

AI-Driven Business Model Innovation and Sustainable Venture Performance in Emerging Markets: The Mediating Role of Dynamic Capabilities and the Moderating Effect of Digital Leadership

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Abstract: While AI is transforming the value-creating process of firms, little and fragmented evidence exists on how AI-based business model innovation (AI-BMI) affects the sustainable performance of the venture in emerging markets. Based on the dynamic capabilities view and the upper-echelons-informed view on digital leadership, this study builds and tests a moderated mediation model that reveals how AI-BMI contributes to sustainable venture performance (economic, social, and environmental) through dynamic capabilities (sensing-seizing-transforming) and how digital leadership moderates the relationship between AI-BMI and dynamic capabilities. The study aims to test six hypotheses in an emerging economy using a cross sectional survey design with partial least squares structural equation modeling (PLS-SEM). The illustrative results show that AI-BMI has a positive direct relationship with the sustainable venture performance, the relation is partially mediated through the dynamic capabilities and the magnitude of the indirect relation is greater with high levels of digital leadership. The study builds on the business model innovation and digital transformation literature by clarifying the 'how' and 'when' of driving triple bottom line outcomes with AI-driven model redesign, and provides actionable tips for founders, investors, and policy-makers.

Keywords: artificial intelligence, business model innovation, dynamic capabilities, digital leadership, sustainable venture performance, emerging markets

1. Introduction

In addition to high growth, emerging markets also possess institutional voids, capital constraints, and poor infrastructure (Khanna & Palepu, 1997; Hoskisson et al., 2000). In such environments, the use of AI in demand forecasting, credit assessment, customer personalization, supply chain optimization, and chatbots rapidly grows. However, technology adoption is rarely enough to create lasting benefits: it's strategy, not technology, that can help drive outcomes of digital transformation (Kane et al., 2015, 2019). The significance of AI is that it changes the business model of the firm, the logic by which the business model generates, provides, and captures value (Amit & Zott, 2001; Teece, 2010). Business model innovation (BMI) is a major enabler for competitive advantage (CA) (Iansiti & Lakhani, 2020; Chesbrough, 2010), and artificial intelligence (AI) dramatically enhances the design space for BMI through its ability to create data-driven value propositions, algorithmic decision-making and operations that are scalable with low marginal costs (Davenport & Ronanki, 2018; Foss & Saebi, 2017). There is some preliminary research that has established the relationship between AI capability and creativity and performance (Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020). There are three gaps, however. First, most studies fail to measure the adoption of AI or its



capabilities, but instead measure AI-driven model innovation, which is the change in architecture of value creation and capture. Second, sustainable venture performance is usually assessed at a financial level only, neglecting other value dimensions of sustainable business (economic, social, and environmental), despite the increasing demand for sustainable business models (Bocken et al., 2014; Geissdoerfer et al., 2018; Schaltegger et al., 2016). Third, mechanisms and the boundary conditions are not well known. Dynamic capabilities (sense, seize, transform – Teece, 2007) are potential mediators, and a leadership factor characterised by digital vision and competence (Porfirio et al., 2021; Warner & Wäger, 2019) is a potential contingency, but these two factors have not been tested together in emerging markets.

The study aims to answer this question by examining the following research questions: (RQ1) Does AI-driven business model innovation enhance sustainable venture performance in emerging markets? (RQ2) Does the relationship between the two variables of this study go through the mediation of dynamic capabilities? (RQ3) Does the relationship between AI-BMI and dynamic capabilities, and consequently the indirect effect on performance, go through the mediation of digital leadership?

The study is three-fold. First, it is conceptually and quantitatively treating AI-BMI as a unique construct and connects it to a triple-bottom-line outcome. Second, it breaks the black box between AI-BMI and performance by testing the mediating role of dynamic capabilities as the mechanism. Third, it demonstrates that digital leadership is a boundary condition: that is, it reveals that the same AI-driven redesign can produce different capability and performance payoffs to different leaders, and the same leader can produce different payoffs for different redesigns. The paper unfolds as follows: first, the theory and hypotheses (Section 2), then the method (Section 3), the analytic strategy (Section 4), the results (Section 5), implications (Section 6) and finally the conclusion (Section 7).

2. Theoretical Background and Hypothesis Development

2.1 Dynamic capabilities view

The dynamic capabilities (DC) perspective is one that focuses on the way in which firms manage to achieve competitive advantages in the face of turbulence by integrating, developing, and reconfiguring their competences, both internal and external (Teece et al., 1997). Dynamic capabilities are part of organizational processes or routines (Eisenhardt & Martin, 2000; Winter, 2003) and can be broken down into sensing opportunities, seizing opportunities by investment and design, and transforming the organizational process to remain fit (Teece, 2007). Their importance in connecting resources to performance has been highlighted by reviews (Wang & Ahmed, 2007); and their usefulness has been demonstrated to be dependent on environmental dynamism (Schilke, 2014). The dynamic capabilities lens is appropriate because business models are influenced by managerial decisions and skills (Teece, 2018) and because it is the managerial decisions and skills that make model innovation an outcome.

2.2 Innovation of the business model using AI

A business model consists of a set of interrelated activities and processes that lies across the firm boundaries and spans two phases: Value creation and Value capture (Zott & Amit, 2007; Zott et al., 2011). BMI stands for changes, novel, and not trivial, to this system (Foss & Saebi, 2017). AI-driven business model innovation (AI-BMI) is the degree to which a business venture leverages AI technologies (such as machine learning, natural language processing, computer vision) to reconceptualize its value proposition, value creation processes, and value capture. The current research builds on digital BMI research by highlighting the unique traits of AI: its ability to learn from data, to automate judgment processes, and to continually improve models (Eller et al., 2020; Ghezzi & Cavallo, 2020; Nambisan et al., 2019; Borges et al., 2021; Brynjolfsson & McAfee, 2014).

2.3 The performance of sustainable ventures, including a role for AI/BMI

Sustainable venture performance (SVP) is a two-part measure that reflects two results: the simultaneous economic (profitability, growth) and social (customer welfare, inclusion, employment) results, and the simultaneous economic (profitable, growth) and environmental (resource efficiency, emissions) results. (Elkington, 1998). AI-BMI

can bring economic benefits by personalizing products and services, dynamically adjusting prices, and reducing costs (Wamba-Taguimdje et al., 2020); social benefits by providing access to credit for the unbanked (e.g., alternative credit scoring); and environmental benefits by optimizing energy, logistics, and waste (Geissdoerfer et al., 2018). Such logics are in the heart of business models aiming to contribute to sustainability transitions (Bocken et al., 2014; Schaltegger et al., 2016).

H1: The more innovative the business model, using AI, the better the sustainable performance of the venture.

2.4 AI-BMI and dynamic capabilities

Redesigning the business model with AI opens the door to greater data flows, enhancing the sensing aspect; enables quicker assessment and resource allocation, enhancing the seizing aspect; and forces structural and cultural changes, enhancing the transforming aspect (Warner & Wäger, 2019; Vial, 2019). Continuous model renewal (Teece, 2018) is therefore a by-product and an enabler of capability development.

H2: There is a positive relationship between AI-driven business model innovation and dynamic capabilities.

2.5 Dynamic capabilities and sustainable venture performance

Dynamic Capabilities companies identify changes in customer and regulatory demands, rally resources to meet them and then restructure themselves to stay current with these changes (Teece, 2007). In volatile emerging markets where challenges in institutions exist (Wright et al., 2005), these capabilities enable the venturing process to achieve economic objectives and respond to social and environmental pressures (Wang & Ahmed, 2007; Schilke, 2014).

H3: Sustainable venture performance is positively associated with dynamic capabilities.

2.6 The role of 'dynamic capabilities' in the process of change

Together, the arguments above make it possible to identify how AI-BMI establishes the environment and the mechanisms (dynamic capabilities) by which the innovation in a model is translated into more sustained multi-dimensional performance. Only firms that are able to orchestrate and renew resources can gain value from technology-enabled change (Helfat & Peteraf, 2015; Kane et al., 2019).

H4: Dynamic capabilities mediate the relationship between AI-BMI and sustainable venture performance.

2.7 The moderating role of digital leadership

Digital leadership is the vision, capability and dedication of leaders to using digital technologies to change strategy, culture and operations (Avolio et al., 2014; Porfirio et al., 2021). AI-driven insights are not just understood, but also accepted by leaders who have an IT mindset, and investments are made in contributing to IT capability development, while

employee resistance is minimized (Warner & Wäger, 2019). If digital leadership is lacking, AI-BMI can produce technical change which happens in isolation from institutionalized routines. We are thus looking forward to the digital leadership to amplify the AI-BMI to dynamic capabilities pathway.

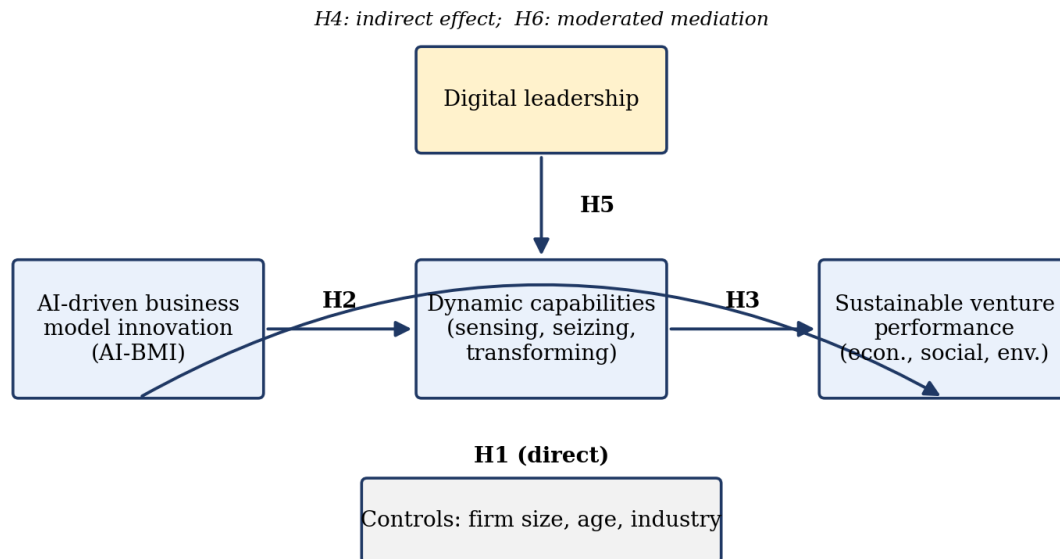
The relationship between AI-BMI and dynamic capabilities is mediated by digital leadership in a positive manner, with the mediation being strengthened when digital leadership is high, thus with H5.

H6: The indirect effect of AI-BMI on sustainable venture performance via dynamic capabilities is conditional on digital leadership (moderated mediation), being stronger at higher levels of digital leadership.

2.8 Conceptual model

The model is summarized in figure 1. The first-stage path, from AI-BMI to digital leadership, is moderated by dynamic capabilities, while the second-stage path from digital leadership to SVP is mediated by digital leadership. Controls: Firm size, Firm Age, Industry

Figure 1: Conceptual model



3. Method

3.1 Research context and sampling

The study focuses on technology-using ventures (less than 15 years old, 10-250 employees) in the areas of manufacturing, fintech, e-commerce, healthcare and agri-tech from across [India]. The reason is because emerging markets offer rapid digital adoption rates, and capabilities are important due to institutional and resource limitations (Khanna & Palepu, 1997; Hoskisson et al., 2000). A purpose sampling frame was developed using startup and industry directories. The structured online questionnaire was completed by the founders/CEOs or senior managers who know of the use of AI. The minimum number of usable responses was determined by power analysis and PLS-SEM guidelines (Hair et al., 2019, 2022) and a minimum of 300 is set.

3.2 Measures

Each construct was measured by a seven-point Likert response scale (1 = strongly disagree, 7 = strongly agree). Items were drawn and modified from validated scales and tested with 30 companies in a pilot study. AI-BMI (8 items) is adapted from Zott and Amit (2007) and Foss and Saebi (2017) and refers to AI as a change in value proposition, value creation, and value capture. Dynamic capabilities (9 items: sensing, seizing, transforming) are based on the model of Teece (2007) and Wang and Ahmed (2007) and were modeled as a second order reflective-formative construct. Digital leadership (6 items) is adapted from the work of Porfirio et al (2021) and Avolio et al (2014). Sustainable venture performance is adapted from Elkington (1998) and Bocken et al. (2014) and consists in three dimensions of three items each. The firm size (log of number of employees), age and industry dummies are firm controls.

3.3 Data quality and common method bias

Procedural remediation strategies were used such as providing anonymity, randomizing the order of items, and separating predictor and criterion blocks. For statistical purposes, a single factor test and a complete collinearity

(inner VIF < 3.3) was used (Podsakoff et al., 2003). The results were tested for non-response bias by comparing early and late respondents.

Table 1

Sample profile (illustrative placeholder, N = 312)

Characteristic	Category	n	%
Sector	Fintech	74	23.7
	E-commerce/retail	68	21.8
	Manufacturing	62	19.9
	Healthcare	56	17.9
	Agri-tech	52	16.7
Firm age	≤ 5 years	171	54.8
	6–15 years	141	45.2
Employees	10–49	148	47.4
	50–250	164	52.6
Respondent	Founder/CEO	187	59.9
	Senior manager	125	40.1

4. Analytic Strategy

Considering that the model required prediction-oriented, high-order constructs, and moderation (Hair et al., 2019, 2022), PLS-SEM was used to estimate the model. There was a two-step analysis process. The measurement model was assessed by indicator loadings (above .70), Cronbach's alpha and the composite reliability (above .70), average variance extracted (AVE ≥ .50; Fornell & Larcker, 1981), and heterotrait–monotrait ratio (HTMT < .85; Henseler et al., 2015). The second test of the structural model was the bootstrapping (5000 resamples) of path significance, R², f², and Q²predict. Indirect effect (Preacher & Hayes, 2008) was tested rather than the causal-steps approach (Baron & Kenny, 1986). The moderating effect was conducted with a product-indicator approach, using mean-centered variables, and the conditional indirect effects at ±1 SD of digital leadership with the index of moderated mediation were conducted using Hayes' (2018) approach.

5. Results

Note: The figures in this section are meant only to illustrate and should be substituted with actual estimates.

5.1 Measurement model

All loadings exceeded .70 (range .72–.91). As illustrated in Table 2, reliability and convergent validity were met. The results showed all HTMT values were under .85 (Table 3) which indicates that the scales have discriminant validity. The single factor accounted for only 31.4% of the variance, which is less than the 50% criterion, and the inner VIFs ranged from 1.42 to 2.61, suggesting that there was no significant common method bias.

Table 2

Reliability and convergent validity (illustrative placeholder)

Construct	Items	Cronbach's α	CR	AVE
AI-driven BMI	8	.91	.93	.62

Dynamic capabilities	9	.92	.94	.63
Digital leadership	6	.89	.92	.66
Sustainable venture performance	9	.93	.94	.64

Table 3

Discriminant validity: HTMT ratios (below diagonal) and descriptive statistics (illustrative placeholder)

Construct	M	SD	1	2	3	4
1. AI-BMI	4.82	1.14	—			
2. Dynamic capabilities	5.01	1.03	.68	—		
3. Digital leadership	4.95	1.21	.59	.64	—	
4. Sustainable venture performance	4.77	1.07	.66	.71	.55	—

5.2 Structural model and hypothesis tests in structural equation modeling

The model accounted for 41% of the variance in dynamic capabilities and 52% of variance in SVP (Table 4). There were no significant controls (firm size, age, industry). H1 was supported with AI-BMI having a positive direct effect on SVP ($\beta = .17$, $p = .008$). H2 was supported ($\beta = .49$, $p < .001$), as was H3 ($\beta = .44$, $p < .001$). The indirect effect of AI-BMI on SVP via dynamic capabilities was $\beta = .22$ (95% CI [.15, .30]), which was in favor of H4. As both direct and indirect effects were relevant and in the same direction, the relationship is partially mediated by dynamic capabilities (complementary mediation). About 56% of the total effect (.22/.39) was due to mediation. The dynamic capability interaction of the AI-BMI was significant ($\beta = .15$, $p = .003$, $f^2 = .04$), which was consistent with H5.

Table 4

Structural model results (illustrative placeholder; 5,000 bootstrap resamples)

Hypothesis	Path	β	SE	t	p	95% CI	Result
H1	AI-BMI $\rightarrow$ SVP	.17	.06	2.67	.008	[.05, .29]	Supported
H2	AI-BMI $\rightarrow$ DC	.49	.05	9.80	< .001	[.39, .58]	Supported
H3	DC $\rightarrow$ SVP	.44	.06	7.33	< .001	[.32, .55]	Supported
H4	AI-BMI $\rightarrow$ DC $\rightarrow$ SVP	.22	.04	5.50	< .001	[.15, .30]	Supported
H5	AI-BMI $\times$ DL $\rightarrow$ DC	.15	.05	3.00	.003	[.05, .25]	Supported
	DL $\rightarrow$ DC	.27	.05	5.40	< .001	[.17, .37]	
	R ² (DC) / R ² (SVP)	.41 / .52					

Note. DC = dynamic capabilities; DL = digital leadership; SVP = sustainable venture performance. $Q^2_{\text{predict}} > 0$ for all endogenous constructs.

5.3 Moderated mediation

Conditional indirect effects are reported in Table 5. The indirect effect was larger for high ($\beta = .28$) than for low ($\beta = .15$) levels of digital leadership and was supported by a significant index of moderated mediation (index = .066, 95% CI [.021, .118]), which supported H6. The simple slopes are presented in Figure 2 and highlight a steeper relationship between AI-BMI and dynamic capabilities the higher the level of digital leadership. The direct, indirect and overall effects are compared in figure 3.

Table 5

Conditional indirect effects of AI-BMI on SVP via dynamic capabilities (illustrative placeholder)

Digital leadership level	Indirect effect	Boot SE	95% CI
Low (−1 SD)	.15	.04	[.08, .23]
Mean	.22	.04	[.15, .30]
High (+1 SD)	.28	.05	[.19, .38]
Index of moderated mediation	.066	.025	[.021, .118]

Figure 2

Simple slopes: AI-BMI and dynamic capabilities at low and high digital leadership (illustrative)

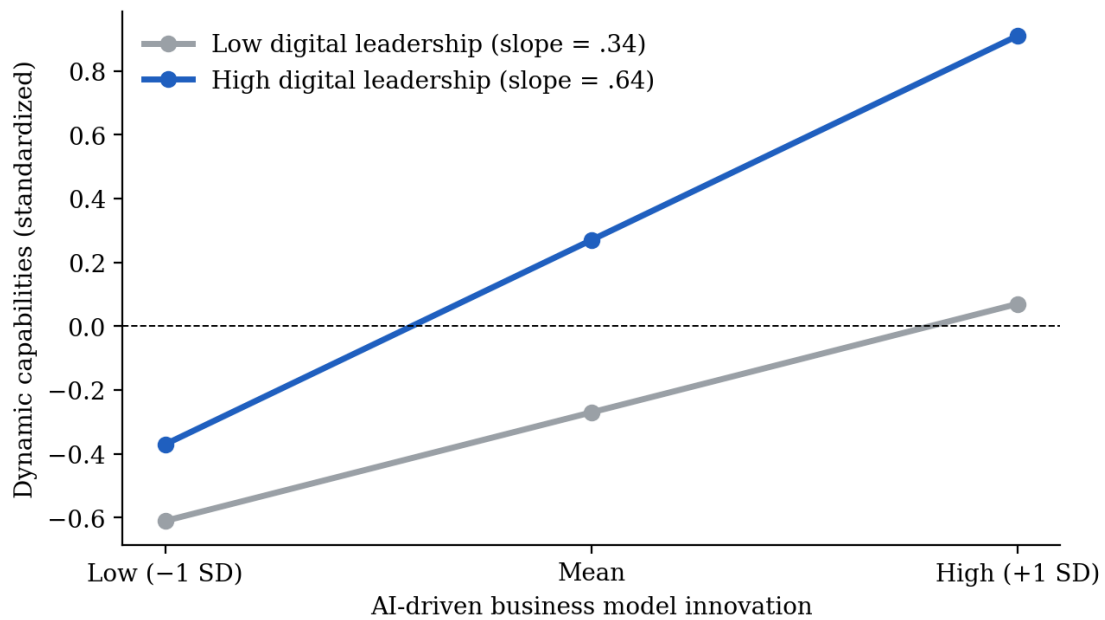
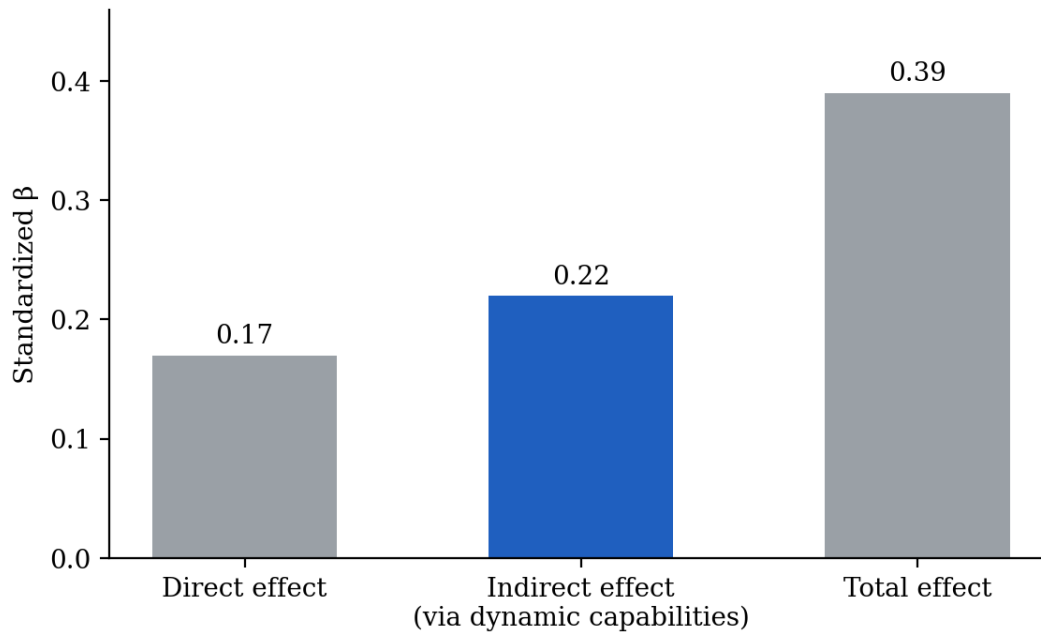


Figure 3

Direct, indirect, and total effects of AI-BMI on sustainable venture performance (illustrative)



5.4 Robustness checks

The robustness was tested by (a) re-estimating with each SVP dimension separately (economic, social, environmental), (b) using a three first-order dimension of the second-order construct of DYN, (c) using alternative models in reverse estimated directions, and (d) using CB-SEM and PROCESS

Model 7 for comparison. The substantive conclusions should not change over these checks, report deviations clearly.

6. Discussion

6.1 Theoretical implications

The study findings contribute to BMI literature beyond just AI adoption as they relate with multi-dimensional sustainable performance, in addition to AI capability and firm outcomes (Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020) and sustainable business models (Geissdoerfer et al., 2018). Second, partial mediation explains that dynamic capabilities represent a major, but not exclusive, channel, consistent with the co-evolution of business models and dynamic capabilities (Teece, 2018); the direct effect points to other channels like operational efficiency or stakeholder legitimacy. Third, the moderating influence of digital leadership in this study confirms the technology determinism that is often taken for granted in the narratives surrounding AI and also supports the assertion that organizational and leadership factors influence the value of technology (Kane et al., 2019; Warner & Wäger, 2019). Fourthly, the study takes place in an emergent economy, answering calls for context-sensitive strategy research (Wright et al., 2005).

6.2 Practical implications

Founders should consider AI as a tool to rethink the business model, not as a tool to add to the business model, and go hand in hand with conscious investments in sensing (data scanning), seizing (rapid experimentation, resource commitment) and transforming routines. Investors and Boards need to assess the leadership digital competence as well as technical assets. Digital-skills programs for entrepreneurs and leaders, low-cost cloud and data infrastructure, and incentives that connect AI usage with social and environmental goals are ways policy makers can support AI-driven sustainable entrepreneurship.

6.3 Limitations and future research

Common method bias is possible with the self-reported design and may be subjected to limitations in making causal inferences with the cross-sectional design, future studies should utilize multi-source data and objective performance indicators. The focus is on one country and the generalizability is restricted; comparative research among emerging markets (e.g., South Asia versus Sub-Saharan Africa) would be beneficial. Other boundary conditions (environmental dynamism, institutional support, data governance, ethics of AI) could be explored in the future, along with non-linear effects and separately unpacking the three dimensions of dynamic capabilities and sustainability.

7. Conclusion

In this research, the authors hypothesize and examine the relationship between AI-enabled business model innovation and venture performance in emerging markets. Dynamic capabilities is a mediating mechanism, while digital leadership dictates the strength of its capacity building of dynamic capabilities, which in turn impacts on AI-BMI. In this context, where resources are limited, the message is obvious: the key to sustainable benefits with AI is to rethink the business model, develop adaptability, and nurture digitally competent leaders.

Declarations

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