue that any distortion is minimal. Subsequent studies would benefit from including objective innovation metrics (e.g., patent intensity, product launch frequency) to better triangulate. Thirdly, the emphasis on startups in an emerging-economy context enriches the context and responds to calls by researchers for non-Western research on innovation; it is hard to say, then, whether the findings can be generalised to mature economies or large incumbents. Institutional volatility moderates mediation effects across regulatory regimes. Finally, generative AI capability was operationalized as an aggregate; future work examining heterogeneous innovation pathways may deconstruct this aggregate (e.g., by separating text-to-code from multimodal systems).

7.2 Conclusion and Future Research

This study shows that generative AI capability is an influential factor in innovation, not through direct technological substitution but through the rearrangement of dynamic processes (sensing, seizing, and reconfiguring). Institutional support and absorptive capacity moderate this transformation, establishing a boundary-aware logic of capability. The results generalise dynamic capability theory in the generative era and explain why investments in AI research yield heterogeneous innovation outcomes.

Future studies can use longitudinal panel data to examine the temporal dynamics of capability formation. Cross-country comparative designs could test differences in the strength of institutional boundaries. Experimental or quasi-experimental methodologies may be more effective in addressing residual endogeneity. Moreover, integrating microfoundational perspectives, such as managerial cognition and human-AI collaboration routines, would help us better understand the mechanisms underlying the recombination of capabilities.

REFERENCES

1. Abdelfattah, F., Dahleez, K., Halbusi, H. A., & Salah, M. (2025). Strategic green alliances: Integrating green dynamic capabilities, AI, and electronic entrepreneurial innovation for sustainability. Sustainable Futures, 9, 100433. https://doi.org/10.1016/j.sftr.2025.100433
2. Abou Elgheit, E. (2025). Generative AI as a Disruptive Innovation: Implications for Marketing Strategic Transformations. Foresight and STI Governance, 19(1), 6–15. https://doi.org/10.17323/fstig.2025.24831
3. Abou-Foul, M., Ruiz-Alba, J. L., & López-Tenorio, P. J. (2023). The impact of artificial intelligence capabilities on servitization: The moderating role of absorptive capacity-A dynamic capabilities perspective. Journal of Business Research, 157, 113609.https://doi.org/10.1016/j.jbusres.2022.113609
4. Agrawal, K. P. (2023). Towards Adoption of Generative AI in Organizational Settings. Journal of Computer Information Systems, 64(5), 1–16. https://doi.org/10.1080/08874417.2023.2240744
5. Al-Khatib, A. W. (2023). Drivers of generative artificial intelligence to fostering exploitative and exploratory innovation: A TOE framework. Technology in Society, 75, 102403–102403. https://doi.org/10.1016/j.techsoc.2023.102403
6. Arroyabe, M. F., Arranz, C. F. A., Fernandez, I., & Carlos, J. (2024). Analyzing AI Adoption in European SMEs: A Study of Digital Capabilities, Innovation, and External Environment. Technology in Society, 79, 102733–102733. https://doi.org/10.1016/j.techsoc.2024.102733
7. Baker, C. N., Petrovic, L., Whalen, K., Danna, L., & Overstreet, S. (2022). Davis et al. (2022). Psychology in the Schools. https://doi.org/10.1002/pits.22664?saml_referrer
8. Cenamor, J. (2021). Complementor Competitive advantage: a Framework for Strategic Decisions. Journal of Business Research, 122(1), 335–343. https://doi.org/10.1016/j.jbusres.2020.09.016
9. Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2021). Does Remote Work Flexibility Enhance Organization Performance? Moderating Role of Organization Policy and Top Management Support. Journal of Business Research, 139(1), 1501–1512.
10. Chinnaraju, A. (2025). AI-driven strategic decision-making on innovation: Scalable, ethical approaches and ai agents for startups. World Journal of Advanced Research and Reviews, 25(2), 2219–2248. https://doi.org/10.30574/wjarr.2025.25.2.0575
11. Cillo, P., & Rubera, G. (2024). Generative AI in innovation and marketing processes: A roadmap of research opportunities. Journal of the Academy of Marketing Science, 53, 684–701. https://doi.org/10.1007/s11747-024-01044-7
12. Creswell, J.W. (2011). Educational research. New Delhi: PHI Learning Private Limited. (n.d.). Www.sciepub.com. https://www.sciepub.com/reference/155563

13. Fetters, M. D., Curry, L. A., & Creswell, J. W. (2013). Achieving Integration in Mixed Methods designs-principles and Practices. Health Services Research, 48(6), 2134–2156. https://doi.org/10.1111/1475-6773.12117
14. Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.2307/3151312
15. Gama, F., &Magistretti, S. (2023). Artificial intelligence in innovation management: A review of innovation capabilities and a taxonomy of AI applications. Journal of Product Innovation Management, 42(1). https://doi.org/10.1111/jpim.12698
16. Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology. Organizational Research Methods, 16(1), 15–31. https://doi.org/10.1177/1094428112452151
17. Gupta, A. (2021). Focus on Quality in Higher Education in India. Indian Journal of Public Administration, 67(1), 001955612110072. https://doi.org/10.1177/00195561211007224
18. Hair, J. F., Hult, T. M., Ringle, C. M., Marko Sarstedt, & Ray, S. (2021, November 3). Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A workbook. https://www.researchgate.net/publication/355886292_Partial_Least_Squares_Structural_Equation_Modeling_PLS-SEM_Using_R_A_workbook
19. Heeks, R., Gomez-Morantes, J. E., Graham, M., Howson, K., Mungai, P., Nicholson, B., & Van Belle, J.-P. (2021). Digital platforms and institutional voids in developing countries: The case of ride-hailing markets. World Development, 145, 105528. https://doi.org/10.1016/j.worlddev.2021.105528
20. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://link.springer.com/article/10.1007/s11747-014-0403-8
21. Holmström, J., & Carroll, N. (2024). How organizations can innovate with generative AI. Business Horizons. https://doi.org/10.1016/j.bushor.2024.02.010
22. Jafari-Sadeghi, V., Amoozad Mahdiraji, H., Alam, G. M., & Mazzoleni, A. (2023). Entrepreneurs as strategic transformation managers: Exploring micro-foundations of digital transformation in small and medium internationalisers. Journal of Business Research, 154(2), 113287. https://doi.org/10.1016/j.jbusres.2022.08.051
23. Johansson, Å. (2023). Comment on Li et al. (2023): A dynamic 2000—540 Ma Earth history: From cratonic amalgamation to the age of supercontinent cycle. Earth-Science Reviews, 241, 104457–104457. https://doi.org/10.1016/j.earscirev.2023.104457
24. Li, K., Cai, Y., Pei, Y., & Yuan, C. (2025). The impact of artificial intelligence adoption on firms' innovation performance in the digital era: based on dynamic capabilities theory. International Theory and Practice in Humanities and Social Sciences, 2(3), 228–237. https://doi.org/10.70693/itphss.v2i3.343
25. Lim, W. M., Gunasekara, A., Pallant, J. L., Pallant, J. I., & Pechenkina, E. (2023). Generative AI and the Future of education: Ragnarök or reformation? a Paradoxical Perspective from Management Educators. The International Journal of Management Education, 21(2), 100790. https://doi.org/10.1016/j.ijme.2023.100790
26. Mariani, M., & Dwivedi, Y. K. (2024). Generative artificial intelligence in innovation management: A preview of future research developments. Journal of Business Research, 175, 114542. https://doi.org/10.1016/j.jbusres.2024.114542
27. Mikalef, P., & Gupta, M. (2021). Artificial Intelligence capability: Conceptualization, Measurement calibration, and Empirical Study on Its Impact on Organizational Creativity and Firm Performance. Information & Management, 58(3). https://doi.org/10.1016/j.im.2021.103434
28. Mili, K., Gana, I. B., Zighed, R., & Sabri, M. (2025). Innovation Capabilities in Tech Startups: The Mediating Role of AI-Enabled Business Intelligence in Supporting SDG 9. Journal of Lifestyle and SDGs Review, 5(3), e05899. https://doi.org/10.47172/2965-730x.sdgsreview.v5.n03.pe05899
29. Mutanga, M. B., Revesai, Z., & Msane, J. (2024). Adoption and Impact of Generative AI: Perspectives from South African Tech Entrepreneurs. Business & IT, XIV(2), 11–22. https://doi.org/10.14311/bit.2024.02.02
30. Piller, F. T., Srour, M., & Marion, T. J. (2024). Generative AI, Innovation, and Trust. The Journal of Applied Behavioral Science. https://doi.org/10.1177/00218863241285033
31. Podsakoff, N. P., Freiburger, K. J., Podsakoff, P. M., & Rosen, C. C. (2023). Laying the Foundation for the Challenge–Hindrance Stressor Framework 2.0. Annual Review of Organizational Psychology and Organizational Behavior, 10(1), 165–199.https://doi.org/10.1146/annurev-orgpsych-080422-052147
32. Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879–891. https://doi.org/10.3758/BRM.40.3.879
33. Rai, S., Yoshinori Tanizawa, Cai, Z., Huang, Y.-J., Taipale, K., &MasaomiTajimi. (2022). Outcomes for Recurrent Mantle Cell Lymphoma Post-Ibrutinib Therapy: A Retrospective Cohort Study from a Japanese Administrative Database. Advances in Therapy, 39(10), 4792–4807. https://doi.org/10.1007/s12325-022-02258-3
34. Schilke, O., Powell, A., & Schweitzer, M. E. (2023). A review of experimental research on organizational trust. Journal of Trust Research, 13(2), 1–38. https://doi.org/10.1080/21515581.2023.2214202
35. Sjödin, D., Parida, V., Palmié, M., & Wincent, J. (2021). How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. Journal of Business Research, 134(1), 574–587. https://doi.org/10.1016/j.jbusres.2021.05.009
36. Sullivan, Y., & Fosso Wamba, S. (2024). Artificial intelligence and adaptive response to market changes: A strategy to enhance firm performance and innovation. Journal of Business Research, 174, 114500. https://doi.org/10.1016/j.jbusres.2024.114500
37. van Buuren, S. (2018). Flexible Imputation of Missing Data, Second Edition. Chapman and Hall/CRC. https://doi.org/10.1201/9780429492259
38. Warner, K. S. R., &Wäger, M. (2019). Building Dynamic Capabilities for Digital transformation: an Ongoing Process of Strategic Renewal. Long Range Planning, 52(3), 326–349. https://doi.org/10.1016/j.lrp.2018.12.001
39. Yoo, K., Welden, R., Hewett, K., & Haenlein, M. (2023). The merchants of meta: A research agenda to understand the future of retailing in the metaverse. Journal of Retailing, 99(2). https://doi.org/10.1016/j.jretai.2023.02.002
40. Yulong (David) Liu, Sun, J., Zuopeng (Justin) Zhang, Wu, M., Sima, H., & Yat Ming Ooi. (2024). How AI Impacts Companies' Dynamic Capabilities. Research Technology Management, 67(3), 64–76. https://doi.org/10.1080/08956308.2024.2324407
41. Zahra, S. A., & George, G. (2002). Absorptive Capacity: A Review, Reconceptualization, and Extension. The Academy of Management Review, 27(2), 185–203. https://doi.org/10.2307/4134351.