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Generative Artificial Intelligence and Sustainable Entrepreneurship: Redefining Business Leadership, Marketing Excellence, and Governance Practices

Dr. Santanu Roy[1*], Dr. R Ganesh Kumar[2], Prof. Abhijeet Wairagade[3], Dr. Panduarng Sudamrao Dabhade[4], Prof. (Dr.) Ajay Bhushan Prasad[5]

[1*]Professor, I.I.L.M Institute for Higher Education, New Delhi, India, Email Id: rsan58@yahoo.co.uk , Orcid Id: 0000-0003-4566-1040
[2]Associate Professor, Department of Management Studies and Research Centre, B.M.S. College of Engineering, PO BOX 1908, Bull Temple Road, Bangalore – 560004
Email Id: ganeshkumarr.mba@bmsce.ac.in Orcid Id: 0000-0002-1472-5585
[3]Assistant Professor, Marketing, MET Institute of PGDM, Mumbai, Maharashtra, India.
Email Id: abhijeetwairagade86@gmail.com, Orcid Id: 0009-0004-2063-5166
[4]Assistant Professor, Department of Economics, Specialization in Development Economics, Shree. Bankat Swami College Beed, Email Id: rjdabhade2013@gmail.com , Orcid Id: 0009-0005-9926-9839
[5]Associate Professor, Gopal Narayan Singh University, Jamuhar, Rohtas, Bihar, Pin Code-821305 India
Email Id- drajaybhushan@gmail.com, Orcid Id : 0009-0005-9989-9582

Abstract
The advent of generative AI is having a profound impact on entrepreneurial strategy, organizational innovation, leadership, and long-term competitive performance. This study explored the impact of the adoption of artificial intelligence on the process of entrepreneurial transformation toward sustainability in terms of leadership support, business model innovation, sustainable competitive advantage, institutional support, cost effectiveness, and firm performance. The study adopted a quantitative secondary-data design and had a managerial dataset of 325 observations. Partial Least Squares Structural Equation Modelling was utilised to assess the measurement reliability, construct validity, structural linkages, explanatory power, and indirect effects. It was discovered that the measurement model had acceptable Average Variance and Cronbach's alpha values over 0.80. extracted values greater than 0.65, demonstrating convergent validity and adequate dependability. The structural results indicated that the use of AI had significant impacts on business model innovation, sustainable competitive advantage, and firm performance. The top direct result of business model innovation was that it created a firm's strongest direct link to its performance, followed by sustainable competitive advantage. AI adoption was strongly encouraged by leadership support, and government support had positive impacts on AI adoption, leadership support and cost effectiveness. Important indirect effects also suggested that AI has impacts on organizational performance via innovation and sustainable competitive capability. The overall results indicate that the strategic contribution of AI is highly reliant on leadership, innovation, institutional support, and responsible organizational practices.

Keywords: Generative artificial intelligence; sustainable entrepreneurship; business model innovation; leadership support; sustainable competitive advantage

Introduction

In today's business landscape, generative artificial intelligence (GenAI) has become an AI revolution that has reshaped the way organizations develop knowledge, design products, communicate with customers, and make decisions. While previous types of AI used to analyze, predict or optimize existing information, GenAI can create text, images, code, ideas, or decision-support content, introducing a wider range of possibilities for human–machine collaboration in entrepreneurial contexts (Hermann & Puntoni, 2024; Kirk & Givi, 2025). This evolution has sparked growing interest among organisations regarding GenAI adoption and the prospect of redefining innovation, productivity, and competitive strategy (Kumar et al., 2025). Concurrently, the increased use of artificial intelligence (AI) has given rise to new managerial, ethical, and policy challenges for organizations to address, which demand a balance between technological opportunity and accountability and responsible use (Dwivedi et al., 2021). This has sparked these debates, as conversational GenAI systems are accessible, enabling entrepreneurs and managers to incorporate AI into their everyday business operations, strategic planning, communication, and decision-making processes (Dwivedi et al., 2023).

The elevation of GenAI is particularly considerable for sustainable entrepreneurship, where companies aim to generate sustainable economic value along with environmental and social considerations. With a growing importance of entrepreneurial success not only in terms of profit but also in terms of resilience, responsible innovation, resource efficiency, and social contribution (Abbas & Bulut, 2024), the field of

sustainable entrepreneurship has grown into a significant research field. AI and big-data tools can support sustainable entrepreneurship in several ways, such as enhanced opportunity recognition, resource planning, innovation processes, and evidence-based decision-making (Bickley et al., 2025). AI-based business models can also play a role in the sustainability-oriented transformation by enhancing efficiency and supporting the redesign of value creation, value delivery and value capture (Di Vaio et al., 2020). GenAI also opens new avenues for ideation, experimentation, product development and business model innovation at comparatively low marginal costs (Kanbach et al., 2024).

Leadership is a essential factor that determines the successful implementation of AI in business and its impact on entrepreneurial results. The strategic value that can be reached with the exploitation of AI technologies hinges on managerial commitment, organizational readiness, employee involvement and the proper combination of these technologies into the occurring decision systems. The automation–augmentation view states that managers should decide which tasks to automate and in which tasks to apply human expertise to complement AI tasks (Raisch & Krakowski, 2021). In sustainable entrepreneurship, balancing digital transformation with long-term stakeholder and sustainability goals is crucial, as leaders navigate this landscape. Sustainable leadership can support organisations in linking the innovation process, responsible growth and strategic decision-making with the broader entrepreneurial purpose (Ribeiro & Leitão, 2024).

Marketing is yet another area that is transforming significantly due to AI and GenAI. Previous studies have shown that AI can transform customer analysis, segmentation, personalization, customer service and customer marketing decision-making (Davenport et al., 2020). Furthermore, strategic frameworks show that AI can improve marketing performance by aligning various machine intelligence levels and tasks to their respective customers and managers (Huang & Rust, 2021). Yet, there are dangers to AI use, such as over-automation, inappropriate targeting, and the inability to decipher complex consumer behaviour (De Bruyn et al., 2020). Recent studies focus on the growing potential of AI in consumer research and digital marketing (Mariani et al., 2022), and further developments of machine learning are enhancing customer analytics and marketing intelligence (Herhausen et al., 2024). GenAI has been able to be applied to various areas such as automated content creation, campaign development, personalisation and creative assistance (Chan & Choi, 2025). Yet, the response of consumers to AI-generated ads can differ based on their perceptions of authenticity, the nature of the message, and their trust in AI systems (Chen et al., 2024), as well as consumer attitudes towards AI more broadly, which are influenced by trust, convenience, identity, and consumer control (Puntoni et al., 2021). Acceptance is thus still crucial to the successful implementation of marketing professionals' organizations (Iyer & Bright, 2024).

However, responsible AI governance has become increasingly significant despite the opportunities. AI governance structures are needed within organizations to ensure transparency, accountability, responsible technology use, and risk management (Mäntymäki et al., 2022). The success of GenAI in achieving sustainable entrepreneurial transformation hinges on the synergy of leadership, marketing, innovation, and governance. In the past, these dimensions have been explored individually, and there was a lack of integration between studies that explore AI adoption and leadership, innovation, sustainable competitive advantage, organizational performance, and more broadly marketing and governance.

Objectives:

Examine how AI affects organisational performance, sustained competitive advantage, and business model innovation.

Evaluate the importance of leadership and institutional support for sustainable entrepreneurial transformation using AI.

Understand the implications of AI-driven changes to organizations for Marketing excellence and responsible governance in the context of Generative AI.

2. Methodology

2.1 Research Design

A quantitative, explanatory and secondary data research strategy was used to explore the role of AI adoption in transformational sustainable entrepreneurship and/or organization. The study placed itself in the context of generative artificial intelligence, and for the empirical study, organizational AI adoption measures were selected from the existing dataset.

2.2 Data Source

The publicly available Mendeley dataset “Dataset of the role of Artificial Intelligence Adoption on Business Model Innovation, Sustainable Competitive Advantage, and Firm Performance” was used in this study (Tran Nha et al., 2026). The data have been compiled based on responses received from 325 managers in companies in various industrial sectors in Vietnam. It was chosen because of its variables that encompass AI adoption, leadership support(LS), business model innovation, sustainable competitive advantage, government support (GS), cost effectiveness (CE), and business performance.

2.3 Study Constructs and Operationalization

The following constructs were analyzed: Artificial Intelligence Adoption (AI), LS, GS, CE, Business Model Innovation (BMI), Sustainable Competitive Advantage (SCA), and Firm Performance (FP). AI was an indicator for the implementation of artificial

intelligence in the organisation, while LS was an indicator for managerial support, GS was an indicator for institutional and governmental support, CE was an indicator for economic efficiency, BMI was an indicator for innovation of business models, SCA was an indicator for the organisations long-term competitive capability, and FP was an indicator for the outcome of the organisation's performance.

2.4 Alignment with Sustainable Entrepreneurship, Leadership, Marketing, and Governance

The operational concept of sustainable entrepreneurship was embodied by BMI, SCA, and FP. The Leadership Support construct was first directly represented as leadership. Governance implications were examined through Government Support as well as the institutional environment in which the adoption of AI takes place. As there was no separate scale measure of marketing excellence in the data set, marketing implications were drawn from business model innovation, competitive advantage, and firm performance, which are treated as separate measured constructs.

2.5 Conceptual Model

The empirical framework focused on AI as a key organizational capability that is influenced by leadership, governmental and economic factors. The sequence of the main structures was envisioned as LS, GS, and CE → AI Adoption → BMIS Competitive Advantage → FP This model allowed them to evaluate the value of adopting AI for sustainable entrepreneurial and organizational results.

2.6 Data Preparation and Screening

The data set and the resulting statistics were examined to check for valid constructs, measurement indicators, structural relationships, and model statistics. The analytical sample was a total of 325 managerial observations. Labels and indicators were kept as per their original definition, and no other observations or variables unrelated to the labels were added to the analysis.

2.7 Measurement Model Assessment

Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to test the measurement model. The internal consistency reliability was measured using Cronbach's alpha and composite reliability, both of which were at and above 0.70, indicating good internal consistency. Convergent validity was tested through Average Variance Extracted (AVE) with a score value of 0.50 or more considered as good convergent validity. Outer loadings were also researched to evaluate the impact of each indicator to each construct.

2.8 Structural Model and Hypothesis Testing

The standardized path coefficient, t, p, confidence interval and coefficient of determination were used to evaluate the structural model. The statistical significance of the relationship between the constructs was determined by bootstrapping, which was available in the data set. A p-value of 0.05 was used for the significance level. Direct and indirect relations between AI adoption, business model innovation, sustainable competitive advantage and firm performance were explored.

2.9 Model Fit and Predictive Assessment

The Standardized Root Mean Square Residual (SRMR) and coefficient of determination (R^2) values were used to evaluate model adequacy. Total model fit was evaluated using SRMR, and the proportion of variance explained in endogenous constructs was evaluated using R^2 values. These measures revealed evidence of the explanatory and predictive power of the proposed model.

2.10 Statistical Software

The analytical method used was PLS-SEM with PLS-SEM Algorithm and Bootstrapping outputs from the attached data set. These outputs were used to validate reliability, validity, path coefficient, significance level, indirect effect, model fit and explanatory power.

2.11 Ethical Considerations

The study was based on a secondary data set that was publicly available and required no direct interaction with people. New personal data or identifiable information was never collected. Construct definitions and statistical output were kept as they were in the original document to ensure transparency and avoid misrepresentation. The adoption of general AI was not viewed as a direct indicator of specific generative AI platforms, and government support was not equal to full internal AI governance.

3. Results

The outcomes of the PLS-SEM were analysed constructed on the measurement model, explanatory power, structural path coefficients, effect size and bootstrapped direct and indirect effects. The analysis was conducted using 325 observations from the managers who were part of the “Dataset of the role of Artificial Intelligence Adoption on Business Model Innovation, Sustainable Competitive Advantage, and Firm Performance.” The results below do not reflect a specific platform usage for GenAI but rather organizational AI adoption, so the original AI construct was retained while interpreting the implications of AI adoption in the context of generative AI and sustainable entrepreneurship.

3.1 Measurement Model Reliability and Validity

For each of the seven constructs, the measuring model's convergent validity and internal consistency were satisfactory. The conventional cut-off point for Cronbach's alpha is 0.7, and as shown in Table 1, it was found that the Cronbach's alpha of the instruments ranged from 0.809 for Cost Effectiveness (CE) to 0.882 for Government Support (GS), both of

which were higher than 0.7. The composite reliability (rho_c) was in the range of 0.885-0.914, and the average variance extracted (AVE) was in the range of 0.656-0.729, which exceeded the suggested value of 0.50. The results support construct reliability and convergent validity.

Table 1. Construct reliability and convergent validity

Construct	Cronbach's α	rho_a	Composite Reliability (rho_c)	AVE	Assessment
Artificial Intelligence Adoption (AI)	0.814	0.823	0.889	0.729	Acceptable
BMI	0.873	0.878	0.913	0.723	Acceptable
CE	0.809	0.841	0.885	0.719	Acceptable
FP	0.869	0.873	0.905	0.656	Acceptable
GS	0.882	0.884	0.914	0.680	Acceptable
LS	0.849	0.854	0.898	0.688	Acceptable
SCA	0.860	0.872	0.905	0.705	Acceptable

The reliability and validity of each instrument are shown in Figure 1 in comparison. The length model was adequate as all structures had AVE values greater than 0.50 and reliability greater than the minimum value recommended.

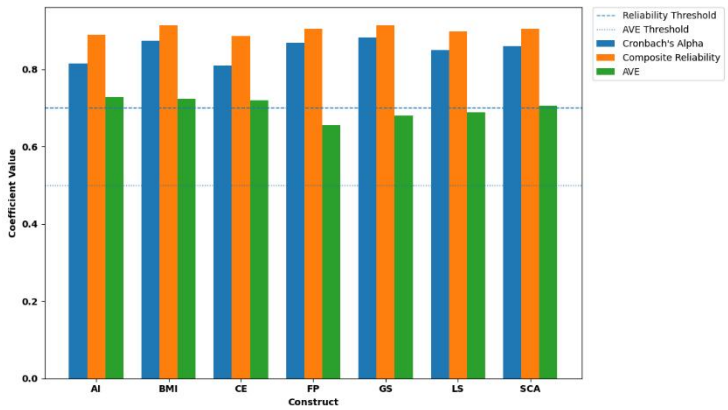

Figure 1. Reliability and convergent validity of the study constructs

The indicator-level assessment also complemented the measurement quality. All the outer loadings were greater than 0.750 as displayed in Table 2, with AI2 having the highest loading (0.906) and SCA5 having the lowest loading (0.750). Therefore, none of the indicators showed a loading that was weak enough to cast doubt on its distinctiveness for the respective latent construct. These indicator loadings are reported in Figure 2, which illustrates that all observed measures had a loading greater than 0.70.

Table 2. Outer loadings of measurement indicators

Construct	Indicator	Outer Loading
AI	AI1	0.833
AI	AI2	0.906
AI	AI3	0.820
BMI	BMI1	0.820
BMI	BMI2	0.871
BMI	BMI3	0.852
BMI	BMI4	0.858

CE	CE1	0.877
CE	CE2	0.874
CE	CE3	0.791
FP	FP1	0.777
FP	FP2	0.827
FP	FP3	0.815
FP	FP4	0.831
FP	FP5	0.798
GS	GS1	0.875
GS	GS2	0.795
GS	GS3	0.837
GS	GS4	0.839
GS	GS5	0.775
LS	LS1	0.822
LS	LS2	0.832
LS	LS3	0.837
LS	LS4	0.826
SCA	SCA2	0.875
SCA	SCA3	0.892
SCA	SCA4	0.835
SCA	SCA5	0.750

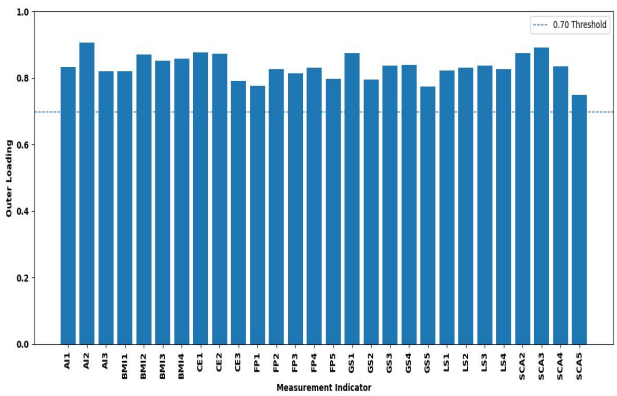

Figure 2. Outer loadings of measurement indicators

The discriminant validity was also good. All principal constructs had HTMT values under 0.70, with the highest value of 0.666 being between CE and FP. This means that the constructs measured were empirically differentiated.

3.2 Explanatory Power and Model Fit

Results of the structural model's explanatory ability are shown in Table 3. Firm Performance had the highest R^2 value of 0.438 and explained the largest amount of variance with the model among the endogenous variables. The model's R^2 is 0.180, which means that variation in the dependent variable, AI use, was described for by individual variables leadership support, government support, and cost effectiveness. Cost effectiveness achieved an R^2 of 0.149, whereas the R^2s of leadership support, sustainable competitive advantage and business model innovation were 0.073, 0.062, and 0.040, respectively.

Table 3. Explanatory power and overall model-fit indices

Endogenous Construct	R^2	Adjusted R^2
AI Adoption	0.180	0.173
Business Model Innovation	0.040	0.037
Cost Effectiveness	0.149	0.143
Firm Performance	0.438	0.429
Leadership Support	0.073	0.070
Sustainable Competitive Advantage	0.062	0.059

Model-Fit Indicator	Saturated Model	Estimated Model
SRMR	0.053	0.130
d_ULS	1.124	6.897
d_G	0.439	0.559
NFI	0.826	0.800

As shown in Figure 3, Firm Performance had a much larger explained variance compared to the other endogenous constructs. The SRMR value at the measurement-model level is 0.053, which is considered a comparatively good fit between the observed and model-implied relationships.

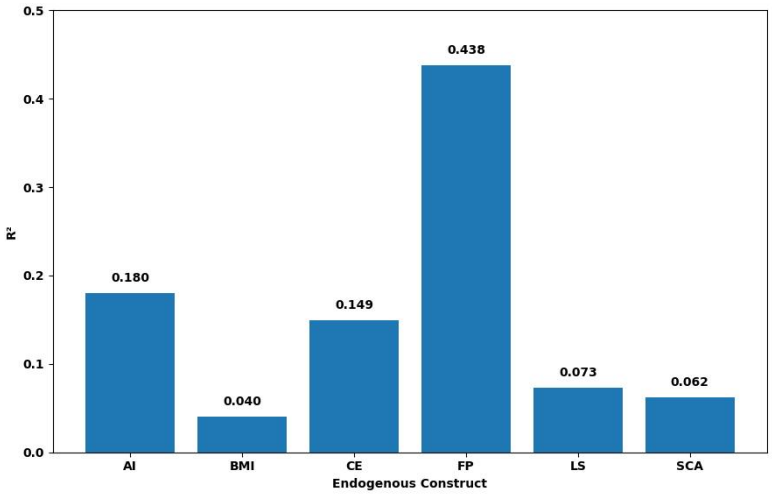

Figure 3. Explained variance (R^2) of endogenous constructs

3.3 Structural Relationships and Direct Effects

The statistical importance of the structural relationships was assessed using bootstrapping. As can be seen in the

results shown in Table 4, most direct relationships proposed were statistically significant. AI adoption had a significant positive effect on Business Model Innovation (β = 0.200, t = 3.569, p < 0.001), Firm Performance (β = 0.125, t = 2.906, p = 0.004), and Sustainable Competitive Advantage (β = 0.249, t = 4.731, p < 0.001). This result shows that higher level of organizational AI adoption was correlated with higher innovation, sustainable competitive positioning, and organizational performance.

Table 4. Structural path coefficients and hypothesis testing

Structural Path	β	STDEV	t-value	p-value	95% CI	Result
AI → BMI	0.200	0.056	3.569	<0.001	0.091–0.309	Significant
AI → FP	0.125	0.043	2.906	0.004	0.043–0.211	Significant
AI → SCA	0.249	0.053	4.731	<0.001	0.143–0.354	Significant
AI × BMI → FP	0.067	0.045	1.495	0.135	−0.025–0.152	Not significant
AI × SCA → FP	0.123	0.046	2.650	0.008	0.030–0.211	Significant
BMI → FP	0.417	0.044	9.442	<0.001	0.328–0.502	Significant
CE → AI	0.106	0.057	1.857	0.063	−0.007–0.214	Not significant
GS → AI	0.177	0.055	3.244	0.001	0.069–0.282	Significant
GS → CE	0.303	0.052	5.798	<0.001	0.200–0.405	Significant
GS → LS	0.270	0.057	4.724	<0.001	0.158–0.381	Significant
LS → AI	0.286	0.057	5.033	<0.001	0.175–0.400	Significant
LS → CE	0.171	0.052	3.282	0.001	0.069–0.269	Significant
SCA → FP	0.321	0.043	7.426	<0.001	0.235–0.407	Significant

The most significant among all direct predictors was Business Model Innovation (β = 0.417), followed by Sustainable Competitive Advantage (β = 0.321) on the Firm Performance predictor. This is a reminder that innovation and maintaining a competitive position are critical in the process of technology adoption to organizational performance. Leadership Support also had a significant effect on AI adoption (β = 0.286, p < 0.001), whereas Government Support significantly predicted AI adoption (β = 0.177, p = 0.001), Cost Effectiveness (β = 0.303, p < 0.001), and Leadership Support (β = 0.270, p < 0.001). However, at the 5% level, the variable of Cost Effectiveness did not significantly predict AI adoption (β = 0.106, p = 0.063). The magnitude and significance of the structural path coefficients are displayed in Figure 4.

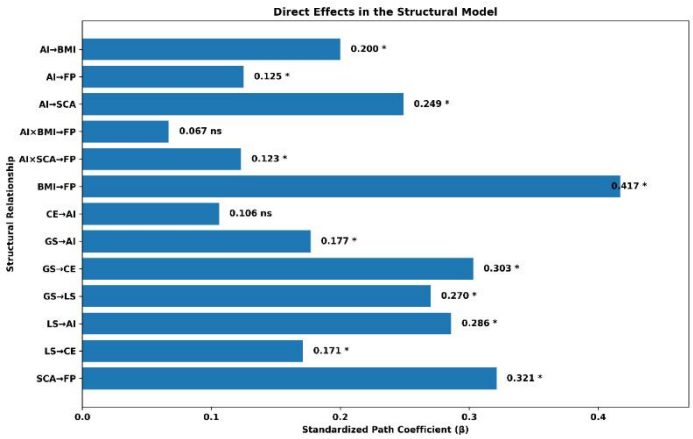

Figure 4. Standardized direct effects in the structural model

Effect Size Assessment

The f^2 statistics also attested to the different contributions of the predictors in practice. As presented in Table 5, the largest effect was observed for BMI → FP (f^2 = 0.289), followed by SCA → FP (f^2 = 0.168). The effects of AI on BMI, SCA and FP were smaller.

Table 5. Effect sizes of structural relationships

Path	f^2	Relative Magnitude
AI → BMI	0.042	Small
AI → FP	0.023	Small
AI → SCA	0.066	Small
AI × BMI → FP	0.008	Negligible
AI × SCA → FP	0.024	Small
BMI → FP	0.289	Moderate

CE → AI	0.012	Negligible
GS → AI	0.032	Small
GS → CE	0.100	Small
GS → LS	0.079	Small
LS → AI	0.090	Small
LS → CE	0.032	Small
SCA → FP	0.168	Moderate

Overall, BMI and SCA appeared to have a more significant impact on firm performance than the direct pathway between AI and performance, which indicates that the value that can be generated from AI is enhanced when adoption of AI is coupled with innovation and sustainable competitive capability.

3.4 Indirect and Moderating Effects

The bootstrapped indirect effects also supported that the use of AI had an indirect effect on organizational outcomes via the mediation processes of innovation and sustainability-related processes. The indirect effect of AI towards the firm performance through BMI was statistically significant (β = 0.083, t = 3.364, p < 0.001) and indicates that business model innovation was a significant mediator between AI and the firm's performance. Table 6 shows the selected indirect and moderating effects.

There was also a significant indirect relationship with BMI, SCA, and FP in relation to AI adoption, which was generated by Leadership Support. For example, the not direct effect of LS → AI → BMI was important (β = 0.061, p = 0.006), while LS → AI → SCA was also significant (β = 0.076, p < 0.001). The sequential pathway LS → AI → SCA → FP continued significant (β = 0.023, p = 0.002).

Table 6. Selected indirect and moderating effects

Relationship	Effect (β)	t-value	p-value	Interpretation
AI → BMI → FP	0.083	3.364	<0.001	Significant mediation pathway
GS → LS → CE	0.046	2.535	0.011	Significant indirect effect
GS → LS → AI → BMI	0.015	2.187	0.029	Significant indirect effect
GS → LS → AI → SCA	0.019	2.470	0.014	Significant indirect effect
LS → AI → BMI	0.061	2.763	0.006	Significant indirect effect
LS → AI → SCA	0.076	3.525	<0.001	Significant indirect effect
LS → AI → SCA → FP	0.023	3.130	0.002	Significant sequential pathway
AI × SCA → FP	0.123	2.650	0.008	Significant moderation
AI × BMI → FP	0.067	1.495	0.135	Non-significant moderation

The relationship between AI and SCA was significant and strongly predicted Firm Performance (β = 0.123, p = 0.008), indicating that the connection between sustainable competitive advantage and organizational performance was unlike by the level of AI adoption. However, there was no statistically significant relationship between AI and BMI (β = 0.067, p = 0.135). The most notable indirect effects are shown in Figure 5, where innovation and sustainable competitive capability serve as links between organizational transformation driven by AI and performance.

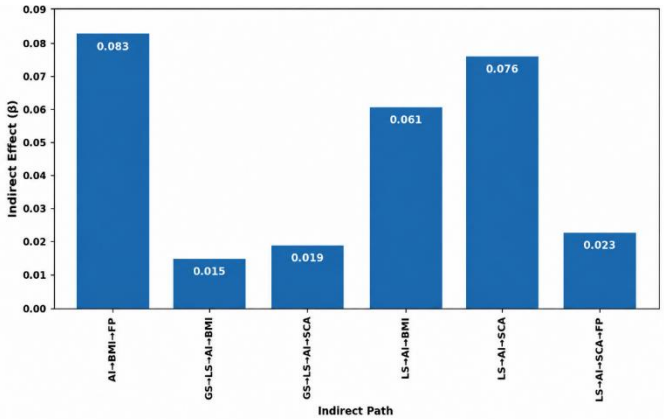

Figure 5. Selected significant indirect effects in the structural model

Overall, findings show that the use of AI directly led to business model innovation, sustainable competitive advantage and firm performance, and leadership support was an important enabler in organizational AI adoption. Sustainable competitive advantage was the second strongest direct predictor of performance, behind business model innovation. The overall hypothesis that AI-powered sustainable entrepreneurship requires leader support as well as institutions, capability to innovate and sustain

competitive advantage is also supported by these findings.

4. Discussion

The results indicate that the use of artificial intelligence has a meaningful impact on innovation, sustainable competitive advantage and firm performance and that conditions for the adoption of AI are influenced by leadership and institutional support. Business model innovation is significantly linked to the positive relationship between AI adoption and the ability to redesign value creation, delivery and operation processes, suggesting that companies are better able to redesign their processes and become more innovative when AI is used in managerial and strategic activities. The outcome reinforces the overall perception of AI as an enabler to digitally transform business and develop new value propositions (Di Vaio et al., 2020). Also, it resonates with recent research that suggests AI-enabled business model innovation can enhance organizational adaptability and strategic renewal, especially for companies aiming for growth that is sustainable in nature (Jorzik et al., 2024a; Jorzik et al., 2024b). These findings are relevant from a GenAI perspective as there is a growing awareness of the support that generative systems can provide to ideation, content creation, scenario development and fast experiments in business model development (Kanbach et al., 2024).

The solid positive connection between AI adoption and sustainable competitive advantage also indicates that businesses can translate AI capability into sustainable advantage. A finding that is consistent with evidence showing that AI can enhance the use of resources, decision quality, innovation capacity and organizational responses, which can impact the competitiveness of organizations that are focused on sustainability (Bickley et al., 2025). It also complements the idea that business model innovation can be a key avenue for AI's role in sustainable competitive advantage for companies (Islam et al., 2025). The indication of the positive impact of sustainable competitive advantage on firm performance confirms this interpretation, as firms achieve the benefits of their technological adoption when it is manifested as a capability that is hard for other firms to replicate.

The most robust direct predictor of firm performance was business model innovation. This finding underscores the importance of not just adopting the technology but also aligning business processes and strategic models with the technology, to reap the value of AI. The importance of AI capabilities supporting organizational creativity and performance has also been highlighted by previous studies, which have linked AI capabilities to organizational resources and managerial practices (Mikalef & Gupta, 2021). This potential for AI's indirect impact on firm performance through business model innovation further bolsters the case for a capability-based lens on understanding the adoption of AI. AI is not just about creating value; it's about enabling innovation, flexibility and new value creation strategies.

The support provided by leadership also demonstrated a strong positive effect on the adoption of AI, further emphasizing the role of managerial backing in digital transformation. This finding aligns with the automation–augmentation view, which holds that management judgment plays a vital role in deciding the role of AI in augmenting human skills instead of replacing them (Raisch & Krakowski, 2021). In sustainable entrepreneurship, leadership is crucial, as managers need to balance the requirements of innovation, employee acceptance, resource investment, and long-term sustainability goals (Ribeiro & Leitão, 2024). Additionally, the indirect relationship between leadership and performance shown by the other variables suggests that leadership plays a role in performance beyond the direct effect of managerial decisions, as it is also a factor that enables and supports technology use and organizational change, two of the other variables in this study.

The external institutional environment was positively related to adoption of AI, leadership support and cost effectiveness, suggesting that government support can drive the readiness of organizations for emerging technologies. These results align with the general theme of the literature, which highlights the role of policy, infrastructure, regulatory and institutional factors in shaping AI adoption (Dwivedi et al., 2021). Government support is not to be confused with internal corporate governance, however. In addition to mechanisms for accountability, transparency, responsibility, risk oversight, and ethical technology management, organizational AI governance also needs to include mechanisms for handling ethical technology management (Mäntymäki et al., 2022). As GenAI becomes more widespread, and raises new questions about data usage, machine-generated content, decision accountability, and machine deployment (Dwivedi et al., 2023), these considerations become particularly relevant.

The marketing implications are also interesting. Beyond internal operations, AI and GenAI can enhance customer analytics, personalization, content creation, market intelligence, and quicker campaign execution, further driving the strategic benefits of digital transformation.In addition to streamlining operations, AI and GenAI can help in customer analytics, personalization, content creation, market intelligence, and faster campaign execution, further amplifying the strategic impact of digital transformation. New organizational creativity and customer interaction are emerging as new aspects of contemporary GenAI adoption (Kumar et al., 2025). However, the present results must not be seen as evidence of marketing excellence, as marketing was not directly measured. Rather, its impact on business model innovation, competitive advantage, and performance is significant and warrants broader implications for market responsiveness and value delivery.

The results show that the implementation of AI in the context of sustainable entrepreneurship is based on a more complex system, including technologies, leadership support, innovations, institutional conditions, and sustainable competitive capacity. The findings, therefore, underscore the fact that the strategic potential of AI is not just about adoption, but about transforming it into novel business models, lasting competitive advantages, responsible governance and better organizational performance.

5. Conclusion

The study contributes to sustainable entrepreneurial and leadership changes with AI in a meaningful way in the presence of effective leadership, innovation capability and favorable institutional conditions. The results indicated that these characteristics of the implemented AI directly contributed to business model innovation, sustainable competitive advantage, and firm performance, with business model innovation as the most significant of these direct contributions to firm performance. Sustainable competitive advantage also had a significant positive influence, suggesting that the value of AI in terms of strategic benefits is intensified when technological benefits are translated into some sort of sustainable and hard-to-imitate organizational benefits. Support from leadership was also a strong enabling factor, which was supportive of AI adoption and helped indirectly achieve outcomes of innovation and sustainability. The effects of government support on adoption, leadership support, and cost-effectiveness were additional influences on AI readiness. The results indicate that the value creation process is not just a technology problem; it is a process that depends on organizational and institutional contexts in which it is adopted. In the broader context of generative AI, these findings highlight how companies can enhance sustainable entrepreneurship by combining AI tools and techniques with strategic leadership, innovative business models and responsible governance practices. Market responsiveness and value creation were not measured directly, but the improvements observed in innovation, competitiveness and performance suggest that marketing excellence was also observed, with implications for the use of GenAI. In conclusion, the key takeaway for achieving sustainable benefits from AI is responsible adoption, robust leadership, and effective technology capability to achieve strategic benefits.

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