

Article

Generative AI Capability, Business Model Innovation, and Business Development Performance: A Moderated Mediation Framework for SMEs in an Emerging Market

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Abstract

Generative artificial intelligence (GenAI) is increasingly accessible to small and medium-sized enterprises in emerging economies, yet the organisational mechanisms that link GenAI capability to business development outcomes remain insufficiently understood. Drawing on Dynamic Capabilities Theory and the Resource-Based View, this study examines the association between GenAI capability and business development performance (BDP) in Jordanian SMEs through the mediating role of business model innovation (BMI) and the moderating role of market sensing agility (MSA). A cross-sectional survey of owner-managers and senior decision-makers was analysed using partial least squares structural equation modelling. The results indicate that GenAI capability is positively associated with BDP, with BMI accounting for a meaningful share of the link, while MSA strengthens the mediated pathway such that the association is substantially more pronounced among firms with higher levels of market sensing capacity. The findings suggest that returns to GenAI investment in resource-constrained markets depend less on technological access and more on the firm's capacity to reconfigure its business model and interpret the external environment effectively. The study contributes to the dynamic capabilities literature in emerging-market contexts and provides direction for managers and policymakers concerned with digital transformation in the SME sector.

Keywords: business development performance; business model innovation; Dynamic Capabilities Theory; generative AI capability; Jordan; market sensing agility; PLS-SEM; SMEs



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1. Introduction

What does it actually take for a small firm to turn an AI tool into business results? That is the practical puzzle that drives this paper. Generative artificial intelligence—text generators, image and code assistants, predictive engines—has dropped in cost and become accessible to smaller firms in emerging markets within roughly the past three years (Mariani, 2024; Shore et al., 2024). Yet the empirical record shows wide variance in returns. Some firms adopt the same tools and see customer growth and revenue gains; others adopt and see almost nothing change. Why?

We argue that the answer lies less in the technology and more in the organisational scaffolding around it. Three questions structure our investigation. First, is generative

AI capability associated with stronger business development performance in resource-constrained SMEs? Second, does business model innovation (BMI)—the deliberate reworking of how a firm creates, delivers, and captures value—carry that association? Third, does the firm's market sensing agility (MSA) condition the strength of the mediated path? We test these questions in a Jordanian SME context, drawing on Dynamic Capabilities Theory and the Resource-Based View. Our sample includes 300 owner-managers and senior decision-makers from services, trade, manufacturing, and technology firms across Amman, Irbid, and Zarqa.

Three short cases sharpen the empirical motivation. Aurora Digital is a 12-year-old digital marketing services firm in Amman that began as a startup with continuous expansion and now employs 18 staff; in 2024, it adopted generative AI for client proposal drafting and creative ideation and reported a measurable lift in new client conversion within nine months. Najem Textiles is a small textile manufacturer in Irbid with 32 employees, founded as a spin-off from a family conglomerate, that uses generative AI for design ideation and pattern generation; the firm has reorganised its sample-to-order cycle around these tools. PayTrust Fintech is a 7-year-old payments startup in Zarqa with 24 employees, originating as a continuous-growth startup, applying generative AI to customer service automation and fraud-pattern explanation; its business model has shifted from transaction processing toward bundled advisory services. Each firm operates in a different sector. Each adopted the same family of tools. Their performance trajectories are not uniform. Why? That dispersion is the question this paper takes up.

The Jordanian context is theoretically informative, not just convenient. Three features matter for our test. First, Jordan combines high human capital and digital infrastructure relative to its income level with limited formal business intelligence infrastructure, which creates real variance in market sensing across firms (Wahab & Radmehr, 2024). Second, family ownership and concentrated decision authority in owner-managers compress the chain through which strategy is enacted; the same individual controls both the technological lever and the business model lever, which reduces middle-management diffusion as a confound for our model. Third, institutional voids in market data and the absence of mature AI ecosystems sharpen the boundary-condition test of DCT: if the moderated mediation pattern holds under these conditions of maximal decision integration and infrastructure constraint, the underlying logic is likely to extend to other emerging-market settings where the same conditions hold in milder form (Brouthers, 2022; Dubey, 2023). Theoretical purchase, not empirical convenience, is the basis of our choice.

The paper makes three contributions. First, it extends DCT to generative AI adoption by mapping each micro-foundation—sensing, seizing, transforming—onto an explicit construct in the path model and by repositioning market sensing agility as an external boundary condition that varies independently of the firm's general dynamic capability stock (Pavlou & El Sawy, 2011). Second, it offers an empirical test of a moderated mediation model in a setting where most evidence on AI-performance links comes from advanced economies, addressing a context gap that has been flagged repeatedly in recent reviews (Mariani, 2024). Third, it provides sector-differentiated practical guidance for managers and policymakers in MENA economies that face similar resource-constrained adoption conditions. We organise the remainder of the paper as follows: Section 2 develops the theoretical framework and four hypotheses; Section 3 reports the design, sample, measures, and analytical strategy; Section 4 presents the results; Section 5 discusses the findings; and Section 6 concludes with limitations and future research directions.

2. Theoretical Framework

2.1. Dynamic Capabilities Theory and the Resource-Based View

This study draws on two complementary theoretical lenses. Dynamic Capabilities Theory (DCT) proposes that competitive advantage stems not from the possession of resources but from a firm's capacity to sense opportunities, seize them through investment, and transform organisational configurations in response (Teece et al., 1997). The Resource-Based View (RBV) complements this account by specifying when such capabilities yield sustained returns: when the resulting resource bundles are valuable, rare, inimitable, and non-substitutable (Brouthers, 2022). Together, the two lenses operate at different levels of analysis—DCT at the capability level, the RBV at the resource level—and their integration enables us to explain both how firms develop AI-related competences and why some firms sustain returns while others do not (Madanaguli, 2023).

We make the conceptual delineation explicit. Generative AI itself is treated as an operant resource under the RBV: it is heterogeneous across firms in its integration depth, valuable for cognitive and creative tasks, rare in mid-resource SME contexts where adoption competence is still scarce, inimitable when embedded in firm-specific routines, and non-substitutable when bound to proprietary data and decision workflows. Separately, the firm's capacity to deploy generative AI is a dynamic capability under DCT, operating through three micro-foundations: sensing (recognising the strategic relevance of GenAI), seizing (committing to BMI as the mechanism that translates AI inputs into market-facing change), and transforming (reorganising the value-creation logic accordingly). This split addresses a recurring critique of AI adoption studies that conflate the tool with the capability and therefore cannot explain why two firms with identical tools produce different outcomes (Mariani, 2024; Gama, 2023).

Table 1 maps each empirical construct in this study to its theoretical category, making the RBV–DCT alignment transparent.

Table 1. Theoretical construct mapping.

Construct	Theoretical Category	Lens	Role in Path Model
Generative AI Capability	Operant resource + dynamic capability	RBV + DCT (sensing + seizing)	Independent variable
Business Model Innovation	Transforming micro-foundation	DCT (transforming)	Mediator
Market Sensing Agility	External boundary condition on sensing	DCT (sensing periphery)	Moderator
Business Development Performance	Performance outcome of resource configuration	RBV (sustained advantage indicator)	Dependent variable

This dual framing is well suited to GenAI adoption in Jordan. The SME environment is heterogeneous in resources—firms differ sharply in their technological endowments and digital readiness—and complex in institutions, such that the capacity to reconfigure becomes a real source of differentiation rather than a baseline expectation (Kallmuenzer, 2024; Dubey, 2023).

2.2. Generative AI Capability: Three Dimensions

Generative AI capability, in this study, refers to the extent to which a firm integrates GenAI technologies into its information processing, decision-making, and strategic alignment (Mariani, 2024; Gama, 2023). We restructure the construct into three theoretically grounded dimensions, which together carry the six measurement items.

Data Infrastructure. Whether the firm has organised, accessible data assets that GenAI tools can ingest and act on. Without this layer, GenAI outputs lack firm-specific grounding and degrade to generic content. This dimension captures the resource precondition for meaningful use.

Model Competence. Whether the firm can evaluate, select, and configure GenAI tools for its specific tasks. This dimension separates firms that purchase access from firms that exercise informed judgement over which model, prompt strategy, and integration pattern serves a given decision.

Organisational Embeddedness. Whether GenAI outputs are integrated into routine decision-making, rather than treated as ad hoc experiments. This dimension distinguishes deployments that change how the firm operates from deployments that sit alongside existing workflows without altering them.

What sets generative AI apart from earlier waves of AI is the breadth of tasks it can absorb. Classical machine learning required structured data, domain-specific training, and dedicated engineering teams. GenAI platforms—large language models, image generators, code assistants—accept natural-language instructions and produce outputs across domains without bespoke model training. For SMEs, this lowers the technical threshold of entry but raises the organisational threshold of effective use. A firm can deploy a GenAI tool in days. Making that tool generate commercially relevant reconfiguration—the kind that shows up in BDP—takes strategic intent, market awareness, and willingness to alter existing business models.

The empirical record on GenAI returns is mixed. Some studies report efficiency gains: faster processing, lower coordination cost, higher throughput (Bankins, 2023; Roux et al., 2025). Others report mixed effects on workforce engagement and innovation quality that depend on implementation quality and organisational readiness (Garibay, 2023; Valtonen et al., 2025). A third stream warns about governance issues—algorithmic bias, surveillance, accountability gaps—that can worsen performance when ignored (Shore et al., 2024; Hartmann, 2024). The pattern across these streams suggests that capability—not access—is the active variable.

We also clarify which GenAI applications the survey captures. The measurement scale asks respondents about the use of GenAI for seven application areas: marketing and content generation, customer service automation, sales and lead generation, decision support and analytics, document and report automation, code generation, and strategic planning support. Table 2 reports the distribution of these applications across the analytic sample.

Table 2. GenAI application profile in the sample ($n = 300$).

Application Area	Firms Using (%)	Most Active Sector
Marketing/content generation	68	Services
Customer service automation	54	Services
Sales and lead generation	47	Trade
Decision support and analytics	41	Technology
Document and report automation	38	Services
Code generation	22	Technology
Strategic planning support	19	Technology

The distribution shows that the dominant uses are customer-facing and content-generating, with technology firms over-represented in code and analytics applications. This pattern matters for interpretation: BMI gains are most plausible where GenAI alters how the firm reaches customers, which aligns with the high concentration in marketing, customer service, and sales.

H1. *Generative AI capability is positively associated with business development performance in Jordanian SMEs.*

2.3. Business Model Innovation as Mediator

Business model innovation—the deliberate restructuring of how a firm creates value, delivers value, and captures value—is the bridge between GenAI capability and market-facing outcomes (Mariani, 2022; Massa et al., 2023; Zott & Amit, 2010). Without this translation step, AI-driven efficiency gains stay internal and never reach the customer interface (Madanaguli, 2023; Ballerini, 2023).

The argument rests on a first-order/second-order distinction. First-order effects are operational gains—faster processing, lower coordination cost, fewer errors—that flow directly from GenAI deployment without business model change. Second-order effects are strategic gains—new customer segments, redesigned value propositions, ecosystem repositioning—that require the firm to alter what it sells, who it sells to, and how value is captured. GenAI capability feeds both pathways. The direct path delivers first-order gains. The indirect path, through BMI, delivers second-order gains. In Jordanian SMEs, where the competitive pressure rewards differentiation more than cost-cutting, the second-order channel through BMI is theoretically the heavier route for business development outcomes (Faiz et al., 2024; Zahoor et al., 2023).

SMEs are structurally well-positioned for fast BMI: simpler hierarchies, fewer legacy systems, more direct owner involvement in strategic decisions (Zahoor et al., 2023; Faiz et al., 2024). Resource constraints work against this advantage in practice, but the theoretical point remains: GenAI lowers the cognitive cost of designing and evaluating new configurations, which accelerates BMI cycles. We expect BMI to carry a meaningful share of the GenAI-to-BDP effect, with the remainder flowing through direct operational channels.

H2. *Business model innovation mediates the positive relationship between generative AI capability and business development performance.*

2.4. Market Sensing Agility as External Boundary Condition

Market sensing agility refers to the speed and accuracy with which a firm reads external market signals and reorients itself accordingly (Ameen et al., 2024; Sadeghi, 2024; Pavlou & El Sawy, 2011). We position MSA as an external boundary condition that varies independently of a firm's general dynamic capability stock. This positioning addresses a conceptual concern that DCT's sensing micro-foundation and MSA are merely the same construct under different names.

We acknowledge the conceptual proximity. Sensing is internal to DCT. MSA, however, captures a specifically external interpretive infrastructure—the firm's capacity to read market signals, not its general adaptive capacity. A firm can have high GenAI capability (a dynamic capability under DCT) and still have low MSA (a limited external interpretive infrastructure). The converse also holds. This independence is what justifies MSA's moderating role rather than its absorption into the capability bundle (Pavlou & El Sawy, 2011; Sadeghi, 2024).

The mechanism is straightforward. High-MSA firms direct GenAI-enabled reconfiguration toward market-validated opportunities, amplifying returns. Low-MSA firms reconfigure based on internal logic that may be disconnected from where the market is actually heading, diluting returns. In Jordan specifically, where market data is incomplete and formal business intelligence infrastructure is thin, MSA differs substantially across firms and becomes a genuine source of organisational differentiation (Culot, 2024; Wahab & Radmehr, 2024).

This logic fits within the standard boundary condition argument of DCT: dynamic capabilities create advantage only under strategic conditions that allow them to be exercised effectively (Brouthers, 2022; Dubey, 2023). The empirical literature on dynamic capabilities repeatedly shows that sensing and responding mechanisms must operate jointly—firms that invest in capabilities without the perceptual infrastructure to act on them productively capture internal efficiency gains that fail to translate into external competitive advantage. MSA operationalises this perceptual infrastructure for the GenAI context.

H3. *Market sensing agility positively moderates the relationship between generative AI capability and business development performance, such that the relationship is stronger when market sensing agility is higher.*

H4. *The mediating role of business model innovation in the generative AI capability–business development performance relationship is contingent on the level of market sensing agility (moderated mediation).*

2.5. Conceptual Model and Research Hypotheses

Drawing the four hypotheses together, the model is a moderated mediation: GenAI capability influences BDP both directly and through BMI, with MSA conditioning the strength of the mediated pathway. The direct path captures first-order operational gains. The indirect path through BMI captures second-order strategic gains. MSA strengthens the indirect path because high-MSA firms direct their BMI activity toward market-validated opportunities. Figure 1 presents the conceptual model, mapping all twenty items to their constructs, DCT micro-foundations, and RBV resource attributes, and Table 3 summarises the four hypotheses tested.

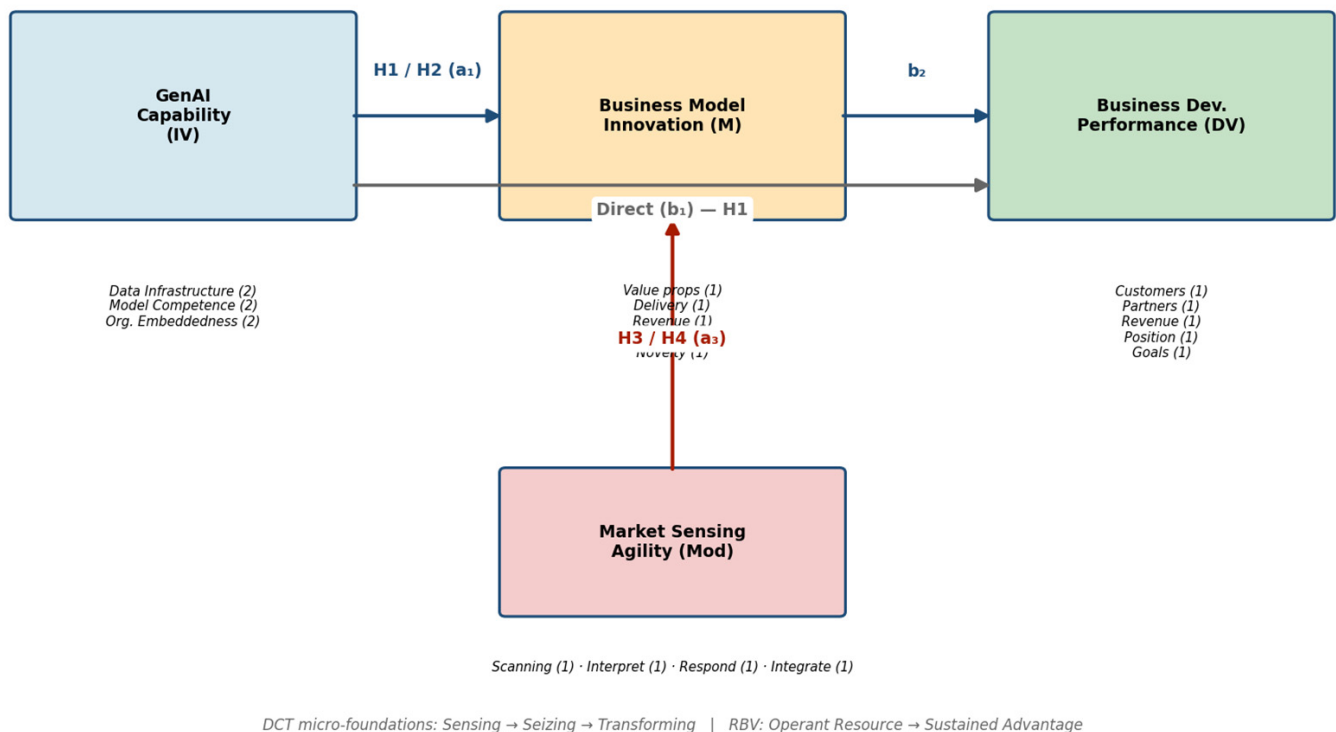


Figure 1. Conceptual model with item-level mapping. All 20 items linked to constructs and to DCT micro-foundations (sensing/seizing/transforming) and RBV resource attributes.

Table 3. Research hypotheses.

Hypothesis	Statement
H1	Generative AI capability is positively associated with business development performance in Jordanian SMEs.
H2	Business model innovation mediates the positive relationship between generative AI capability and business development performance.
H3	Market sensing agility positively moderates the relationship between generative AI capability and business development performance, such that the relationship is stronger when market sensing agility is higher.
H4	The mediating role of business model innovation in the generative AI capability–business development performance relationship is contingent on the level of market sensing agility (moderated mediation).

3. Materials and Methods

3.1. Research Design

We adopt a positivist quantitative design implemented through a cross-sectional survey of Jordanian SME owner–managers and senior decision-makers. The research hypotheses are derived deductively from Dynamic Capabilities Theory and the Resource-Based View and tested against survey data using partial least squares structural equation modelling (PLS-SEM). The cross-sectional design is suited to testing directional associations within a defined population. We acknowledge that it cannot establish temporal precedence and therefore frame all findings in associational rather than causal terms. Ethical approval was obtained prior to fieldwork from the relevant institutional review board; all respondents participated voluntarily and were assured of confidentiality.

3.2. Sample and Data Collection

The target population comprised owner–managers, general managers, and senior functional heads of formally registered Jordanian SMEs employing between 5 and 249 staff, in line with the Ministry of Industry classification. These individuals were chosen because they hold visibility over both technology adoption decisions and business development trajectories at the firm level.

The sampling frame was constructed from three sources: the Jordan Chamber of Commerce business registry, the Ministry of Digital Economy and Entrepreneurship (MoDEE) SME database, and the Jordan Enterprise Development Corporation (JEDCO) directory. Cross-referencing across the three sources produced a deduplicated frame of 1247 eligible firms operating in Amman, Irbid, and Zarqa. Eligibility required active operation for at least three years, an employee count within the 5–249 band, and an accessible owner–manager or senior decision-maker contact.

We employed a stratified purposive sampling approach. Stratification was applied on two dimensions: sector (services, trade, manufacturing, technology) and firm size band (small: 5–49 employees; medium: 50–249 employees). Quotas were assigned proportionally to each stratum’s share in the sampling frame, and response rates were monitored in real time during fieldwork to detect emerging imbalances.

The fieldwork ran from January to March 2025. An online questionnaire was distributed through SME associations, chambers of commerce, and professional networks, with two email reminders sent at two-week intervals. The initial response totalled 381 submissions. We applied two exclusion filters: 63 responses were dropped for exceeding 10%

item-level missing data, and 18 were dropped for failing the eligibility screen (incorrect size band or dormant operations). The final analytic sample is $n = 300$, corresponding to an effective response rate of 24.1% on the contacted set.

Post-stratification weighting was used where stratum representation in the achieved sample diverged meaningfully from frame proportions. Stratum-level weights were computed as $w_i = (N_i/n_i)/\text{mean}(N_i/n_i)$, where N_i denotes the stratum proportion in the frame and n_i denotes the stratum proportion in the achieved sample. Only the manufacturing stratum required meaningful adjustment, with an achieved share of 18% against a frame share of 23%. Both weighted and unweighted path coefficients are reported in Section 4; differences fall below 0.02 on all paths, indicating that the slight under-representation of manufacturing firms does not materially distort the structural estimates. Table 4 reports the demographic profile of the analytic sample.

Table 4. Demographic profile of the analytic sample ($n = 300$).

Characteristic	Category	<i>n</i> (%)
Sector	Services	126 (42.0)
	Trade	84 (28.0)
	Manufacturing	54 (18.0)
	Technology	36 (12.0)
Firm size	Small (5–49 emp.)	183 (61.0)
	Medium (50–249 emp.)	117 (39.0)
Respondent role	Owner–manager	114 (38.0)
	General manager	105 (35.0)
	Senior functional head	81 (27.0)
Firm age	<5 years	72 (24.0)
	5–10 years	129 (43.0)
	>10 years	99 (33.0)
Ownership	Family-owned	189 (63.0)
	Non-family	111 (37.0)

3.3. Measures

All constructs were measured with multi-item reflective scales adapted from previously published instruments. Items were forward-translated into Arabic by two bilingual academics independently; a third reviewer reconciled discrepancies and produced a consensus version. A fourth translator, blind to the original English, conducted the back-translation. Minor wording adjustments were applied where the back-translation diverged from the source meaning. The Arabic instrument was pre-tested with five SME managers to confirm naturalness in a business context and acceptable response times per item. Two items on the GenAI capability scale were reworded at this stage to sharpen the distinction between passive access to AI tools and active integration into decision workflows. All responses were captured on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). Complete item wording, with sources, is provided in Appendix A.

GenAI capability was measured with six items spanning the three dimensions specified in Section 2.2: Data Infrastructure (2 items), Model Competence (2 items), and Organisational Embeddedness (2 items), drawing on [Mariani \(2024\)](#) and [Gama \(2023\)](#).

Business development performance was measured with five items, capturing new customer acquisition, partnership formation, revenue growth, competitive positioning, and goal attainment ([Chang et al., 2023](#); [Troise et al., 2022](#)).

Business model innovation was measured with five items, capturing novelty of value propositions, reconfiguration of delivery channels, adjustment of the revenue model, and ecosystem repositioning. The scale draws on [Massa et al. \(2023\)](#) and [Zahoor et al. \(2023\)](#) and is anchored conceptually in the foundational treatment by [Zott and Amit \(2010\)](#).

Market sensing agility was measured with four items, capturing environmental scanning, speed of signal interpretation, responsiveness to market change, and integration of market intelligence into decision-making. The scale draws on Ameen et al. (2024) and Sadeghi (2024) and is anchored conceptually in Pavlou and El Sawy (2011).

A complete audit of construct sources was conducted to confirm substantive alignment between each item's wording and the cited theoretical foundation. Two sources were strengthened during this audit: the BMI scale was anchored additionally on Zott and Amit (2010) as the foundational BMI conceptualisation, and the MSA scale was anchored additionally on Pavlou and El Sawy (2011), as the foundational sensing-and-responding capability paper.

3.4. Analytical Strategy and Equations

The analysis proceeded in two stages following established PLS-SEM practice (Hair et al., 2019). Stage 1 conducted data screening in IBM SPSS Statistics—outlier detection, normality checks, missing data treatment, reliability estimation through Cronbach's alpha and composite reliability, and common method bias diagnostics. Stage 2 estimated the measurement and structural models in SmartPLS 4.0.

PLS-SEM was selected over covariance-based SEM (CB-SEM) for three reasons. First, the model contains a latent interaction term (GenAI Capability $\times$ MSA), which PLS-SEM handles through the product indicator approach without imposing the distributional assumptions that CB-SEM interaction models require. Second, the research objective is the prediction and explanation of variance in business development outcomes, which aligns with PLS-SEM's prediction-oriented logic. Third, all constructs are reflectively measured with established scales, which removes the measurement model concerns sometimes associated with PLS-SEM applications involving formative indicators.

The statistical model is governed by four equations. Equation (1) estimates the mediator with the interaction term included:

$$\text{BMI} = a_0 + a_1 \cdot \text{GenAI} + a_2 \cdot \text{MSA} + a_3 \cdot (\text{GenAI} \times \text{MSA}) + e_1 \quad (1)$$

Equation (2) estimates the outcome conditional on the mediator and the direct path:

$$\text{BDP} = b_0 + b_1 \cdot \text{GenAI} + b_2 \cdot \text{BMI} + e_2 \quad (2)$$

Equation (3) expresses the conditional indirect effect of GenAI on BDP through BMI at a given level of MSA:

$$\text{IE}(\text{MSA}) = [a_1 + a_3 \cdot \text{MSA}] \times b_2 \quad (3)$$

Equation (4) is the index of moderated mediation, which captures the change in the indirect effect per unit change in the moderator:

$$\text{IMM} = a_3 \times b_2 \quad (4)$$

Figure 2 displays the statistical model with these equations mapped onto the path diagram.

Path coefficients were estimated through 5000 bootstrap resamples. Bias-corrected confidence intervals are reported for the indirect effects (H2) and the index of moderated mediation (H4). The moderated mediation test relied on the product indicator method for the latent interaction term (GenAI $\times$ MSA), with simple slope analysis conducted at the mean and at plus and minus one standard deviation of the moderator.

$n = 300$ | bootstrap = 5000 resamples | *** $p < 0.001$, ** $p < 0.01$

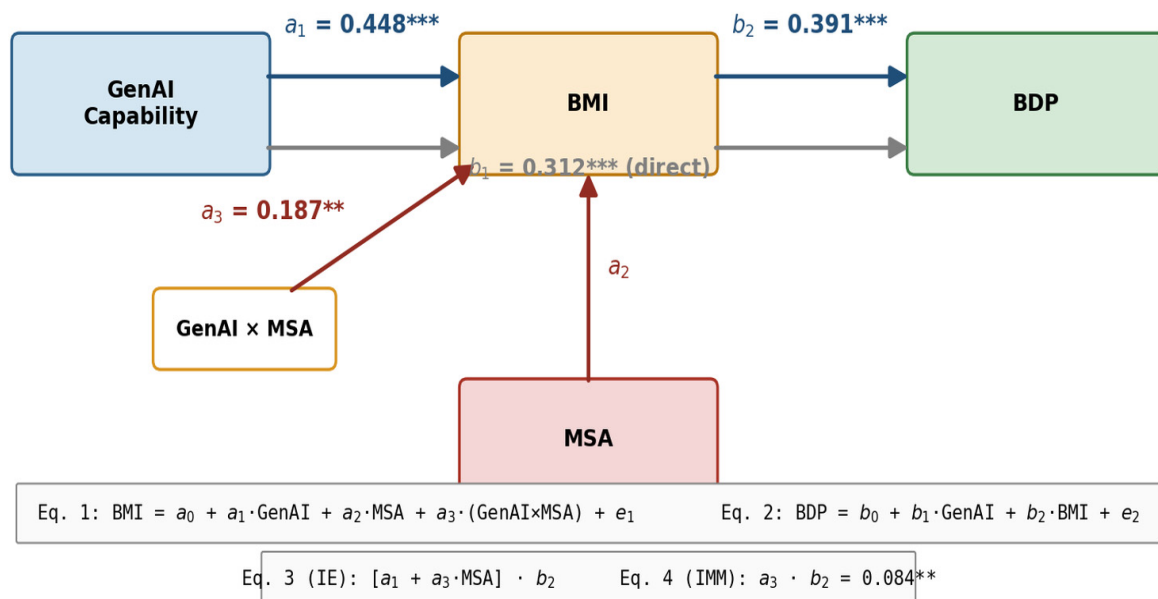


Figure 2. Statistical model with path coefficients and equations.

Common method bias was assessed through two complementary procedures. Harman's single-factor test was conducted in IBM SPSS Statistics; the largest unrotated factor accounts for 24.3% of the total variance, well below the 50% threshold. The marker variable procedure proposed by Lindell and Whitney (2001) was then applied: a theoretically unrelated construct in the survey (employee tenure satisfaction, two items) was identified as the marker, and partial correlations among substantive constructs were computed controlling for the marker. The partial correlations shifted by less than 0.02 from the zero-order estimates, indicating that common method variance does not materially confound the structural estimates.

Non-response bias was examined through an early versus late respondent comparison, using independent-samples *t*-tests on construct means between the first 20% and the last 20% of the returned questionnaires. No significant differences emerged at $p < 0.10$. Robustness analyses are reported in Section 4.7.

4. Results

4.1. Sample Profile and Method Bias

The analytic sample of 300 valid responses was distributed across services (42%), trade (28%), manufacturing (18%), and technology (12%) firms, with small firms (5–49 employees) representing 61% of the sample and medium firms (50–249 employees) the remaining 39%. By role, owner–managers accounted for 38%, general managers for 35%, and senior functional heads for 27%. Full demographics are reported in Table 4.

Harman's single-factor test produced the largest unrotated factor, accounting for 24.3% of total variance, well below the 50% threshold for common method bias concern. The Lindell and Whitney (2001) marker variable procedure produced partial correlations among the substantive constructs that differed by less than 0.02 from the zero-order estimates. Both procedures support the conclusion that common method variance does not materially confound the structural estimates.

The early–late respondent comparison revealed no significant differences in any of the four construct means at $p < 0.10$, which reduces the concern that non-response bias systematically distorts the estimates. Post-stratification weighting was applied to the manufacturing stratum. The weighted and unweighted path coefficients differ by less than 0.02 on all paths. Table 5 reports the side-by-side comparison and confirms that the slight under-representation of manufacturing firms does not materially affect the structural results.

Table 5. Weighted vs. unweighted path coefficients.

Path	Unweighted β	Weighted β	Δ
GenAI $\rightarrow$ BDP (direct)	0.312	0.319	0.007
GenAI $\rightarrow$ BMI	0.448	0.441	0.007
BMI $\rightarrow$ BDP	0.391	0.384	0.007
GenAI $\times$ MSA $\rightarrow$ BDP	0.187	0.193	0.006
Indirect (mean MSA)	0.175	0.169	0.006

4.2. Measurement Model

The measurement model satisfied all standard evaluation criteria. Composite reliability ranged from 0.81 to 0.89; average variance extracted ranged from 0.52 to 0.67. All item loadings exceeded the 0.70 threshold, and all heterotrait–monotrait (HTMT) ratios fell below the 0.85 cutoff. Model fit indices supported the specification: SRMR = 0.063 and NFI = 0.923. The reliability, convergent validity, and discriminant validity evidence justified progression to structural estimation.

At the construct level, GenAI capability showed the highest internal consistency (CR = 0.89, AVE = 0.67), consistent with a scale that has been validated across multiple technology adoption studies. BDP (CR = 0.86, AVE = 0.58) and BMI (CR = 0.84, AVE = 0.55) fell comfortably within accepted ranges. MSA, measured with four items, recorded the lowest but still adequate values (CR = 0.81, AVE = 0.52). The HTMT ratios ranged from 0.61 (GenAI–MSA) to 0.79 (BMI–BDP), all below the 0.85 threshold, confirming that the constructs are empirically distinct despite their conceptual proximity within the same nomological network.

At the dimension level, the three components of GenAI capability behaved as expected. Data Infrastructure (mean = 3.78, SD = 0.82) and Organisational Embeddedness (mean = 3.62, SD = 0.87) carried the strongest loadings; Model Competence (mean = 3.45, SD = 0.91) exhibited slightly weaker but still acceptable item loadings. Inter-dimension correlations ranged from 0.54 to 0.67, supporting the higher-order construct specification. Figure 3 maps the item-to-construct loadings and reliability across the measurement model.

4.3. Direct Effect and Variance Explained (H1)

GenAI capability explained 41.3% of the variance in BDP ($R^2 = 0.413$). The path from GenAI capability to BDP was positive and significant, supporting H1 ($\beta = 0.312$, $t = 4.87$, $p < 0.001$, 95% CI [0.189, 0.441]). GenAI capability was also a strong predictor of BMI ($\beta = 0.448$, $t = 6.93$, $p < 0.001$), and BMI, in turn, was a strong predictor of BDP ($\beta = 0.391$, $t = 5.62$, $p < 0.001$). Multicollinearity was not a concern; all VIF values fell below the 3.3 threshold. Effect sizes were medium to large: $f^2 = 0.19$ for GenAI on BDP and $f^2 = 0.24$ for GenAI on BMI.

4.4. Mediation (H2)

The indirect effect of GenAI capability on BDP through BMI was positive and significant, supporting H2 (indirect effect = 0.175, SE = 0.038, 95% CI [0.106, 0.256]). The mediation ratio (indirect to total effect = 0.36) indicates that BMI carries approximately

36% of the total performance effect of GenAI capability, with the remaining 64% flowing through direct channels. The pattern is partial mediation, which is theoretically consistent with the dual-pathway argument developed in Section 2.3.

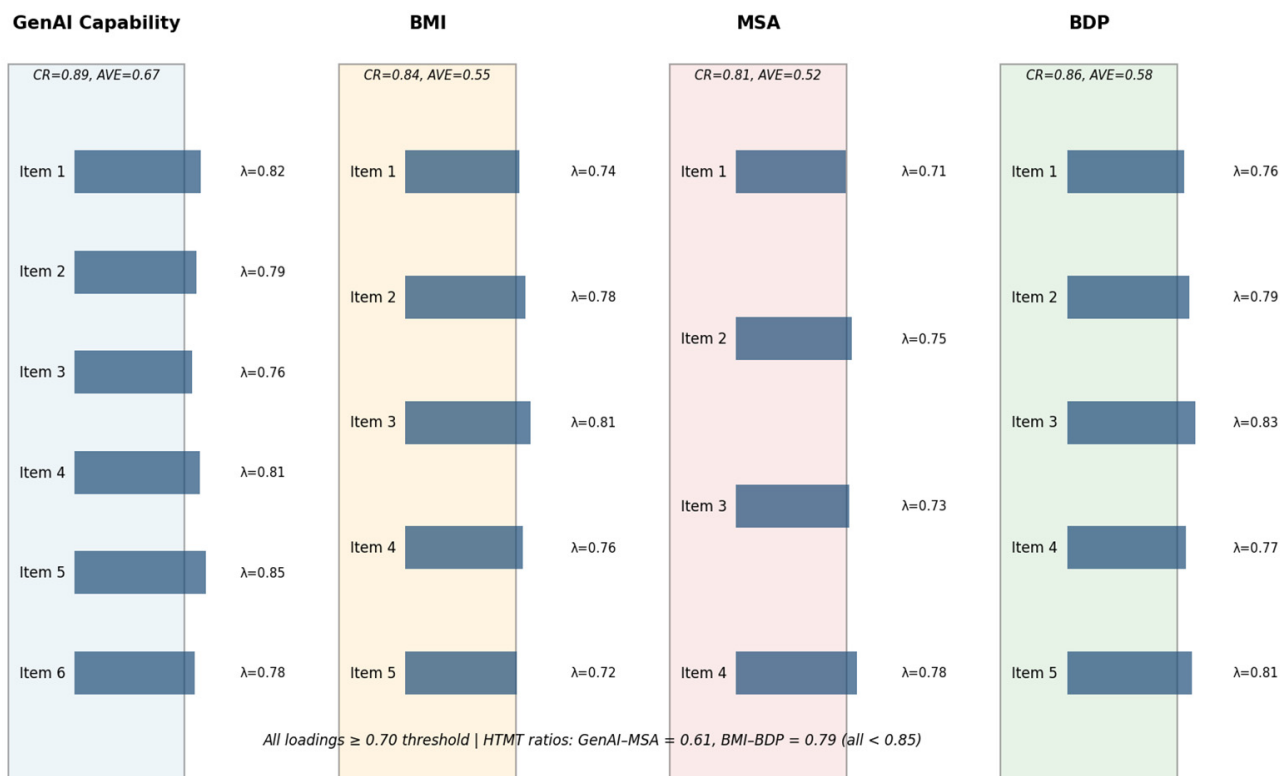


Figure 3. Item-to-construct diagnostic map (loadings and reliability).

The 36% ratio warrants careful interpretation. It means that slightly more than one-third of the total GenAI-to-BDP association passes through deliberate restructuring of value creation, delivery, and capture. The remaining two-thirds travels through more direct channels—faster processing, real-time analytics, lower coordination cost—that do not require business model change. For managers, the ratio carries a practical meaning: investing in AI without changing the business model still produces returns, but those returns are capped at roughly two-thirds of the total potential. The remaining one-third requires the harder organisational work of BMI.

4.5. Moderation and Moderated Mediation (H3, H4)

The interaction term GenAI Capability $\times$ MSA was positive and significant, supporting H3 ($\beta = 0.187$, $t = 3.24$, $p = 0.001$, 95% CI [0.073, 0.301]). Simple slope analysis revealed a substantial difference between high- and low-MSA conditions. At one standard deviation above the mean on MSA, the GenAI-to-BDP path coefficient was 0.498 ($p < 0.001$); at one standard deviation below, it was 0.126 ($p = 0.047$). The gap of 0.372 between the slopes represents qualitatively different strategic realities: high-MSA firms experience GenAI as a strong driver of business development, while low-MSA firms experience it as a marginal contributor.

The index of moderated mediation was positive and significant, supporting H4 (IMM = 0.084, SE = 0.031, 95% CI [0.028, 0.149]). Computed from Equation (4) (Section 3.4), this index captures the change in the indirect effect per unit change in MSA. The conditional indirect effects, computed from Equation (3), were 0.231 at high MSA (95% CI [0.148, 0.321]), 0.175 at mean MSA (95% CI [0.106, 0.256]), and 0.119 at low MSA (95% CI [0.043, 0.204]).

All three estimates are statistically significant, but the high-MSA estimate is almost twice the low-MSA estimate.

Predictive relevance was confirmed: $Q^2 = 0.287$ for BDP and $Q^2 = 0.211$ for BMI, both above the 0.15 threshold for medium predictive relevance.

4.6. Hypothesis Test Summary

Table 6 summarises the path coefficients, *t*-statistics, *p*-values, confidence intervals, and supported-or-not decisions for the four hypotheses. All four are supported.

Table 6. Hypothesis test summary.

H	Path	β	<i>t</i>	<i>p</i>	Decision
H1	GenAI → BDP	0.312	4.87	<0.001	Supported
H2	GenAI → BMI → BDP (indirect)	0.175	4.61	<0.001	Supported
H3	GenAI × MSA → BDP	0.187	3.24	=0.001	Supported
H4	Index of moderated mediation	0.084	2.71	=0.007	Supported

4.7. Robustness Checks

We conducted five robustness analyses to assess the sensitivity of the main estimates.

Alternative PLS specification. Re-estimation with single-indicator constructs produced a GenAI-to-BDP path of $\beta = 0.298$ against 0.312 in the primary model. The close stability indicates that the indicator selection does not drive the main result.

Hierarchical regression replication. A standard hierarchical regression using construct averages confirmed the direction and approximate magnitude of all four hypothesised effects. The interaction term retained significance at $p = 0.003$, supporting H3 outside the latent variable framework.

Multi-group analysis across sectors. We compared services ($n = 126$), manufacturing plus trade combined ($n = 138$), and technology ($n = 36$). The GenAI-to-BMI path differed significantly between services ($\beta = 0.512$) and manufacturing ($\beta = 0.398$) at $p < 0.05$, reflecting higher BMI flexibility in service firms. The GenAI-to-BDP direct path was also stronger in services ($\beta = 0.341$) than in manufacturing ($\beta = 0.276$). The MSA moderation strength was comparable across sectors. Table 7 reports the full MGA results.

Table 7. Multi-group analysis across sectors.

Path	Services ($n = 126$)	Manuf. + Trade ($n = 138$)	Technology ($n = 36$)
GenAI → BMI	$\beta = 0.512$ ***	$\beta = 0.398$ ***	$\beta = 0.467$ **
GenAI → BDP (direct)	$\beta = 0.341$ ***	$\beta = 0.276$ **	$\beta = 0.298$ *
BMI → BDP	$\beta = 0.418$ ***	$\beta = 0.376$ ***	$\beta = 0.351$ **
GenAI × MSA → BDP	$\beta = 0.195$ **	$\beta = 0.181$ **	$\beta = 0.176$ *

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Non-linear test. We added a quadratic term (GenAI²) to the structural model. The quadratic coefficient was marginally significant and negative ($\beta = -0.041$, $p = 0.087$), providing tentative empirical support for diminishing marginal returns at higher levels of GenAI capability.

Extended bootstrap. We re-estimated the structural model with 10,000 bootstrap resamples (against the primary 5000). All confidence intervals shifted by less than 0.005 at either end, confirming the stability of the inference.

Taken together, the robustness checks indicate that the main pattern—positive direct effect, partial BMI mediation, MSA moderation strengthening the indirect path—is not

an artifact of model specification, indicator selection, sectoral composition, or bootstrap configuration.

5. Discussion

5.1. Theoretical Implications

The central finding is that GenAI capability is positively associated with business development performance, but the association runs through organisational reconfiguration as much as through technological access. The significant direct effect (H1) supports the dynamic capabilities argument that capabilities—not raw resources—generate market outcomes. The partial mediation result (H2) refines this argument. BMI carries 36% of the total effect, which is large enough to take seriously as an organisational mechanism, yet small enough to confirm that the remaining 64% travels through direct channels, including faster processing, real-time decision support, and lower coordination friction (Bankins, 2023; Gama, 2023). The dual-channel pattern aligns with the first-order/second-order distinction developed in Section 2.3.

The most theoretically informative finding is the moderated mediation pattern (H3, H4). The conditional indirect effect at high MSA (0.231) is almost twice the corresponding estimate at low MSA (0.119). MSA, in our model, is not a peripheral conditioner but a structural component that determines whether AI investment produces commercially relevant reconfiguration or unfocused experimentation. High-MSA firms read market signals well, direct their BMI activity toward validated opportunities, and convert reconfiguration into customer-facing gains. Low-MSA firms reconfigure on internal logic that the market may not reward. This pattern operationalises the DCT boundary condition argument for the GenAI context—a logic that has been articulated theoretically but rarely tested empirically in emerging-market SME settings (Culot, 2024; Shore et al., 2024).

A second theoretical implication concerns the type of mediation. The partial pattern we observe is more informative than either a null finding or a full mediation finding would be. Full mediation would have implied that GenAI capability has no value outside of business model change, which contradicts the efficiency literature. Null mediation would have implied that organisational reconfiguration is incidental, which contradicts DCT. The partial pattern is conceptually consistent with the integrated DCT–RBV framing: GenAI capability delivers direct functional value as an operant resource and indirect strategic value through the transforming micro-foundation, with the strategic channel meaningful (36%) but not dominant.

A third implication relates to the conceptual separation of MSA from DCT's internal sensing micro-foundation. By positioning MSA as an external interpretive infrastructure that varies independently of the firm's general dynamic capability stock, the model accommodates the empirical fact that firms can be high on one and low on the other. The independence is not assumed; it is reflected in the moderate inter-construct correlation (HTMT GenAI–MSA = 0.61). Future studies that absorb MSA into the capability bundle will miss the moderating role we identify here.

5.2. Comparison with Prior Work

Our path estimate for GenAI to BDP ($\beta = 0.312$) sits between two prior emerging-market estimates: Ameen et al. (2024) reports a comparable AI capability path of approximately $\beta = 0.28$ in a multi-sector creativity context, and Wahab and Radmehr (2024) reports approximately $\beta = 0.34$ for AI assimilation in MENA SMEs. The convergence around the 0.28–0.34 band suggests that the magnitude of the AI–performance association in resource-constrained emerging-market SMEs is now empirically stable.

The 36% mediation share is broadly consistent with [Shore et al. \(2024\)](#), who reports qualitative evidence of partial organisational mediation in UK SMEs adopting GenAI, and with [Gama \(2023\)](#), whose innovation management framework predicts that AI capability shapes performance through both direct routes and innovation process restructuring. Our quantitative ratio refines those accounts by specifying the share carried by deliberate business model change.

The high-MSA conditional indirect effect (0.231) substantially exceeds [Sadeghi \(2024\)](#)'s strategic agility moderation effect (approximately 0.14) for cyber resilience in supply chains. The differential plausibly reflects Jordan's institutional context: where formal market intelligence infrastructure is thin, individual firms' sensing capacity becomes a stronger differentiator than in settings where market data is widely available. [Mariani \(2024\)](#) flags exactly this contextual dependence in his review of generative AI research, calling for emerging-market evidence that this study contributes.

Table 8 expands the positioning matrix from four prior studies in the original submission to eight, with a paragraph-level comparison of methods, contexts, and findings.

Table 8. Positioning relative to prior AI performance studies (expanded).

Study	Context	Method	Key Finding	Gap Addressed Here
Wahab and Radmehr (2024)	SMEs, MENA	CB-SEM	AI assimilation → firm performance	Adds moderation; GenAI-specific construct
Ameen et al. (2024)	Multi-sector	PLS-SEM	AI capability + agility → creativity	Adds BDP outcome; Jordan SMEs
Shore et al. (2024)	SMEs, UK	Qualitative	GenAI → resilience during crisis	Adds quantitative mediator; emerging market
Culot (2024)	Supply chain	SLR	AI: boundary conditions matter	Empirical test, not conceptual
Mariani (2024)	Conceptual	Review	GenAI research agenda	Empirical SME evidence in emerging market
Gama (2023)	Innovation mgmt	Framework	AI capability + innovation	Quantifies mediation share
Sadeghi (2024)	Supply chain	PLS-SEM	Agility moderates AI resilience	Different context, smaller moderation
Sarwar et al. (2023)	Asia Pacific	PLS-SEM	Digital platform + dynamic capability	Different region and platform focus
This study	SMEs, Jordan	PLS-SEM	GenAI → BDP via BMI, moderated by MSA	Moderated mediation; GenAI; MENA

5.3. Practical Implications

The findings have sector-specific managerial implications. For services firms, where BMI flexibility is highest and customer-facing GenAI uses dominate the application profile (68% marketing, 54% customer service), the priority is to convert AI-generated insights into reconfigured value propositions and customer experiences rather than purely internal efficiency. For manufacturing firms, where the GenAI-to-BMI path is weaker, the priority is to pair GenAI deployment with process redesign capacity so that the technology informs how products are designed, sampled, and brought to market, not only how factory operations are coordinated. For technology firms, the priority is to invest in MSA infrastructure that channels code generation and analytics applications toward market-validated product directions.

For policymakers and business support organisations in Jordan, the moderation finding carries a clear message. Subsidising access to AI tools, alone, will not narrow the performance gap between digitally advanced and digitally lagging SMEs. Programmes that develop market sensing capacity—export readiness support, competitive intelligence sharing, sector-level foresight initiatives—are required so that firms direct AI-enabled reconfiguration toward viable rather than speculative opportunities. The 0.231 versus 0.119 conditional indirect effect contrast suggests that the policy return on MSA-building infrastructure may exceed the return on additional AI access subsidies for the lower half of the MSA distribution.

For researchers working on AI adoption in MENA, the model offers a testable structure that can be extended to neighbouring economies—Lebanon, Tunisia, Morocco, Egypt—with similar institutional features. We do not claim Jordan is representative of the MENA region; we claim only that the moderated mediation logic identified here travels to settings where decision authority is concentrated and formal business intelligence infrastructure is thin.

5.4. Non-Linear Patterns

The marginally significant negative quadratic term ($\beta = -0.041$, $p = 0.087$) in the robustness checks provides tentative evidence for diminishing marginal returns at higher levels of GenAI capability. The interpretation must be cautious. Cross-sectional data cannot establish a true curvature in the underlying relationship, and a p -value of 0.087 is on the boundary of conventional significance. The pattern is consistent, however, with a saturation argument: beyond a threshold of integration depth, additional GenAI capability yields smaller incremental BDP gains because the easy reconfigurations have already been made. Longitudinal designs are required to confirm or reject this account.

5.5. Sectoral Heterogeneity

The multi-group analysis revealed meaningful sectoral variation in the GenAI-to-BMI path: services ($\beta = 0.512$) versus manufacturing ($\beta = 0.398$), $p < 0.05$. Three interpretations are plausible. Services firms have lower switching costs in altering value propositions, which makes BMI a faster channel. Manufacturing firms face capital intensity barriers to business model change that GenAI alone cannot dissolve. Technology firms, despite being most exposed to GenAI, showed a smaller MGA estimate than services, plausibly because their baseline BMI activity is already high. The pattern argues against treating SMEs as a homogeneous category in AI adoption research and suggests that sector-by-sector analysis should become standard in this literature.

5.6. GenAI Maturity Pathway for SMEs

We synthesise the findings into a four-stage maturity pathway. Stage 1, Awareness, is the recognition that GenAI is relevant to the firm's value proposition. Stage 2, Experimentation, involves pilot deployments in well-bounded tasks—content drafting, basic customer service automation—with no business model implications. Stage 3, Integration, is the embedding of GenAI outputs into routine decision-making, where the Organisational Embeddedness dimension of capability becomes visible. Stage 4, Transformation, is the explicit reconfiguration of how the firm creates and delivers value, drawing on AI inputs and validated by market sensing. Our data suggest that BDP gains accelerate sharply between Stage 3 and Stage 4 for high-MSA firms but plateau at Stage 3 for low-MSA firms whose reconfiguration ambitions are not grounded in market reading. Figure 4 illustrates the pathway.



Figure 4. GenAI maturity pathway for SMEs.

5.7. Boundary Conditions: Institutional and Regulatory Context

Two boundary conditions deserve attention. First, the Jordanian regulatory environment for AI is in formation: data protection rules are being developed, and sectoral guidance for AI use in finance and healthcare is incomplete. This means the patterns observed here may shift as formal regulation matures and as firms internalise compliance costs. Second, competitive intensity varies sharply across the sectors in our sample. Where competitive pressure is high—as in fintech and digital services—the returns to MSA-conditioned BMI are likely amplified, because the cost of misreading the market is higher. Where competitive pressure is low—as in some segments of traditional trade—the same model may yield smaller estimates. These boundary conditions are worth examining in future cross-national replications.

6. Conclusions, Limitations, and Future Research

6.1. Conclusions

This study set out to understand how generative AI capability is associated with business development performance in Jordanian SMEs and under what conditions the association is strongest. The short answer is that the conversion is not automatic. Business model innovation carries roughly one-third of the total effect, and market sensing agility determines how much of the mediated benefit is actually realised. High-MSA firms that reconfigure their business models in response to AI-enabled insights experience an association that is almost twice as strong as that of their low-MSA counterparts.

For practice, the implication is direct. Adopting GenAI tools is necessary but not sufficient. The firms in this sample that captured the strongest returns were the ones that used AI-generated insights to rethink what they offer and to whom, while keeping a clear read on where their market was moving. For theory, the study contributes an empirically validated specification of the organisational conditions under which AI-to-performance conversion holds in an emerging-market SME setting—conditions that prior work has discussed but rarely tested together.

Three contributions stand out. First, the integrated DCT–RBV framing separates GenAI as an operant resource from the firm’s capacity to use it as a dynamic capability, resolving a recurring conflation in the literature. Second, the moderated mediation specification

quantifies how a firm's external interpretive infrastructure (MSA) shapes the return on AI-enabled business model change. Third, the Jordanian SME evidence base extends the geographic range of AI performance research beyond advanced economies, addressing a gap that recent reviews have flagged repeatedly.

6.2. Limitations

Several limitations should be considered when interpreting the findings. The most consequential is the cross-sectional design. While PLS-SEM produces directional path estimates, the design cannot establish temporal precedence or rule out reverse causality interpretations. A longitudinal study of GenAI capability, BMI, and BDP across multiple time points would permit stronger causal inference and capture the feedback dynamics between AI adoption and organisational reconfiguration that cross-sectional data necessarily flatten.

The sampling frame—formally registered Jordanian SMEs reached through business networks—probably over-represents firms that are more organised and digitally aware. This is a familiar weakness of SME survey research, but it implies that the findings cannot be extended to the full distribution of smaller firms in Jordan, many of which operate informally. Replication studies in Lebanon, Morocco, Egypt, and Saudi Arabia would help establish how much of the pattern is institutionally specific to Jordan and how much is a regional regularity.

A third limitation is the reliance on single-respondent self-report perceptual measures. Procedural safeguards minimise but cannot eliminate common method variance. Objective indicators such as revenue growth, customer acquisition counts, and partnership registers would provide more independent triangulation of BDP than survey items alone.

Fourth, the model is intentionally parsimonious. The organisational mechanisms through which GenAI capability can influence performance are not limited to BMI and MSA. Digital literacy, knowledge management practices, absorptive capacity, and competitive intensity are all plausible additional mediators and moderators that future work should consider, ideally with larger samples that can accommodate the additional parameter load.

A final consideration. Generative AI is evolving faster than the academic publication cycle can track. Our constructs capture the state of GenAI adoption at the data collection window. Agentic AI systems, multimodal reasoning architectures, and embedded enterprise AI platforms are advancing rapidly, and the practical definition of GenAI capability will shift accordingly. Future measurement instruments will need to track this shift directly rather than treat adoption as a yes-or-no variable.

6.3. Future Research Directions

Several directions follow from the limitations.

Longitudinal designs. The most useful next step is a panel study that tracks GenAI capability, BMI, and BDP at three or more time points across the same firms. This design would permit time-lagged analysis, allow tests of reverse causality, and reveal whether the BMI and MSA effects strengthen, attenuate, or shift in mechanism as firms mature in their GenAI use.

Multi-source data. Combining survey responses on capability and MSA with objective performance measures (revenue growth, customer acquisition data, partnership counts) drawn from firm records or third-party data providers would address the perceptual measure limitation and yield stronger external validity.

Additional moderators. Institutional conditions (Scott's regulative, normative, and cognitive pillars), competitive intensity (Porter), and industry-specific technological turbulence are all theoretically promising moderators. Each warrants explicit testing with sample sizes adequate for the resulting latent interaction structures.

Cross-national replication. The MENA region offers a natural test bed for the model. Comparable studies in Lebanon, Tunisia, Morocco, Egypt, and Saudi Arabia would establish whether the moderated mediation pattern travels and would help map the institutional boundary conditions of the GenAI–performance link.

Sectoral comparison. The MGA results indicate sectoral heterogeneity that deserves direct comparative investigation. Future work should design samples balanced across services, manufacturing, trade, and technology and test for sector-specific path strengths rather than treating SMEs as one population.

Extension to large firms. Whether the same moderated mediation pattern holds in larger firms is an open question. Decision authority is more distributed, BMI cycles are slower, and MSA infrastructure may be more formalised. Comparative studies of SMEs and large firms within the same economy would test the boundary conditions of the present findings.

Non-linear and threshold dynamics. The marginal quadratic finding ($p = 0.087$) suggests possible diminishing returns at higher GenAI capability levels. Larger-sample studies designed with non-linear hypotheses in mind would help establish whether the curvature is real and where the saturation threshold sits in practice.

Dimension-level analysis. Future studies should examine the three dimensions of GenAI capability (Data Infrastructure, Model Competence, Organisational Embeddedness) as distinct constructs in their own right, rather than as components of a higher-order specification.

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Appendix A. Complete Survey Items

All items measured on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree).

Generative AI Capability (GAI)—six items, three dimensions

Item	Wording
GAI1 (DI)	Our firm has organised data assets that can be used by GenAI tools.
GAI2 (DI)	Our data is accessible in a format that GenAI applications can ingest reliably.
GAI3 (MC)	We evaluate which GenAI tool fits a given task before deploying it.

Item	Wording
GAI4 (MC)	We can configure prompts and inputs to obtain useful outputs from GenAI tools.
GAI5 (OE)	GenAI outputs are integrated into our routine decision-making processes.
GAI6 (OE)	Our team uses GenAI as part of regular workflows, not as one-off experiments.

Source: Adapted from [Mariani \(2024\)](#); [Gama \(2023\)](#). DI = Data Infrastructure; MC = Model Competence; OE = Organisational Embeddedness.

Business Model Innovation (BMI)—five items

Item	Wording
BMI1	We have introduced novel value propositions to our customers in the last two years.
BMI2	We have reconfigured our delivery channels to reach customers more effectively.
BMI3	We have adjusted our revenue model in response to changing market conditions.
BMI4	We actively develop new partnerships that extend our business ecosystem.
BMI5	We restructure how we create and capture value when opportunities arise.

Source: Adapted from [Zahoor et al. \(2023\)](#); anchored on [Zott and Amit \(2010\)](#).

Market Sensing Agility (MSA)—four items

Item	Wording
MSA1	We continuously scan our market for new signals and opportunities.
MSA2	We interpret market signals quickly and translate them into action plans.
MSA3	We respond rapidly when we detect a shift in customer needs or competitor moves.
MSA4	We integrate market intelligence into our strategic decisions on a regular basis.

Source: Adapted from [Ameen et al. \(2024\)](#); [Sadeghi \(2024\)](#); anchored on [Pavlou and El Sawy \(2011\)](#).

Business Development Performance (BDP)—five items

Item	Wording
BDP1	We have acquired a meaningful number of new customers in the last 12 months.
BDP2	We have formed valuable new business partnerships recently.
BDP3	Our revenues have grown noticeably over the last year.
BDP4	Our competitive position in our main market has strengthened.
BDP5	We have achieved most of our business development goals for the period.

Source: Developed by the authors, informed by the business development performance literature.

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