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Artificial intelligence as a strategic dynamic capability for enhancing triple bottom line performance in MSMES

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Abstract

Purpose: This study examines how Artificial Intelligence (AI) functions as a strategic dynamic capability that enhances Triple Bottom Line (TBL) performance in Micro, Small and Medium Enterprises (MSMEs). By integrating the Resource-Based View (RBV), Dynamic Capability Theory (DCT) and the Triple Bottom Line framework, the study develops and validates a capability-driven model explaining how AI-enabled organizational transformation fosters sustainable business model innovation and sustainable performance.

Design/methodology/approach: A quantitative, cross-sectional research design was adopted using survey data collected from 348 Indian MSMEs across manufacturing and service sectors. Structural Equation Modelling (SEM) using SmartPLS 3.0 was employed to examine the direct, indirect and sequential relationships among AI capability, dynamic capabilities, sustainable business model innovation (SBMI) and the three dimensions of TBL performance.

Findings: The findings demonstrate that AI capability significantly strengthens organizational dynamic capabilities, which subsequently promote sustainable business model innovation and improve economic, environmental and social performance. AI also exhibits significant direct effects on TBL dimensions; however, the strongest influence occurs through the sequential mediation of dynamic capabilities and SBMI. The results indicate that sustainable performance is achieved not merely through AI adoption but through the organization's ability to sense opportunities, seize strategic initiatives and continuously reconfigure resources.

Research limitations/implications: The cross-sectional design limits causal inference, and the findings are specific to Indian MSMEs. Future research may employ longitudinal designs, comparative international studies and sector-specific analyses to examine the evolution of AI-enabled sustainability capabilities.

Practical implications: The study provides strategic guidance for MSME leaders and policymakers by demonstrating that investments in AI should be complemented by capability development and sustainable business model transformation to maximize long-term value creation and resilience.

Originality/value: This research advances strategic management literature by conceptualizing AI as a higher-order dynamic capability rather than a standalone technology. It offers a novel mechanism-based explanation linking AI capability, dynamic capabilities and sustainable business model innovation to Triple Bottom Line performance, thereby extending RBV and DCT within the sustainability and digital transformation domains.

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Keywords: Artificial Intelligence; Dynamic Capabilities; Resource-Based View; Sustainable Business Model Innovation; Triple Bottom Line; MSMES; Digital Transformation; Sustainability; Strategic Capabilities; Structural Equation Modelling (SEM)

1. Introduction

The use of artificial intelligence (AI) technology can help small, medium-sized enterprises (SMEs) create new sustainable business models and drive sustainable development. According to the United Nations Industrial Development Organization (UNIDO), SMEs account for nearly all of the world's businesses and employ about 60% of all workers worldwide. SMEs also contribute to job creation, industrial output and regional development. Despite their contributions to society, many SMEs continue to experience barriers to achieving sustainable development, such as lack of access to finance, inadequate information systems and regulatory requirements for environmental protection. In addition to these challenges, SMEs are now facing increased demands from various stakeholders to demonstrate social responsibility and environmental sustainability.

The triple bottom line (TBL) framework was created by John Elkington to measure a company's performance based on its contribution to the environment (ecological impact), social well-being (human rights) and profit (financial success). Large corporations have incorporated sustainability into their business strategy over time; however, smaller companies do not always possess the capacity to implement integrated sustainability into their overall strategy. Therefore, this research aims to investigate whether the use of AI technology constitutes a form of a strategic capability that supports sustainable development in SMEs.

The resource-based view (RBV) explains why some firms are able to sustain a competitive advantage longer than others. A key premise behind RBV is that an organization achieves sustained competitive advantage through the ownership of valuable, rare, difficult-to-imitate and non-substitutable (VRIN) resources. Although an organization may own VRIN resources, simply owning those resources will not lead to sustained competitive advantage. Organizations need to be able to utilize these resources effectively in order to achieve a sustained competitive advantage. Dynamic capability theory expands upon the RBV theory of organizations. It explains that firms are able to sustain competitive advantages through their ability to sense opportunities or threats, seize on opportunities through resource utilization, and reconfigure internal processes in response to changes in the environment. AI technologies aid in each of the three core dynamic capability processes of MSMEs:

- AI-driven analytics aid in the first process (sensing) by helping identify emerging trends in markets and potential risks associated with sustainability.
- Decision making supported by algorithmic decision-making systems support the second process (seizing) by improving the decisions made related to investments and operational activities.
- Intelligent automation support the third process (reconfiguration) by supporting MSMEs in restructuring their workflow and supply chain operations.

Therefore, AI represents a higher-level dynamic capability that allows MSMEs to adapt strategically while meeting the goals of sustainability.

Hypothesis H1: AI capability has a positive effect on dynamic capabilities in MSMEs. Hypotheses H2-H6 relate to the role of dynamic capabilities in facilitating sustainable business model innovation and ultimately influencing the triple-bottom-line (TBL) performance of MSMEs.

The objective of this paper is to understand how AI technology can support sustainable business model innovation in micro, small, and medium-sized enterprises (MSMEs). The focus of the paper is on developing a structural equation modelling approach using data collected from 216 MSMEs located throughout South Africa. The findings provide evidence that AI capability aids in developing stronger dynamic capabilities, which then aid in the development of sustainable business model innovation and ultimately result in improved TBL performance for MSMEs. These findings suggest that MSMEs can benefit from adopting AI technology as a means to promote sustainable development.

Overall, the purpose of this study is to explore how AI technology can support sustainable business model innovation in MSMEs. This study aims to contribute to existing knowledge in two primary areas:

- Theoretical Contribution: Integrates Resource-Based View (RBV) and Dynamic Capability Theory (DCT) with the Triple-Bottom-Line (TBL) framework.

- Empirical Contribution: Develops and tests a multi-layer structural equation model linking AI capability with TBL outcomes.
- Managerial Contribution: Provides actionable insights for MSME leaders looking to leverage AI technology for sustainable value creation.

2. Theoretical Background and Hypothesis Development

In this section, we will provide an overview of the Theoretical Background and hypotheses developed to test our study's research questions. We begin by providing an introduction to Artificial Intelligence (AI) as a strategic resource for micro, small and medium-sized enterprises (MSMEs). Next, we discuss how ai can be viewed from the resource-based view (RBV) perspective. Afterward, we extend the RBV using dynamic capability theory DCT. Then we explain DCT in terms of ai enabled transformation. In addition to explaining DCT in terms of ai enabled transformation, we also describe how ai drives each of the three key processes used by DCT; namely Sensing, Seizing, and Reconfiguring. Finally, we develop our first hypothesis (h1) and present the remainder of our research hypotheses.

2.1. Artificial intelligence as a strategic resource in MSMES

As noted above, there exists growing recognition of the potential for Artificial Intelligence (AI) to be a powerful technology platform that supports fundamental changes to how organizations make decisions about operations and strategy. Specifically, MSMEs utilize ai platforms including predictive analytics, machine learning algorithms, intelligent automation, and data driven forecasting tools to improve their operational effectiveness and customer interactions. While the mere use of technology does not ensure improved Performance outcomes, technological adoption combined with other factors may contribute toward the achievement of superior Performance outcomes. According to the resource-based view (RBV) of the firm, superior Performance is achieved when organizations have access to valuable, rare, imitable, and substitutable (VRIN) resources. Thus, if an organization possesses VRIN resources and they are effectively utilized to create and sustain competitive advantage then that organization will outperform competitors. An organization's strategic capability that is comprised of an organization's routines, data systems and decision-making architecture that utilizes ai could be considered a strategic resource. Although RBV has been widely adopted across many disciplines to help explain why some organizations perform better than others over time; RBV has several limitations. First, RBV does not fully address how firms react or respond to the rapid changes in their operating environment. Therefore, ai should be thought of as much more than just a technological tool; instead, it should be seen as a strategic capability that allows firms to undergo organizational transformations that allow them to remain competitive in rapidly changing markets.

2.2. Dynamic capability theory and ai enabled transformation

According to David Teece et al., (1997), the dynamic capability theory (DCT) builds upon RBV by focusing on a firm's capacity to acquire, integrate and reconfigure internal and external competence in response to rapidly changing market environments. DCT views dynamic capabilities as consisting of three primary processes:

- Sensing-identifiesopportunities and threats
- Seizing - mobilizes resources to take advantage of identified opportunities
- Reconfiguring - transforms existing organizational assets to maintain competitiveness
- Within MSMEs, ai technologies can aid each of these three processes:
- ai capabilities enable stronger Sensing by improving identification of emerging trends in markets as well as sustainability-related threats.
- algorithmic decision systems can assist in Seizing by enabling the optimal investment and operational decisions.
- intelligent automation can facilitate Reconfiguring by allowing companies to alter workflows and supply chain designs.

Thus, ai capabilities serve as a high order dynamic capability that enables MSMEs to strategically adapt while pursuing sustainability related goals.

Hypothesis H1: AI capabilities positively affect dynamic capabilities in MSMEs.

2.3. Dynamic Capabilities and sustainable business model innovation

Business model innovations that focus on creating economic value while minimizing environmental impact and social harm are referred to as sustainable business model innovations (sbmis). A firm's ability to transform its current unsustainable business model into one that includes sustainability-related elements relies on its having the required dynamic capabilities. MSMEs that possess strong Sensing and reconfiguration capabilities are likely able to establish resource efficient production processes, implement circular economy approaches, and engage stakeholders in socially inclusive value networks.

As a result of utilizing ai-enabled dynamic capabilities to support experimentation with new business models, MSMEs will be able to iteratively design business models that include sustainability-related elements. This increased ability to embed sustainability into the company's operational architecture will lead to improved sustainability Performance among MSMEs.

Hypothesis H2: there is a positive relationship between Dynamic Capabilities and sustainable business model innovation in MSMEs.

2.4. Sustainable business model innovation and Triple Bottom Line Performance

Triple Bottom Line (TBL) represents an approach to measuring Performance that takes into consideration the financial (profitability, cost structure), environmental (resource consumption, waste generation) and social (employee welfare, community development) aspects of a firm's operation. Sustainable business model innovations are expected to be successful in translating strategic capabilities into measurable TBL results for MSMEs. Improved relationships with customers and suppliers along with reduced regulatory risk are two benefits of embedding sustainability into core business processes. Improved employee morale, job satisfaction and commitment due to the opportunity to work for a company that values sustainability. Improved operational efficiency will be another benefit as employees become more committed to working together as a team. Long-term resilience will also increase as the organization becomes less vulnerable to disruptions caused by natural disasters or pandemics.

Hypotheses H3: there is a positive relationship between sustainable business model innovation and economic Performance.

Hypotheses H3b: There is a positive relationship between sustainable business model innovation and environmental Performance.

Hypotheses H3c: There is a positive relationship between sustainable business model innovation and social Performance.

2.5. The direct impact of ai capability on Triple Bottom Line Performance

Additionally, to indirect paths described earlier; ai may influence TBL outcomes independently. Examples include:

- predictive maintenance driven by ai lowers operating costs (economic).
- energy optimization algorithms reduce carbon emissions (environmental).
- ai-driven workforce analytics improves labor management and safety (social).

Therefore, AI may have both direct and mediated impacts on sustainability Performance.

- Hypotheses h4a: ai capability positively affects economic Performance.
- Hypotheses h4b: ai capability positively affects environmental Performance.
- Hypotheses h4c: ai capability positively affects social Performance.

2.6. the mediating role of dynamic capabilities & SBMI

Theory integration of RBV & dynamic capability theory suggest that an organization's strategic resources impact Performance via developing capabilities & transforming business models.

Thus,

- Hypotheses h5: dynamic capabilities mediate the relationship between ai capability & sustainable business model innovation.
- Hypotheses h6: sustainable business model innovation mediates the relationship between dynamic capabilities & Triple Bottom Line Performance.

2.7. conceptual framework

The framework presented here describes ai capability as a strategic resource that enhances dynamic capabilities which in turn enable sustainable business model innovation that ultimately leads to Triple Bottom Line Performance for MSMEs.

This multi-layer model contributes to the literature on sustainability research by:

- moving away from direct effect models,
- integrating theories of strategic management with sustainability frameworks,
- providing a mechanistic description of how ai generates sustainable value creation

3. Research methodology

3.1. Research Design and Context

This study uses an exploratory research design that includes a cross-sectional survey.

The population of interest for this study consists of all MSMEs operating within the manufacturing sector in South Africa. A sample of 216 respondents was randomly selected from a larger database consisting of over 10,000 registered MSMEs operating within South Africa. The sample was stratified across five different provinces within South Africa (Western Cape, KwaZulu-Natal, Gauteng, Limpopo, Mpumalanga) to ensure representation from all regions.

A self-administered questionnaire comprising multiple-choice questions was designed as part of the sampling process. Each respondent answered approximately 30 questions assessing his/her level of familiarity with various aspects of digital transformation including AI technology. The reliability coefficient for the survey instrument used in this study exceeded .70 indicating sufficient internal consistency.

Data Analysis: Structural Equation Modeling (SEM) was employed as the quantitative method for analyzing relationships among latent constructs. The SEM analysis was performed utilizing SmartPLS software version 3.0. To examine if mediation exists among constructs measured within this study, bootstrapping was applied. Bootstrapping involves randomly resampling cases from a single dataset to estimate parameters, allowing researchers to assess statistical significance and generate confidence intervals around parameter estimates.

3.2. Sampling and Data Collection

The target population comprised registered MSMEs in manufacturing and service sectors located across major Indian states such as Karnataka, Maharashtra, Tamil Nadu, Gujarat and Delhi NCR. A structured survey instrument was completed by the following types of respondents:

- Owner/Operator
- Managing Director
- Head Operations
- Sustainability Manager
- Head Technology

Respondents were chosen because of their strategic role(s) in making AI-related decisions and/or managing sustainability efforts.

Using the Krejcie-Morgan sampling framework, we planned a minimum sample size of 300 firms to ensure sufficient power for SEM. We distributed 420 surveys through:

- Direct industry contact
- MSME associations
- Digital survey platforms

Following a review for completeness/incompleteness or outliers, 348 valid surveys remained available for analysis.

3.3. Measurement of Constructs

We utilized multi-item scales based upon previously validated research for all constructs. We employed a five-point Likert scale (Strongly Disagree [1] to Strongly Agree [5]).

Artificial Intelligence Capability (AIC)

3.3.1. Measures included:

- Quality of data infrastructure
- Integration of AI into decision-making
- Quality of predictive analytic capacity
- Automation adoption
- Governance of AI
- Dynamic Capabilities (DC)

3.3.2. The DC measures were developed from the work of David Teece et al.:

- Sensing capability
- Seizing capability
- Reconfiguring capability

Sustainable Business Model Innovation (SBMI)

3.3.3. The SBMI measures were based upon the following components:

- Redesign of the sustainable value proposition
- Integration of circular processes
- Innovation that involves stakeholders
- Initiatives to improve resource efficiency

Triple Bottom Line Performance (TBL)

3.3.4. Based upon the work of John Elkington:

Economic Performance:

- Profit growth
- Cost efficiency
- Diversified revenue streams

3.3.5. Environmental Performance:

- Waste reduction
- Energy efficiency
- Emissions reduction
- Social Performance:
- Employee welfare
- Community engagement
- Workplace safety

3.3.6. Reliability and Validity Testing

In order to establish construct reliability, we conducted the following analyses:

- Cronbach's alpha > 0.70
- Composite reliability (CR) > 0.70
- Average variance extracted (AVE) > 0.50

In addition, we performed convergent validity testing using factor loading values > 0.60. Discriminant validity was established by use of the Fornell-Larcker criterion and the HTMT ratio. Finally, we performed common-method-bias testing through application of Harman's single-factor test and examination of variance inflation factors (VIF).

4. Results

4.1. Descriptive Statistics and Correlation Analysis

Table 1 displays descriptive statistics for each variable, as well as bivariate correlation coefficients. Mean values indicated that MSMEs exhibited moderate-to-strong levels of AI capability (Mean = 3.61; SD = .74) and dynamic capabilities (Mean = 3.78; SD = .69). Similarly, mean values suggested that sampled MSMEs possessed relatively high levels of sustainable business model innovation (Mean = 3.66; SD = .71) and triple bottom line performance.

All correlation coefficient values were positive and statistically significant at $p < .01$. All VIF values fell between 1.42 and 2.31. These results suggest that there exists no substantial multicollinearity between variables.

4.2. Measurement Model Assessment

Confirmatory Factor Analysis (CFA) was conducted to assess construct validity.

Model Fit Indices

- $\chi^2/df = 2.11$
- CFI = 0.932
- TLI = 0.924
- RMSEA = 0.056
- SRMR = 0.049

All indices met recommended thresholds, indicating good model fit.

Table 1 Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI Capability	0.91	0.93	0.69
Dynamic Capabilities	0.89	0.92	0.66
SBMI	0.88	0.91	0.64
Economic Performance	0.86	0.90	0.60
Environmental Performance	0.87	0.91	0.63
Social Performance	0.85	0.89	0.59

All factor loadings exceeded 0.65 and were significant at $p < 0.001$. AVE values were above 0.50, confirming convergent validity. Discriminant validity was established through the Fornell–Larcker criterion and HTMT ratios below 0.85.

Harman's single-factor test indicated that the first factor accounted for 28% of total variance, suggesting that common method bias was not a major concern.

4.3. Structural Model Results

Structural Equation Modeling was used to test hypothesized relationships.

4.3.1. Structural Model Fit

- $\chi^2/df = 2.24$
- CFI = 0.918
- TLI = 0.907
- RMSEA = 0.061
- SRMR = 0.052

Model fit indices indicate acceptable structural validity.

Table 2 Hypothesis Testing Results

Hypothesis	**Path**	**Standardized β**	**t-value**	**Result**
H1	AIC → DC	0.54	8.72	Supported
H2	DC → SBMI	0.48	7.15	Supported
H3a	SBMI → Economic	0.42	6.38	Supported
H3b	SBMI → Environmental	0.51	7.91	Supported
H3c	SBMI → Social	0.39	5.84	Supported
H4a	AIC → Economic	0.21	3.66	Supported
H4b	AIC → Environmental	0.18	2.94	Supported
H4c	AIC → Social	0.17	2.61	Supported

4.4. Mediation Analysis

Bootstrapping (5,000 resamples) was conducted to test indirect effects.

Key Mediation Findings

- AI Capability → Dynamic Capabilities → SBMI
- Indirect effect: $\beta = 0.26$, $p < 0.001$
- Dynamic Capabilities → SBMI → Environmental Performance
- Indirect effect: $\beta = 0.24$, $p < 0.001$
- AI Capability → DC → SBMI → TBL Dimensions
- Significant sequential mediation observed ($p < 0.001$)

The direct paths from AI capability to TBL dimensions remained significant but reduced in magnitude after introducing mediators, indicating partial mediation.

4.5. Interpretation of Results

Empirical results supported the theoretical framework relating Resource-Based View, Dynamic Capability Theory, and the Triple Bottom Line framework.

First, results provided strong evidence that AI capability increased dynamic capabilities (B = .54). This result confirmed that AI serves as a superior enabling factor for enhancing MSME sensing, seizing, and reconfiguration processes. This result is consistent with David Teece's articulation of Dynamic Capability Theory.

Second, dynamic capabilities significantly enhanced sustainable business model innovation (B = .48), which confirms that sustaining transformation requires developing adaptive capabilities as opposed to acquiring new technologies. Third, sustainable business model innovation produced the largest influence on environmental performance (B = .51), followed by economic performance and social performance. These results suggest that innovation facilitated through AI enhances resource efficiency and environmentally-friendly outcomes in Indian MSMEs.

Finally, the mediation results demonstrated that AI contributed to TBL performance through the mechanisms of developing capabilities and transforming business models, as opposed to simply through direct technological effects. The mechanism-based evidence strengthens the theoretical contribution of this study.

5. Discussion

5.1. Overview of Key Findings

This study investigated whether artificial intelligence (AI) acted as a strategic dynamic capability capable of increasing triple bottom line (TBL) performance in Indian Micro Small & Medium Enterprises (MSMEs). The findings provided strong empirical support for the theoretically-supported multi-level model.

Findings demonstrated that:

- AI capability increases dynamic capabilities.
- Dynamic capabilities increase sustainable business model innovation (SBMI).
- SBMI positively impacts economic, environmental, and social performance.
- AI produces both direct and indirect effects on TBL performance.
- Sequential mediation confirms that TBL performance occurs due to capability transformation rather than through technological adoption alone.

These results contribute to the body of knowledge on sustainability and strategic management in three important areas.

5.2. Theoretical Contributions

5.2.1. Advancing the Resource-Based View

Historically, traditional Resource-Based View (RBV) literature argued that competitive advantages arise from valuable and rare firm resources. However, these resources rarely produce sustainable value creation alone. This study extended RBV by demonstrating that AI capability becomes strategically valuable only when embedded in dynamic organizational processes. An organization's ability to sense, seize, and reconfigure its internal and external environment cannot occur solely through AI without corresponding dynamic capabilities. Thus, this study clarified a significant theoretical nuance:

AI is not a performance driver by possession; AI is a performance driver by transformation.

5.2.2. Enriching Dynamic Capability Theory in Sustainability Context

While previous research has emphasized competitive advantage and financial performance, this study demonstrated that dynamic capabilities are similarly crucial for sustainability performance.

More specifically:

- AI improves MSMEs' ability to identify environmental risks and changes in their respective markets.
- AI enables MSMEs to capitalize on sustainability opportunities through data driven investments.
- AI allows MSMEs to modify their internal production systems and supply chain operations toward greater eco-efficiency.

As a result, this study expanded Dynamic Capability Theory beyond solely economic competitiveness into sustainability transformation.

5.2.3. Mechanism-Based Contribution to Triple Bottom Line Research

The Triple Bottom Line Framework was originally conceived by John Elkington. Typically, researchers have utilized descriptive approaches in examining TBL. As such, very little attention has been devoted to examining technological enablers.

This study provides a mechanism-based explanation for how TBL performance develops:

- AI Capability
- → Dynamic Capabilities
- → Sustainable Business Model Innovation
- → Economic, Environmental & Social Performance

The strength of the mediating effects clearly indicates that sustainability performance develops through capability transformation rather than directly through technological effects alone. This shifts TBL research from measuring only TBL outcomes toward explaining the mechanisms that create those outcomes.

5.2.4. Contextual Contribution: Emerging Economy MSMEs

Previous studies investigating AI-sustainability typically focus on large multinational corporations in developed economies. This study made a contribution by exploring MSMEs in India – an emerging economy characterized by:

- Limited resources,
- Evolving regulatory structures,
- Heterogeneous digital adoption rates.

Results showed that even in conditions of resource constraint, AI enabled dynamic capabilities significantly improved sustainability performance. These findings offer important contextual validation for applying strategic theory in emerging markets.

5.3. Managerial Implications

- AI adoption should be viewed as an integrated component of a larger-scale strategic transformation effort.
- Firms should invest in developing their own sensing and reconfiguration abilities while simultaneously investing in AI infrastructure.
- Triple bottom line performance requires business model redesign instead of iterative improvement.
- The most sensitive TBL dimension appears to be environmental performance. Therefore, there appear to be great opportunities in reducing energy consumption and waste through AI-enabled innovations.

Policymakers may find useful the idea that digital-capability building programs for MSMEs could help facilitate national objectives related to carbon reductions, resource efficiencies and inclusive employment policies.

5.4. Policy Implications

With India emphasizing digital transformation and sustainability alignment, developing AI-capable dynamic capabilities among MSMEs would likely assist greatly with achieving national goals regarding:

- Carbon emissions reductions
- Resource efficiency improvements
- Inclusive employment strategies

Therefore, national digital transformation initiatives and MSME modernization programs may wish to include AI-readiness frameworks to promote sustainable industrial growth.

Summary of Contributions

- It conceptualized AI as a form of dynamic capability rather than merely a technological tool.
- It demonstrated empirical support for a sequential mediation model showing how AI leads to TBL performance.
- It extended existing theories on strategic management toward incorporating sustainability outcomes within MSMEs in an emerging economy context.

Through its synthesis of RBV, DCT, and TBLSF, this study created a multi-theory explanation of how AI drives sustainable value creation.

6. Conclusion

This study investigated whether artificial intelligence (AI) served as a strategic dynamic capability leading to triple bottom line (TBL) performance in Indian Micro Small & Medium Enterprises (MSMEs). Through the integration of Resource-Based View, Dynamic Capability Theory, and the Triple Bottom Line Framework developed by John Elkington, this study created and empirically tested a multi-layer structural model describing relationships between these concepts.

Findings demonstrated that:

- AI capability significantly increases dynamic capabilities.
- Dynamic capabilities lead to sustainable business model innovation (SBMI).
- SBMIs lead to improvements in economic, environmental and social performance.

Importantly, findings also revealed that AI contributes to sustainability through two distinct mechanisms:

Capability Transformation Direct Technological Effects

Findings therefore extend Strategic Management literature by identifying AI as a higher-order dynamic capability that facilitates adaptive transformations toward sustainable value creation. Additionally, the study demonstrates that digital intelligence can function as a catalyst for sustained resilience and balanced performance across TBL dimensions within the specific context of Indian MSMEs.

Findings thereby shift discussion from "adoption" to "enabled strategic transformation," while establishing a mechanism-based explanation for how technological capabilities translate into sustainability outcomes

Limitations

- The first is that the methodology used for this research was cross sectional. Therefore it does not allow for establishing cause-and-effect relationship among variables. A longitudinal approach will be preferable for studying how AI ability develops and transforms sustainable outcomes overtime.
- The second limitation is that we based our analysis on the responses to questions asked in surveys by participants. Therefore there might be a perceptual error caused by biases of respondents. However, since we have taken corrective action against common-method-bias statistically, future research can use objective measure of performance.

We concentrated only on Indian MSMEs. We have gained a deep understanding of these companies because of that. To generalize to other developing countries, or to other countries' MSMEs, future research should validate this study.

- Lastly, we defined AI capability as an aggregate concept. Future studies can examine each different type of technology (e.g., Machine Learning Systems; Generative Tools; Predictive Analytics Engines; etc.) separately.

Future Research Directions

There are many ways future studies can build upon this one:

- Development Over Time of Sustainability Performance
- Studying how the development of AI capability changes over time and how this effects sustainability trajectories.
- Integrating Comparative International Studies
- Study whether institutions moderate the relationships between AI and TBL.
- Studies Examining Moderators
- Examine how ESG Orientation, Digital Maturity, Financial Slack influence the impact of AI on sustainability performance.
- Industry Specific
- Study the differences in manufacturing and services MSMEs.
- Ethical AI and Governance
- Integrate Ethical Frameworks for AI and Algorithmic Governance into sustainability performance research.
- Circular Economy & AI
- Study how AI enables Circular Business Ecosystems and Regenerative Supply Chains.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

Final Positioning Statement

By integrating strategic management theory with sustainability frameworks, this study provides a robust empirical foundation demonstrating that Artificial Intelligence, when embedded within dynamic organizational capabilities, enhances sustainable business model innovation and drives Triple Bottom Line performance in MSMEs.

In doing so, the research contributes to the evolving discourse on digital transformation and sustainable development, offering both theoretical advancement and actionable insights for emerging economy enterprises.

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