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From AI Use to Sustainable Value Creation Through Entrepreneurial Reconfiguration and Business Model Innovation in SMEs: Evidence from an Emerging Economy

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Abstract

Artificial intelligence (AI) is increasingly used by small- and medium-sized enterprises (SMEs), but its role in sustainable business transformation remains unclear, especially in emerging economies where adoption is often fragmented and experimental. This study examines how AI use is associated with Sustainable Value Creation through Entrepreneurial Reconfiguration Capability (ERC) and Business Model Innovation (BMI). ERC refers to a firm's capability to interpret AI-enabled opportunities, recombine existing resources, govern experimentation with new value configurations, and decide which AI-related initiatives should be scaled. Using survey data from 385 SMEs in four Ecuadorian sectors and Partial Least Squares Structural Equation Modeling (PLS-SEM), the study tests a sequential model linking AI use, ERC, BMI, and Sustainable Value Creation. The findings show positive associations between AI use and ERC, ERC and BMI, and BMI and Sustainable Value Creation. The results suggest that AI adoption alone is unlikely to be associated with sustainable value unless SMEs develop entrepreneurial capabilities that connect AI use with business model innovation. The study contributes by shifting the focus from AI adoption to AI-enabled entrepreneurial transformation in SMEs from an emerging-economy context. Future research should examine moderating factors related to digital maturity, institutional support, environmental dynamism, firm size, and sectoral conditions.

Keywords: artificial intelligence; entrepreneurial reconfiguration capability; business model innovation; sustainable value creation; SMEs; digital transformation; dynamic capabilities



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1. Introduction

Artificial intelligence (AI) is reshaping how firms create, deliver, and capture value. In small- and medium-sized enterprises (SMEs), AI is increasingly used to improve operational efficiency, decision-making, customer interaction, and innovation capacity [1,2]. However, AI integration in SMEs—particularly in emerging economies—remains uneven and often experimental, constrained by limited resources, data availability, managerial capabilities, and institutional support [3,4]. Digital transformation research emphasizes that the strategic value of digital technologies depends not only on adoption, but also on organizational change, capability development, and business model transformation [5,6].

Prior studies have mainly examined the determinants and outcomes of AI adoption. Drawing on the Technology–Organization–Environment model, the Technology Acceptance Model, the Resource-Based View, dynamic capabilities, and analytics capability research, this literature identifies technological readiness, organizational resources, managerial perceptions, and environmental pressures as key conditions for implementation [7–11]. More recent work also shows that AI-enabled transformation depends on digital maturity, data readiness, managerial capabilities, and alignment with broader strategic change [12,13]. Although valuable, this adoption-oriented perspective provides less insight into how fragmented AI use becomes connected to deeper organizational transformation. Many SMEs adopt AI through isolated applications, such as chatbots, automated marketing tools, predictive analytics, or decision-support systems, without changing the underlying logic through which they create, deliver, and capture value.

Business Model Innovation (BMI) is therefore central to understanding AI-enabled transformation. BMI refers to changes in the firm's value proposition, value delivery architecture, revenue logic, customer relationships, and broader mechanisms of value creation [14–16]. This lens is more appropriate than adoption intensity or operational performance alone because AI-related efficiency gains may remain limited unless they are connected to business model redesign. Recent studies show that AI capabilities can support BMI when firms scale AI through feedback loops, value creation processes, and value capture mechanisms [17,18]. Research on generative AI reinforces this view by suggesting that AI may affect business models not only through automation, but also through knowledge use, value design, and organizational experimentation [19–21].

An entrepreneurship perspective helps explain this transformation because it emphasizes opportunity interpretation, experimentation, and resource recombination under uncertainty [22,23]. From this view, AI is not only a technological resource but also a trigger for entrepreneurial action. However, the intersection between AI use, entrepreneurial reconfiguration, and BMI remains insufficiently theorized. Existing capability-based perspectives explain adaptation, learning, and resource renewal, but they do not fully specify the entrepreneurial micro-processes through which SMEs reinterpret AI-enabled possibilities and translate them into business model change.

To address this gap, this study introduces Entrepreneurial Reconfiguration Capability (ERC), defined as the firm's capability to reinterpret AI-enabled opportunities, recombine resources, govern experimentation, and scale promising initiatives under uncertainty. ERC is not proposed as a replacement for dynamic capabilities or as another label for digital capability. Rather, it is introduced as a narrower and process-specific construct that builds on capability-based and entrepreneurship-oriented perspectives while addressing a specific transformation problem: how SMEs convert fragmented or experimental AI use into BMI. Its novelty lies in integrating elements usually examined separately: the AI-specific technological trigger, entrepreneurial opportunity interpretation, resource recombination under constraints, experimental governance, and selective scaling into business model change.

The proposed model links AI use, ERC, BMI, and Sustainable Value Creation (SVC). The central argument is that AI use does not automatically produce sustainable value. Instead, AI use becomes strategically meaningful when firms reinterpret its possibilities, recombine existing resources, experiment with new configurations, and incorporate selected changes into their business models. SVC is considered the final outcome because AI-enabled transformation should be assessed not only through efficiency or financial performance, but also through organizational adaptability and social or environmental contribution [24]. This view is consistent with research suggesting that digitalization contributes to sustainability when it is embedded in broader organizational and strategic transformation rather than treated as a standalone technological investment [25].

Empirically, the study is grounded in Ecuadorian SMEs, where AI adoption remains limited and uneven. Prior evidence reports an AI Adoption Intensity Index of approximately 0.04, with AI use concentrated in marketing and customer-facing activities, while finance, logistics, and human resource management show negligible adoption [26,27]. This pattern is reinforced by limited human capital, insufficient data availability, and restricted financial capacity, which hinder the transition from experimental use to strategic implementation. Ecuador therefore provides an analytically relevant setting for examining how SMEs may move from fragmented AI use toward BMI and SVC under conditions of resource constraint and low digital maturity.

The objective of this study is to examine how AI use is associated with SVC in SMEs through a sequential organizational mechanism involving ERC and BMI. Rather than treating AI adoption as a purely technological phenomenon, the study focuses on the entrepreneurial and organizational processes through which AI use may become connected to business model transformation and sustainability-oriented outcomes. Because AI use, ERC, BMI, and SVC are latent organizational constructs, the study applies PLS-SEM to assess the measurement model, estimate structural relationships, and test the indirect pathway linking AI use to SVC through ERC and BMI. Given the cross-sectional nature of the data, the analysis is interpreted in terms of theoretically grounded associations rather than causal effects.

To guide the analysis, the study addresses four research questions:

- RQ1. How is AI use associated with Entrepreneurial Reconfiguration Capability in SMEs?
- RQ2. How is Entrepreneurial Reconfiguration Capability associated with Business Model Innovation?
- RQ3. How is Business Model Innovation associated with Sustainable Value Creation?
- RQ4. Does the relationship between AI use and Sustainable Value Creation operate through a sequential mechanism involving Entrepreneurial Reconfiguration Capability and Business Model Innovation?

The scope of the study is deliberately bounded. AI is examined at the organizational-use level, rather than in terms of the technical performance of specific systems. Entrepreneurship is examined through opportunity interpretation, resource recombination, experimental governance, and scaling judgment. Sustainability is operationalized through SVC, which captures economic performance, organizational adaptability, and social or environmental contribution. Thus, the study does not propose a general theory of AI, entrepreneurship, and sustainability, but tests a specific sequential mechanism linking AI use, ERC, BMI, and SVC in SMEs from an emerging-economy context.

This study contributes to the literature in three ways. First, it addresses a transformation gap in AI-SME research by explaining how fragmented AI use may become connected to business model change. Second, it conceptualizes and operationalizes ERC as an AI-contingent entrepreneurial capability that links technology use to BMI through opportunity interpretation, resource recombination, experimental governance, and scaling judgment. This contribution is framed as a theoretically bounded extension of existing capability-based perspectives, not as a claim that prior constructs are insufficient in all contexts. Third, it provides empirical evidence from Ecuadorian SMEs showing that AI use is associated with SVC through a sequential pathway involving ERC and BMI, rather than assuming a direct or automatic relationship between AI adoption and sustainability outcomes.

2. Theoretical Framework

2.1. Artificial Intelligence in SMEs: Beyond Adoption

Artificial intelligence (AI) has become a strategic resource for firms seeking to improve decision-making, optimize operations, and generate new forms of value. Its relevance is

especially high for SMEs because these firms often operate under constraints of capital, data, time, and specialized knowledge. However, AI use in SMEs remains uneven and frequently limited to narrow applications, particularly in emerging economies where digital infrastructure, financing, and advanced human capital are less available [12,13]. Digital transformation research reinforces this point by showing that the strategic value of digital technologies depends not only on adoption, but also on organizational change, capability development, and business model transformation [5,6].

Most research on AI in SMEs has adopted an implementation or adoption lens, emphasizing technological readiness, managerial perceptions, organizational capabilities, and environmental conditions. This perspective has generated important insights, but it explains AI uptake more effectively than the mechanisms through which AI use becomes a source of deeper transformation. In practice, many SMEs adopt AI in isolated ways without modifying the logic through which they create, deliver, and capture value. The unresolved issue is therefore not adoption alone, but the firm's ability to convert AI use into entrepreneurial and organizational reconfiguration.

This limitation is especially visible in emerging economies. Prior evidence from Ecuador shows that AI use among SMEs remains low and concentrated in customer-facing activities, while logistics, finance, and human resource management show minimal integration [26,27]. Shortages in talent, structured data, and financial resources further restrict firms' capacity to move from experimentation toward strategically embedded use. Thus, the theoretical challenge is no longer only to explain whether SMEs adopt AI, but how they transform its use into sustained business innovation.

This argument is consistent with recent studies and policy-oriented reports showing that AI adoption among SMEs is shaped by uneven digital capabilities, limited access to high-quality data, managerial skills, and the broader productivity divide between digitally advanced and digitally constrained firms [12,13]. It also aligns with generative AI research suggesting that AI reshapes knowledge processes, decision-making, and business model experimentation rather than functioning only as an automation tool [19–21]. Therefore, research on AI in SMEs should move beyond adoption determinants and examine the organizational mechanisms through which AI use becomes associated with innovation, competitiveness, and sustainable value creation.

2.2. Business Model Innovation as the Transformation Target

Business Model Innovation (BMI) provides a suitable lens for understanding structural transformation beyond incremental process improvement. A business model explains how a firm creates value, delivers it to customers and stakeholders, and captures value in return [14,15]. From an activity-system perspective, BMI involves reconfiguring the interdependent activities that shape the organization's value proposition, value delivery architecture, and revenue logic [16].

BMI is especially relevant in technologically turbulent environments because digital technologies rarely generate sustained advantage through efficiency gains alone. Their strategic impact emerges when firms use them to redesign relationships with customers, partners, channels, cost structures, and revenue sources. Digital transformation research similarly emphasizes that technology-driven change becomes strategically meaningful when it affects organizational structures, value creation mechanisms, and business models [5,6].

In the AI context, this point is crucial. AI can automate tasks, support forecasting, personalize services, and improve decision-making, but these benefits remain operational unless they induce broader shifts in the business model. Recent studies show that AI capabilities may enable BMI through feedback loops, scaling processes, value creation

mechanisms, and value capture redesign [17,18]. Generative AI reinforces this logic because it may affect not only operational efficiency, but also value propositions, customer interaction, knowledge creation, and innovation processes [19,21].

Therefore, if the goal is to explain transformation rather than mere adoption, BMI should be treated as the core organizational target of AI-enabled change. Recent research conceptualizes BMI as a continuous and capability-driven process in which firms redesign their value architecture in response to technological change, environmental dynamism, and sustainability demands [14,28–30]. This view is also consistent with evidence that digitalization contributes to sustainability and performance when embedded in broader organizational transformation rather than treated as a standalone technological investment [25].

2.3. Dynamic Capabilities and Their Limits

The dynamic capabilities perspective offers an essential strategic foundation for understanding transformation under change. Dynamic capabilities refer to the firm's ability to sense opportunities and threats, seize them through timely decisions, and reconfigure its resource base accordingly [10]. This framework is highly relevant to AI because the value of AI depends not only on access to technology, but also on the firm's capacity to integrate, adapt, and renew its resources and routines.

In SMEs, dynamic capabilities help explain why some firms use emerging technologies more effectively than others. Firms with stronger learning, flexibility, and reconfiguration capabilities are better positioned to experiment with AI, absorb its insights, and align it with strategic objectives. Prior research on digital transformation and analytics capabilities supports this interpretation by showing that dynamic capabilities help firms convert digital resources into innovation, strategic renewal, and performance outcomes [31,32]. From this perspective, AI-enabled transformation could be explained through established capability-based reasoning without necessarily introducing a new construct.

However, the dynamic capabilities framework remains broad and does not fully specify the entrepreneurial dimension of AI-enabled transformation in SMEs. It clarifies how firms sense opportunities, seize them, and reconfigure resources under change, but it is less precise in explaining how managers reinterpret fragmented AI use as a business opportunity, recombine constrained resources, govern experimentation, and decide whether AI-related initiatives should be scaled into BMI. Therefore, a more focused construct is analytically useful for examining the specific mechanism addressed in this study.

Research on microfoundations further shows that dynamic capabilities operate through managerial cognition, organizational learning, and decision-making processes [33]. This is especially relevant in SMEs, where strategic decisions are often centralized. Thus, the argument is not that dynamic capabilities are theoretically insufficient in general, but that they remain broad for the specific transformation problem examined here. Entrepreneurial Reconfiguration Capability (ERC) builds on the microfoundational logic of dynamic capabilities while specifying the entrepreneurial processes that connect AI use with business model change.

2.4. Entrepreneurship, Effectuation, and Resource Recombination

Entrepreneurship theory contributes the process orientation needed to explain how AI use may become a source of business transformation. Digital entrepreneurship highlights how digital technologies reshape entrepreneurial agency by lowering experimentation costs, accelerating feedback, and making opportunity enactment more fluid and iterative [34]. In such contexts, the firm does not merely deploy technology; it explores how technology can open new paths for organizing and monetizing value.

Effectuation theory reinforces this point by arguing that, under uncertainty, firms do not rely only on predictive planning but act through experimentation, available means, and progressive opportunity development [23]. This is consistent with AI use in SMEs, where adoption rarely begins with a fully designed strategy. Instead, it often starts through tentative trials with chatbots, content generation, analytics, or decision-support tools. Whether these trials remain isolated or evolve into business model change depends on how the firm learns from them and reorients them strategically.

Resource recombination and entrepreneurial bricolage offer a further anchor. Under constraints, firms may create novelty by recombining existing assets rather than acquiring entirely new ones. Entrepreneurial actors can construct new solutions from limited means, while innovation may emerge from novel combinations of previously separate resources and routines [35,36]. In SME settings, this logic is highly pertinent: AI often enters the firm not as a fully integrated system, but as a set of tools that must be connected with existing data, routines, capabilities, and market knowledge.

Together, these perspectives suggest that transformation depends not merely on adoption or adaptation, but on the firm's entrepreneurial ability to reinterpret AI, experiment with it, and recombine it into new configurations of value creation. This view connects dynamic capabilities and entrepreneurship because both emphasize opportunity-driven action, strategic flexibility, and resource recombination under uncertainty [10,23,34–36]. It also aligns with generative AI research, suggesting that AI may reshape knowledge creation, experimentation, and business model design rather than functioning only as an automation technology [19–21].

2.5. Entrepreneurial Reconfiguration Capability

Building on the preceding discussion, this study introduces Entrepreneurial Reconfiguration Capability (ERC) as the central mediating mechanism between AI use and Business Model Innovation (BMI). ERC is defined as the firm's capability to interpret AI use as an entrepreneurial opportunity and to deliberately recombine resources, govern experimentation, and scale selected initiatives under uncertainty.

ERC is located at the intersection of dynamic capabilities, digital entrepreneurship, effectuation, and resource recombination/bricolage, but it is not reducible to any single perspective. Dynamic capabilities provide the general logic of sensing, seizing, and reconfiguring resources under technological change [10,37]; digital entrepreneurship explains how digital technologies enable opportunity-oriented action [34]; effectuation contributes the logic of experimentation under uncertainty [23]; and recombination/bricolage explains how firms create novelty by rearranging available resources [35,36]. The novelty of ERC lies in integrating these streams around a specific transformation problem: how SMEs convert fragmented or experimental AI use into BMI through opportunity interpretation, resource recombination, experimental governance, and scaling judgment.

These four dimensions capture complementary manifestations of entrepreneurial reconfiguration. Opportunity interpretation refers to the cognitive process by which firms frame AI as a source of new business opportunities. Resource recombination captures the rearrangement of existing assets, routines, data, and knowledge around AI-enabled opportunities. Experimental governance reflects the ability to test, learn, and adjust AI-related initiatives under uncertainty. Scaling judgment captures the managerial assessment of whether AI-enabled experiments should be expanded into broader business model changes. Together, these dimensions define ERC as a capability that connects AI use with BMI.

ERC is not proposed as a replacement for dynamic capabilities or as a relabeling of existing capability-based constructs. Dynamic capabilities provide a broad theoretical

explanation of how firms sense opportunities, seize them, and reconfigure resources under changing conditions [10,37]. Prior research has also shown that dynamic capabilities can explain strategic renewal, digital innovation, business model change, and the conversion of digital resources into performance outcomes [31,32]. Therefore, AI-enabled transformation could plausibly be explained through established capability-based theories.

However, this broader logic is less specific regarding the entrepreneurial micro-processes through which SMEs reinterpret fragmented AI use as a business opportunity, recombine constrained resources, govern experimentation, and decide whether AI-related initiatives should be scaled into BMI. ERC is introduced to specify this more focused mechanism. In this respect, ERC builds on the microfoundational logic of dynamic capabilities, particularly the role of managerial cognition, interpretation, and judgment [33], while narrowing the analytical focus to AI-contingent entrepreneurial reconfiguration.

ERC differs from general dynamic capabilities in three ways. First, it is explicitly AI-contingent because it explains how AI use becomes a trigger for entrepreneurial transformation. Second, its focal outcome is not generic adaptation or firm performance, but BMI. Third, it emphasizes opportunity reinterpretation, experimentation, resource recombination, and scaling judgment, which are more entrepreneurship-oriented than the broader sensing–seizing–reconfiguring sequence. Thus, ERC should be understood as a bounded and process-specific extension of capability-based reasoning rather than as a competing theory of organizational adaptation.

To clarify these boundaries, Table 1 compares ERC with five adjacent constructs that could also explain AI-enabled transformation: dynamic capabilities, entrepreneurial orientation, absorptive capacity, digital capability, and organizational ambidexterity. These constructs are treated as plausible alternative explanations against which the added value of ERC must be assessed.

Table 1. Conceptual distinction between ERC and related constructs.

Related Construct	Main Conceptual Focus	Difference from ERC
Dynamic capabilities	Broad ability to sense, seize, and reconfigure resources under environmental change [10,37]; digital transformation research also links dynamic capabilities with strategic renewal and business model change [32].	ERC is more specific: it focuses on AI-triggered entrepreneurial reinterpretation, experimentation, resource recombination, and business model transformation.
Entrepreneurial orientation	Strategic posture toward innovativeness, proactiveness, and risk-taking [38].	ERC is not a general orientation or attitude; it is a capability for transforming AI-enabled opportunities into new business model configurations.
Absorptive capacity	Ability to acquire, assimilate, transform, and exploit external knowledge [39,40].	ERC is not limited to external knowledge processing; it emphasizes entrepreneurial action, experimentation, and recombination around AI-enabled possibilities.
Digital capability	Ability to deploy, integrate, and manage digital technologies; digital transformation research emphasizes technology-enabled organizational change and capability development [5,6].	ERC goes beyond digital deployment by explaining how AI use is interpreted and converted into BMI.
Organizational ambidexterity	Ability to balance exploration and exploitation [41].	ERC does not primarily address the balance between exploration and exploitation; it explains how AI-enabled experimentation is selectively scaled into business model change.

As shown in Table 1, ERC is conceptually narrower and more process-specific than dynamic capabilities because it does not describe organizational adaptation in general. Instead, it captures the entrepreneurial process through which AI use is interpreted, recombined, experimentally governed, and selectively scaled into business model change. ERC is therefore introduced as a complementary construct that extends, rather than duplicates, existing theories of capability development and innovation.

The added value of ERC is conditional rather than universal. ERC is most relevant when the research problem concerns how firms transform fragmented or experimental AI use into BMI under uncertainty and resource constraints. In such settings, established constructs may explain important parts of the phenomenon but not the full sequence examined here. Dynamic capabilities explain broad adaptation and resource reconfiguration; digital capability explains technology deployment and integration; absorptive capacity explains knowledge acquisition and assimilation; entrepreneurial orientation explains a strategic posture toward innovation and risk-taking; and organizational ambidexterity explains the balance between exploration and exploitation. By contrast, ERC combines the AI-specific trigger, entrepreneurial opportunity interpretation, resource recombination, experimental governance, and scaling judgment toward business model change.

When the research focus is general organizational adaptation, digital technology deployment, external knowledge absorption, or exploration–exploitation balance, these established constructs may provide a sufficient explanation without requiring ERC. However, none of them simultaneously captures the AI-specific trigger, the entrepreneurial reinterpretation process, and the business-model-level outcome examined in this study. ERC therefore explains a specific transformation mechanism that existing constructs address only partially: how SMEs convert AI-enabled possibilities into BMI through entrepreneurial reinterpretation, recombination, experimentation, and scaling judgment.

This distinction is particularly relevant in emerging-economy SMEs, where AI use often begins as fragmented experimentation rather than as a fully integrated digital transformation strategy. In the Ecuadorian context, where firms frequently face resource scarcity, ERC is both theoretically meaningful and empirically relevant because it captures how SMEs rely on reinterpretation, recombination, experimentation, and selective scaling rather than large-scale technological investment.

2.6. ERC, Business Model Innovation, and Sustainable Value Creation

The role of ERC becomes clearer when Business Model Innovation (BMI) is connected to sustainability. Sustainable business model innovation extends BMI by emphasizing not only economic value, but also environmental and social value creation. From this perspective, firms innovate not only to improve profitability, but also to redesign their models in ways that reduce negative externalities, improve resource efficiency, and support broader societal outcomes [30,42,43]. Recent evidence also suggests that digitalization contributes to sustainability and performance when embedded in broader organizational transformation rather than treated as an isolated technological investment [25].

In the AI context, this connection is especially relevant because AI may support value creation and value capture through new business model configurations rather than through operational efficiency alone [18]. Accordingly, AI should not be framed only as a productivity technology, but as a resource that may support Sustainable Value Creation (SVC) when mediated by entrepreneurial reconfiguration and BMI.

Recent sustainability research also suggests that value creation should be understood in relation to responsibility, transparency, and governance. Studies on sustainability disclosure and corporate governance show that sustainability-oriented practices are increasingly linked to accountability mechanisms and responsible managerial behavior, reinforcing the

need to understand SVC beyond short-term financial performance [44,45]. Although this literature does not directly examine AI-enabled transformation, it supports the broader view that BMI should be evaluated in relation to economic, social, environmental, and governance-oriented outcomes.

Accordingly, the proposed logic is not that AI directly generates sustainable value. Rather, AI use may support ERC; ERC may enable firms to transform their business models; and these reconfigured business models may become the basis for SVC. This sequence offers a more process-oriented explanation than a direct-effects view because it helps explain why some SMEs remain at the level of operational experimentation, while others convert AI into broader innovation trajectories.

2.7. Conceptual Model and Hypotheses Development

Based on the preceding arguments, this study proposes a sequential model in which AI Use is associated with Entrepreneurial Reconfiguration Capability (ERC), ERC is associated with Business Model Innovation (BMI), and BMI is associated with Sustainable Value Creation (SVC). The model is presented in Figure 1.

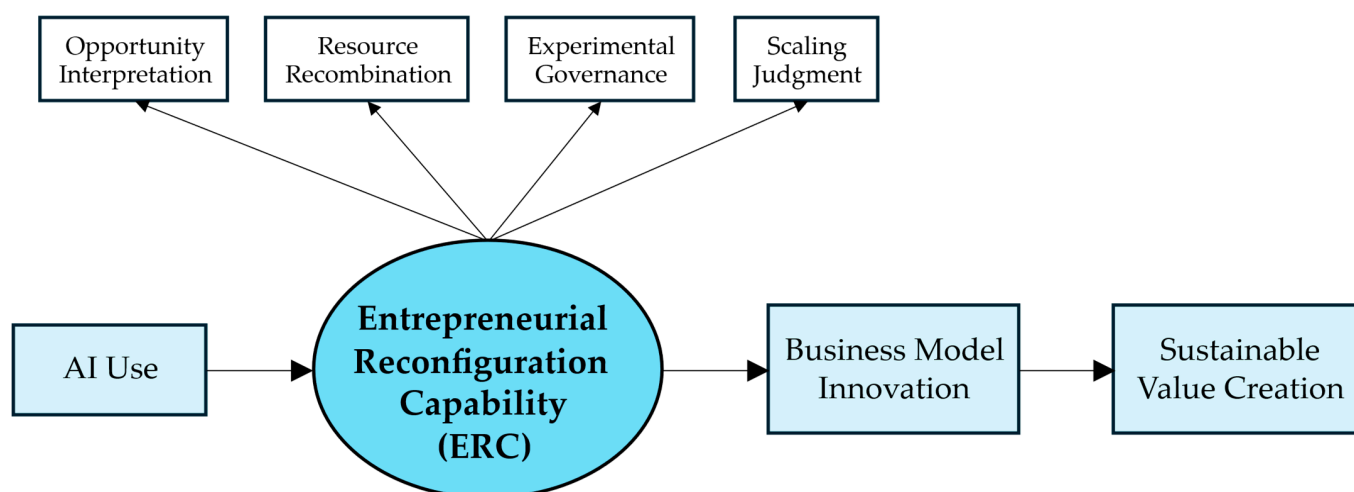


Figure 1. Conceptual framework of AI-enabled entrepreneurial reconfiguration. The figure presents the theoretical sequence proposed in the study, positioning ERC as the central entrepreneurial–organizational mechanism linking AI Use with Business Model Innovation and Sustainable Value Creation. ERC is represented through its four dimensions: opportunity interpretation, resource recombination, experimental governance, and scaling judgment.

In this framework, AI Use refers to the breadth, depth, and organizational integration of AI applications across business activities. AI is conceptualized as a technological input that may expand information-processing capacity, decision-making support, and innovation opportunities. However, AI use does not automatically imply strategic transformation. Its organizational relevance depends on whether firms can interpret AI-enabled possibilities, recombine resources, experiment with new configurations, and selectively scale initiatives into business model change.

ERC is positioned as the entrepreneurial–organizational capability through which AI use may become associated with BMI. It captures opportunity interpretation, resource recombination, experimental governance, and scaling judgment. BMI is treated as the transformation outcome because it reflects changes in value proposition, value delivery, and value capture [14–16]. SVC is treated as the final outcome because the study examines whether business model changes are associated with economic performance, organizational adaptability, and social or environmental contribution [24,30,42,43].

From a dynamic capabilities perspective, technological resources become strategically relevant when firms can sense opportunities, seize them, and reconfigure resources [10,37]. In SMEs, this capability is especially important because resource constraints often limit large-scale digital transformation. Therefore, firms reporting broader and more embedded AI use are expected to report stronger entrepreneurial reconfiguration processes.

H1. *AI use is positively associated with Entrepreneurial Reconfiguration Capability in SMEs.*

ERC extends this logic by incorporating insights from digital entrepreneurship, effectuation, and entrepreneurial bricolage [23,34–36]. These perspectives suggest that innovation under uncertainty depends on experimentation, recombination of available means, and progressive opportunity interpretation. In the AI context, ERC may help SMEs move beyond isolated technological applications and connect AI-enabled insights with changes in how value is created, delivered, and captured.

H2. *Entrepreneurial Reconfiguration Capability is positively associated with Business Model Innovation.*

BMI involves modifications in the firm's value proposition, value delivery mechanisms, and value capture logic [14–16]. In sustainability-oriented contexts, business model changes may help firms align economic performance with adaptability and social or environmental value [30,42,43]. Therefore, firms reporting higher levels of BMI are expected to report stronger SVC outcomes.

H3. *Business Model Innovation is positively associated with Sustainable Value Creation.*

The model also examines whether ERC mediates the association between AI Use and BMI. This mediation logic is grounded in the idea that AI use alone may be insufficiently associated with business model transformation unless firms develop the capability to interpret AI-enabled opportunities, recombine resources, and experiment with new value configurations.

H4. *Entrepreneurial Reconfiguration Capability mediates the relationship between AI use and Business Model Innovation.*

Finally, the model examines whether BMI mediates the association between ERC and SVC. Although ERC reflects the capability to reinterpret opportunities and reconfigure resources, sustainable value is more likely to be reported when these entrepreneurial processes are incorporated into concrete business model changes.

H5. *Business Model Innovation mediates the relationship between Entrepreneurial Reconfiguration Capability and Sustainable Value Creation.*

Taken together, these hypotheses articulate a sequential transformation mechanism in which AI use is not expected to be directly or automatically associated with SVC. Instead, the model proposes that AI use is associated with ERC, ERC is associated with BMI, and BMI is associated with SVC. This sequence reflects the theoretical pathway examined in the study, not the only possible relationship among the constructs.

Alternative configurations are plausible. AI use may be directly associated with BMI or SVC, and BMI may also reinforce ERC over time by creating new routines, learning processes, experimentation practices, and scaling capabilities. Similarly, firms with stronger prior BMI may be more likely to develop ERC when adopting AI. For this reason, the empirical analysis also assesses an alternative model including direct effects. However,

the present model positions ERC before BMI because the study focuses on the capability through which SMEs reinterpret AI-enabled possibilities and connect them with business model change. Given the cross-sectional design, the proposed sequence is interpreted as a theoretically grounded association rather than as definitive evidence of temporal precedence or causality.

This theoretical structure informs the methodological design. Because the framework involves latent constructs, a sequential mediation structure, and a multidimensional higher-order construct, the empirical analysis requires a method capable of assessing both measurement quality and structural relationships. PLS-SEM was therefore selected because it enables the simultaneous evaluation of construct reliability and validity, path coefficients among latent variables, and indirect associations within a prediction-oriented model.

3. Materials and Methods

3.1. Research Design and Methodological Alignment

This study adopts a quantitative, cross-sectional, and theory-testing design to examine the relationships among AI Use, Entrepreneurial Reconfiguration Capability (ERC), Business Model Innovation (BMI), and Sustainable Value Creation (SVC) in SMEs. The quantitative approach is appropriate because the study evaluates theoretically derived relationships among latent organizational constructs through a structured conceptual model. Since the data were collected at a single point in time, the design supports the analysis of theoretically grounded associations, but not definitive causal effects.

The empirical dataset is structured at the firm level. Each observation corresponds to one SME and contains the response of an owner, manager, or senior decision-maker regarding the firm's AI use, entrepreneurial reconfiguration practices, business model innovation, and sustainable value creation. The final dataset includes 385 valid observations from Ecuadorian SMEs. All constructs were measured using multi-item Likert scales, allowing AI Use, ERC, BMI, and SVC to be modeled as latent variables.

The methodological design follows the objective of the study. The proposed framework does not estimate the technical performance of specific AI systems or establish a causal effect of AI adoption. Instead, it examines whether AI use is associated with SVC through a sequential organizational mechanism involving ERC and BMI. Figure 2 summarizes the main methodological stages, from theoretical definition and item adaptation to validation, data collection, data screening, and PLS-SEM analysis. To further clarify the coherence among the research objective, construct specification, analytical procedure, and the type of inference supported, Table 2 presents the study's methodological alignment.

To test the proposed model, the study employs Partial Least Squares Structural Equation Modeling (PLS-SEM). This method is suitable because it enables simultaneous assessment of the measurement and structural models, supports mediation analysis among latent constructs, and allows ERC to be modeled as a reflective–reflective higher-order construct. It is also appropriate for organizational survey data from SMEs in an emerging-economy context, where prediction-oriented modeling and flexibility regarding distributional assumptions are relevant.

PLS-SEM was selected to evaluate construct reliability, convergent validity, discriminant validity, path coefficients, explanatory power, effect sizes, predictive relevance, and indirect effects. Accordingly, the analytical strategy assesses whether AI Use is associated with ERC, whether ERC is associated with BMI, and whether BMI is associated with SVC.

Although the direction of the relationships is derived from theory, the cross-sectional design does not establish temporal precedence among AI Use, ERC, BMI, and SVC. Therefore, longitudinal or experimental designs would be required to confirm causal mechanisms.

The structural paths are interpreted as theoretically grounded associations, an interpretation maintained in the discussion, conclusions, and limitations.

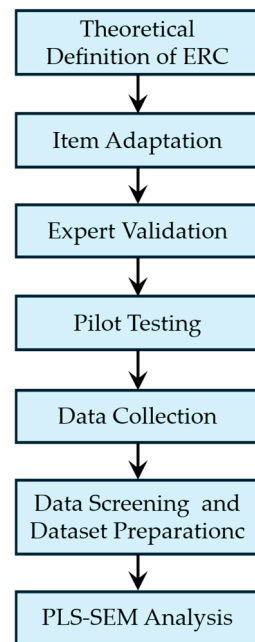


Figure 2. Methodological flow of the study. The figure summarizes the main stages of the research process: theoretical definition of ERC, item adaptation, expert validation, pilot testing, data collection, data screening and dataset preparation, and PLS-SEM analysis.

Table 2. Alignment between research objective, construct specification, and methodological approach.

Research Component	Methodological Implication	Analytical Procedure	Type of Inference Supported
AI-enabled transformation in SMEs	AI Use, ERC, BMI, and SVC are modeled as latent constructs	Measurement model assessment	Reliability and validity of construct measurement
Sequential transformation mechanism	The model specifies the pathway AI Use → ERC → BMI → SVC	Structural model assessment	Theoretically grounded associations among constructs
Entrepreneurial Reconfiguration Capability	ERC is specified as a higher-order construct composed of opportunity interpretation, resource recombination, experimental governance, and scaling judgment	Hierarchical component model estimation	Empirical assessment of ERC as a multidimensional capability
Indirect link between AI Use and SVC	The relationship is expected to operate through ERC and BMI	Mediation analysis with bootstrapping	Indirect associations rather than direct causal effects
Cross-sectional firm-level data	Temporal precedence cannot be established	Cautious interpretation of path coefficients	Associational, not definitive causal, conclusions

3.2. Population and Sample

The target population consists of SMEs operating in four main sampled sectors in Ecuador: services, commerce, information technology, and industry. These sectors were selected because they represent the largest share of the national SME base and include activities with varying levels of digital maturity, customer interaction, data intensity, and operational complexity. The Ecuadorian SME context is analytically relevant because AI adoption remains limited, uneven, and predominantly experimental.

A total of 385 firms were included in the study, satisfying the conventional sample size requirement for a 95% confidence level and a 5% margin of error, assuming maximum variability. To improve representativeness, the sample followed a proportional stratified design based on two criteria: economic sector and firm size. First, the four focal sectors

were selected because they represent the largest share of Ecuadorian SMEs and include activities with different levels of digital maturity, customer interaction, data intensity, and operational complexity. Second, the target number of firms per sector was defined proportionally to each sector's weight in the SME population. Third, firms were classified by size according to the number of employees, distinguishing microenterprises, small enterprises, and medium-sized enterprises. This procedure was intended to improve empirical coverage of the sampled SME population while preserving the analytical focus on sectors where AI-enabled business model transformation is more likely to be observable. The proportional distribution is presented in Table 3.

Table 3. Distribution of Ecuadorian SMEs and proportional sample size.

Sector	Population (SMEs)	% Share	Sample Size (<i>n</i>)
Services	508,450	39.64	177
Commerce	385,733	30.08	134
IT	140,854	10.98	49
Industry	71,530	5.58	25
Total (focus sectors)	1,106,567	86.28	385

Note: The sample focuses on services, commerce, information technology, and industry, which together represent 86.28% of the national SME base. Other sectors, including agriculture, construction, and health, were not included in the sampling frame and jointly account for the remaining 13.72%. Therefore, the findings should be interpreted primarily in relation to the four sampled sectors.

This sectoral focus defines the empirical scope of the study. Accordingly, the findings should be interpreted as applying primarily to SMEs operating in the four sampled sectors, rather than to all Ecuadorian SMEs or to sectors with substantially different technological, regulatory, or operational conditions. This delimitation is consistent with the study's objective of examining AI-enabled business model transformation in sectors where digital tools and customer-facing innovation are more readily observable.

Firms were also classified by size in accordance with Ecuadorian regulations: microenterprises (1–9 employees), small enterprises (10–49 employees), and medium-sized enterprises (50–99 employees). The final sample comprised 292 microenterprises (75.84%), 68 small enterprises (17.66%), and 25 medium-sized enterprises (6.50%). This composition reflects the actual structure of the Ecuadorian SME population rather than a sampling imbalance.

Overall, the sampling design provides an analytically coherent basis for examining AI use and its relationship with entrepreneurial reconfiguration, business model innovation, and sustainable value creation. The inclusion of different sectors and firm sizes also allows the model to capture heterogeneity in organizational conditions and levels of digital maturity within the Ecuadorian SME context.

3.3. Data Collection Procedure

Data were collected through a structured questionnaire administered electronically between January and March 2026. The online format facilitated access to firms located in different regions of Ecuador and enabled the collection of standardized firm-level responses from SMEs operating in the sampled sectors.

The questionnaire was distributed through professional and academic networks, business associations, and direct contact with SME owners and managers. This multi-channel strategy was used to increase coverage across sectors and firm sizes and to reach firms with different levels of digital maturity. Because the study did not rely on a single closed list of invited firms, a conventional response rate could not be calculated with precision. To mitigate this limitation, representativeness was addressed through proportional stratifica-

tion by sector and firm-size category, and the final sample followed the sectoral structure defined in the sampling design.

Respondent role was used as an eligibility criterion. Valid responses were required to come from owners, managers, or senior decision-makers with knowledge of the firm's AI use, organizational practices, business model changes, and value creation processes. These respondents were considered appropriate because the study examines managerial assessments and reported organizational practices rather than the technical performance of specific AI systems. Before completing the questionnaire, participants were informed of the study's academic purpose, the voluntary nature of participation, and the confidential treatment of the information provided. However, the final database did not retain a disaggregated respondent-role variable. Therefore, the study can confirm that all respondents met the required decision-making profile, but it cannot report the precise distribution among owners, managers, and senior decision-makers.

The questionnaire was designed to reduce overly general responses. Instead of asking respondents to provide a single global assessment of whether AI improved productivity, each construct was measured using multiple items adapted from the prior literature. AI Use captured the breadth and embeddedness of AI applications; ERC captured opportunity interpretation, resource recombination, experimental governance, and scaling judgment; BMI captured changes in value proposition, value delivery, and value capture; and SVC captured economic, adaptive, and social or environmental outcomes. This multi-item structure allowed the study to assess theoretically defined constructs rather than broad subjective claims about AI benefits.

Before analysis, the dataset was screened for completeness and eligibility. Responses were excluded when they were incomplete, contained substantial missing information, or did not correspond to an owner, manager, or senior decision-maker. The remaining responses were reviewed for missing values, inconsistent response patterns, and duplicate entries. After this screening process, 385 valid firm-level observations were retained. The final dataset was then coded and prepared for PLS-SEM, including measurement model evaluation, structural model estimation, mediation analysis, robustness checks, and common method bias assessment.

Nevertheless, questionnaire data may introduce perceptual consistency and social desirability bias. To mitigate this concern, the questionnaire was administered confidentially, and the analysis included statistical checks for common method bias. Accordingly, the findings are interpreted as associations based on managerial assessments and reported organizational practices, rather than as objective evidence of productivity gains or definitive causal effects.

3.4. Measurement Instrument

The measurement instrument was developed from the established literature and adapted to the context of AI-driven entrepreneurial transformation in SMEs. All items were measured using a five-point Likert scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Table 4 presents the constructs, item codes, measurement statements, and literature sources.

The questionnaire items were selected to ensure content validity, while minor wording adjustments improved clarity and contextual relevance without altering the theoretical meaning of the constructs. AI Use (AIU), Business Model Innovation (BMI), and Sustainable Value Creation (SVC) were modeled as reflective first-order constructs. AIU captures the extent, diversity, and integration of AI applications across organizational activities. BMI captures changes in value proposition, value delivery, and value capture. SVC integrates economic performance, organizational adaptability, and sustainability-oriented outcomes.

Table 4. Measurement items and sources.

Construct	Code	Measurement Item	Source
AI Use	AIU1	Our firm uses AI applications across multiple business functions.	Wamba et al. [11]; OECD [2]
	AIU2	AI tools are integrated into our core business processes.	Wamba et al. [11]
	AIU3	AI is used to support decision-making in our organization.	Brynjolfsson and McAfee [1]
	AIU4	Our use of AI goes beyond isolated applications and is embedded in operations.	OECD [2]
Opportunity Interpretation	OPI1	We actively interpret AI as a source of new business opportunities.	Nambisan [34]; Shane and Venkataraman [22]
	OPI2	We use AI insights to identify new market or customer opportunities.	Nambisan [34]
	OPI3	AI helps us rethink how value can be created in our business.	Teece [29]; Helfat and Peteraf [33]
Resource Recombination	RRC1	We combine AI tools with existing resources to develop new solutions.	Fleming [36]; Baker and Nelson [35]
	RRC2	Our firm reconfigures existing processes by integrating AI capabilities.	Teece [10]
	RRC3	We creatively reuse available resources to implement AI-based initiatives.	Baker and Nelson [35]
Experimental Governance	EXG1	We systematically experiment with AI applications before scaling them.	Sarasvathy [23]
	EXG2	Our firm encourages trial-and-error approaches when implementing AI.	Sarasvathy [23]
	EXG3	We learn from failures and adjust our AI-related initiatives accordingly.	Nambisan [34]
Scaling Judgment	SCJ1	We evaluate which AI initiatives should be expanded across the organization.	Teece [10]; Sjödin et al. [17]
	SCJ2	Our firm carefully decides when to scale AI-driven innovations.	Teece [10]; Åström et al. [18]
	SCJ3	We prioritize AI initiatives that demonstrate strategic value.	Teece [29]
Business Model Innovation	BMI1	We have introduced significant changes in our value proposition.	Zott and Amit [16]; Foss and Saebi [14]
	BMI2	We have modified how we deliver value to customers.	Zott and Amit [16]
	BMI3	We have changed how our firm captures value (e.g., revenue models).	Teece [15]
Sustainable Value Creation	SVC1	Our firm has improved its long-term economic performance.	George et al. [24]
	SVC2	Our firm has enhanced its ability to adapt to changing environments.	Teece [29]
	SVC3	Our firm contributes to environmental or social sustainability.	Bocken et al. [42]

Note. All measurement items were adapted from the prior literature.

Entrepreneurial Reconfiguration Capability (ERC) was conceptualized as a multi-dimensional higher-order construct reflecting the firm's ability to transform AI-enabled possibilities into business model innovation through entrepreneurial action. Specifically, ERC was modeled as a reflective–reflective hierarchical component model composed of four first-order dimensions: opportunity interpretation (OPI), resource recombination (RRC), experimental governance (EXG), and scaling judgment (SCJ). This specification follows the theoretical assumption that these dimensions are interrelated manifestations of the same underlying entrepreneurial reconfiguration capability.

The hierarchical structure of ERC was estimated using the repeated indicators approach. Table 5 summarizes the construct structure and measurement specification.

Table 5. Construct structure (hierarchical model).

Construct	Type	Dimensions	Measurement Mode
AI Use (AIU)	First-order	—	Reflective
Entrepreneurial Reconfiguration Capability (ERC)	Second-order	OPI, RRC, EXG, SCJ	Reflective–Reflective (HCM)
Business Model Innovation (BMI)	First-order	—	Reflective
Sustainable Value Creation (SVC)	First-order	—	Reflective

ERC was modeled as a reflective–reflective hierarchical component model because its four dimensions are conceptualized as manifestations of a broader latent capability rather than as independent causal components. Firms with higher ERC are theoretically expected to show stronger opportunity interpretation, greater resource recombination, more systematic experimental governance, and more developed scaling judgment. Therefore, a reflective–reflective specification was considered more appropriate than a formative specification, which would imply that the dimensions operate as independent components that jointly create ERC.

A key distinction in the measurement model concerns the boundary between AI Use and ERC. AI Use captures the extent, diversity, and embeddedness of AI applications across organizational functions; therefore, it represents the technological input available to the firm. ERC captures the entrepreneurial–organizational capability through which the firm interprets, reorganizes, tests, and selectively scales AI-enabled possibilities. Thus, AI Use measures whether and how AI is used, whereas ERC measures what the firm does entrepreneurially with AI-enabled possibilities.

3.5. Instrument Validation

To ensure content validity, clarity, and contextual adequacy, the measurement instrument underwent a multi-stage validation process before full-scale data collection. First, ERC was developed deductively from the literature on dynamic capabilities, digital entrepreneurship, effectuation, and resource recombination/bricolage. This process identified four theoretically grounded dimensions: opportunity interpretation, resource recombination, experimental governance, and scaling judgment.

Second, the initial item pool was reviewed by 18 experts with experience in entrepreneurship, innovation, digital transformation, and organizational research. The experts assessed item relevance, clarity, theoretical fit, and contextual adequacy, with particular attention to whether the ERC items captured entrepreneurial reconfiguration processes rather than general AI adoption or generic organizational capabilities. Based on their feedback, several items were refined to improve wording precision and reduce conceptual overlap.

Third, the questionnaire was pilot tested with 35 SME owners and managers. The pilot test assessed item comprehensibility, response burden, and suitability for the Ecuadorian

SME context. Participants identified unclear or repetitive wording and indicated whether the items reflected practices observable in their firms. Minor wording adjustments were introduced, but no dimension was removed because all four dimensions were considered theoretically necessary to represent ERC.

As a new higher-order construct, ERC was therefore developed through theoretical domain definition, dimensional specification, item adaptation, expert assessment, pilot testing, and empirical validation. This process provides initial evidence of content and measurement adequacy, but it should not be interpreted as definitive proof of ERC's theoretical distinctiveness. Further comparative validation is needed to determine whether ERC provides explanatory value beyond established capability-based constructs. Table 6 summarizes this process.

Table 6. ERC construct development and validation process.

Stage	Purpose	Procedure	Outcome
Theoretical domain definition	Define ERC conceptually	Review of the dynamic capabilities, digital entrepreneurship, effectuation, and resource recombination/bricolage literature	ERC defined as an AI-contingent entrepreneurial reconfiguration capability
Dimensional specification	Identify ERC dimensions	Deductive mapping of theoretical mechanisms	Four dimensions retained: OPI, RRC, EXG, SCJ
Item adaptation	Develop measurement items	Adaptation of items from the prior literature and contextual adjustment to AI-enabled transformation	Initial ERC item pool developed
Expert validation	Assess content validity	Expert review of relevance, clarity, theoretical fit, and contextual adequacy	Items refined for clarity and reduced overlap
Pilot testing	Assess respondent comprehension	Pilot test with SME owners/managers	Minor wording adjustments introduced
Measurement validation	Assess empirical adequacy	Reliability, AVE, second-order loadings, HTMT, cross-loadings	ERC retained as reflective–reflective higher-order construct

3.6. Data Analysis Technique

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) implemented in SmartPLS. This technique was selected because it is suitable for prediction-oriented research, models with mediation relationships, and the estimation of higher-order constructs such as Entrepreneurial Reconfiguration Capability (ERC).

A two-stage analytical procedure was followed. First, the measurement model was assessed through indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Indicator reliability was evaluated through outer loadings, internal consistency through Cronbach's alpha and composite reliability, convergent validity through average variance extracted (AVE), and discriminant validity through the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT).

Second, the structural model was evaluated through path coefficients (β), statistical significance using bootstrapping with 5000 resamples, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2). Mediation effects were also assessed to test the indirect relationships proposed in H4 and H5. Because ERC was conceptualized as a higher-order construct, it was estimated using the repeated indicators approach, allowing the simultaneous assessment of first-order and second-order components within the PLS-SEM framework.

3.7. Model Evaluation Criteria

The evaluation of the PLS-SEM model prioritized predictive accuracy and explanatory power rather than global goodness-of-fit indices typically associated with covariance-based SEM. This approach is consistent with the prediction-oriented logic of PLS-SEM and with the study's objective of examining the mechanisms through which AI use is associated with business model innovation and sustainable value creation.

Accordingly, the assessment focused on R^2 , Q^2 , and f^2 . R^2 values were interpreted as indicators of explanatory strength for the endogenous constructs; Q^2 values greater than zero were taken as evidence of predictive relevance; and f^2 values were used to assess the relative contribution of each exogenous construct to the explained variance of the dependent variables. Together, these criteria provided the basis for evaluating the explanatory and predictive performance of the proposed model.

4. Results

4.1. Measurement Model Assessment

The measurement model was assessed following established PLS-SEM criteria, including indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

Indicator reliability was examined through outer loadings. As reported in Table A4 (Appendix A), all indicators exceeded the recommended threshold of 0.70, with values ranging from 0.861 to 0.904, and all loadings were statistically significant ($p < 0.001$). Table A1 provides the individual loadings for all first-order constructs, with values consistently above 0.85.

Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (CR). As shown in Table A2, Cronbach's alpha ranged from 0.836 to 0.909, while CR ranged from 0.901 to 0.936 for the first-order constructs. Convergent validity was evaluated using the average variance extracted (AVE), with all constructs exceeding the minimum threshold of 0.50. For the higher-order ERC construct, CR and AVE are reported in Table 7.

Table 7. Higher-order construct reliability and convergent validity.

Construct	Model Specification	Composite Reliability (CR)	AVE
Entrepreneurial Reconfiguration Capability (ERC)	Second-order reflective (repeated indicators)	0.805	0.509

Note. Because ERC was modeled as a higher-order construct in the second stage, the table emphasizes composite reliability and AVE, mirroring the structure of the reference article.

Because Entrepreneurial Reconfiguration Capability (ERC) was modeled as a higher-order construct, its measurement quality was further assessed through the loadings of its first-order dimensions. As shown in Table 8, all dimensions exhibited substantial and statistically significant loadings, ranging from 0.668 to 0.757. Scaling Judgment (0.757) and Opportunity Interpretation (0.740) showed the strongest contributions, followed by Resource Recombination (0.684) and Experimental Governance (0.668).

Although Experimental Governance (0.668) and Resource Recombination (0.684) were slightly below the conventional 0.70 threshold, both dimensions were retained for theoretical and methodological reasons. Removing either dimension would narrow the conceptual domain of ERC: Resource Recombination captures the rearrangement of routines, data, knowledge, and resources around AI-enabled opportunities, while Experimental Governance captures trial, learning, adjustment, and controlled experimentation under

uncertainty. Methodologically, the higher-order construct achieved acceptable reliability and convergent validity, with CR = 0.805 and AVE = 0.509. These results support the empirical coherence of ERC as a higher-order construct, although they should not be interpreted as definitive evidence that ERC is theoretically superior to alternative capability-based constructs.

Table 8. Higher-order construct loadings.

Higher-Order Construct	Dimension	Loading	t-Value	p-Value	Decision
Entrepreneurial Reconfiguration Capability	Experimental Governance	0.668	17.015	<0.001	Retained
	Opportunity Interpretation	0.740	26.895	<0.001	Retained
	Resource Recombination	0.684	20.082	<0.001	Retained
	Scaling Judgment	0.757	32.751	<0.001	Retained

Discriminant validity was assessed using the Fornell–Larcker criterion, the heterotrait–monotrait ratio (HTMT), and cross-loadings. The Fornell–Larcker results are reported in Table A5. The square roots of AVE were higher than the corresponding inter-construct correlations for all constructs: AI Use (0.886), Business Model Innovation (0.892), Experimental Governance (0.867), Opportunity Interpretation (0.888), Resource Recombination (0.896), Scaling Judgment (0.890), and Sustainable Value Creation (0.898). These results support discriminant validity according to the Fornell–Larcker criterion.

At the first-order level, the HTMT values reported in Table A3 were below the recommended threshold of 0.90. At the higher-order level, most construct pairs also met the recommended criterion. However, the HTMT value between AI Use and ERC was 0.950, exceeding the conservative 0.90 threshold. This result indicates a relevant discriminant validity concern and requires cautious interpretation.

Conceptually, AI Use and ERC are related but distinct constructs. AI Use captures the extent to which AI applications are adopted, integrated, and used across business processes; therefore, it reflects the firm’s technological input. ERC captures the firm’s capacity to reinterpret AI-enabled possibilities, recombine existing resources, govern experimentation, and scale promising initiatives under uncertainty. Thus, AI Use measures whether and how AI is used, whereas ERC measures what the firm does entrepreneurially and organizationally with AI-enabled possibilities.

Given the elevated HTMT value between AI Use and ERC, a bootstrapped HTMT inference test was conducted using 5000 bootstrap subsamples. The confidence intervals are reported in Table 9.

Table 9. Discriminant validity: HTMT values and bootstrapped confidence intervals.

Construct Pair	HTMT Value	95% Bootstrap CI	Validity
Business Model Innovation (BMI)–AI Use (AIU)	0.558	[0.486–0.624]	Established
Entrepreneurial Reconfiguration Capability (ERC)–AI Use (AIU)	0.950	[0.911–0.993]	Requires cautious interpretation
Entrepreneurial Reconfiguration Capability (ERC)–Business Model Innovation (BMI)	0.765	[0.695–0.830]	Established
Sustainable Value Creation (SVC)–AI Use (AIU)	0.396	[0.311–0.478]	Established
Sustainable Value Creation (SVC)–Business Model Innovation (BMI)	0.651	[0.587–0.709]	Established
Sustainable Value Creation (SVC)–Entrepreneurial Reconfiguration Capability (ERC)	0.595	[0.505–0.678]	Established

Note. HTMT confidence intervals were obtained using 5000 bootstrap subsamples. Discriminant validity is supported when the confidence interval does not include 1.000. The AI Use–ERC relationship is interpreted cautiously because its HTMT value exceeds the conservative 0.90 threshold.

The bootstrapped confidence intervals remained below 1.000 for all construct pairs. However, because the AI Use–ERC point estimate was 0.950, this relationship was interpreted cautiously rather than treated as fully resolved by the HTMT inference test alone.

Additional checks were conducted to examine whether AI Use and ERC were operationally redundant. First, item content was reassessed. AI Use items refer to the use, integration, and embeddedness of AI tools across organizational functions and decision-making processes. In contrast, the ERC dimensions refer to opportunity interpretation, resource recombination, experimental governance, and scaling judgment. Second, the first-order HTMT values between AI Use and the four ERC dimensions remained below 0.90: Experimental Governance–AI Use = 0.557, Opportunity Interpretation–AI Use = 0.652, Resource Recombination–AI Use = 0.633, and Scaling Judgment–AI Use = 0.671. Third, the cross-loadings reported in Table A7 showed that the ERC dimensions loaded more strongly on ERC than on AI Use, BMI, or SVC.

Taken together, the Fornell–Larcker criterion, bootstrapped HTMT inference test, item-content reassessment, first-order HTMT values, and cross-loading inspection support treating AI Use and ERC as empirically close but not operationally redundant. Nevertheless, these checks do not fully eliminate the discriminant validity concern because the AI Use–ERC HTMT point estimate exceeds the conservative 0.90 threshold. Consequently, the AI Use–ERC relationship and the structural paths involving ERC are interpreted with caution, and future studies should further validate this distinction using longitudinal data, alternative samples, multi-source designs, and competing measurement specifications.

4.2. Structural Model Results

The structural model results are presented in Table 10 and illustrated in Figure 3. All hypothesized relationships were positive and statistically significant. AI Use was strongly associated with Entrepreneurial Reconfiguration Capability (ERC) ($\beta = 0.783$, $p < 0.001$). ERC was positively associated with Business Model Innovation (BMI) ($\beta = 0.630$, $p < 0.001$), and BMI was positively associated with Sustainable Value Creation (SVC) ($\beta = 0.651$, $p < 0.001$).

Table 10. Hypothesized structural paths and standardized effects.

Relationship	Standardized Effect (β)	<i>p</i> -Value	Hypothesis Support
AI Use (AIU) → Entrepreneurial Reconfiguration Capability	0.783	<0.001	Supported
Business Model Innovation (BMI) → Sustainable Value Creation (SVC)	0.651	<0.001	Supported
Entrepreneurial Reconfiguration Capability → Business Model Innovation (BMI)	0.630	<0.001	Supported

The magnitude of the path coefficients is consistent with the proposed sequential pattern. The strongest association appears at the AIU–ERC stage, followed by substantial associations in the ERC–BMI and BMI–SVC paths. This pattern supports the internal coherence of the proposed model. However, these findings should be interpreted as empirical support for the specific mechanism examined in this study, not as definitive evidence that ERC is theoretically superior to alternative capability-based constructs.

The results are also consistent with the proposed sequential mediation logic. However, because the original theoretical model did not specify direct paths from AI Use to BMI or SVC, full mediation is not inferred from this model alone. To address this issue, an alternative partial mediation model including direct effects is reported in the robustness section.

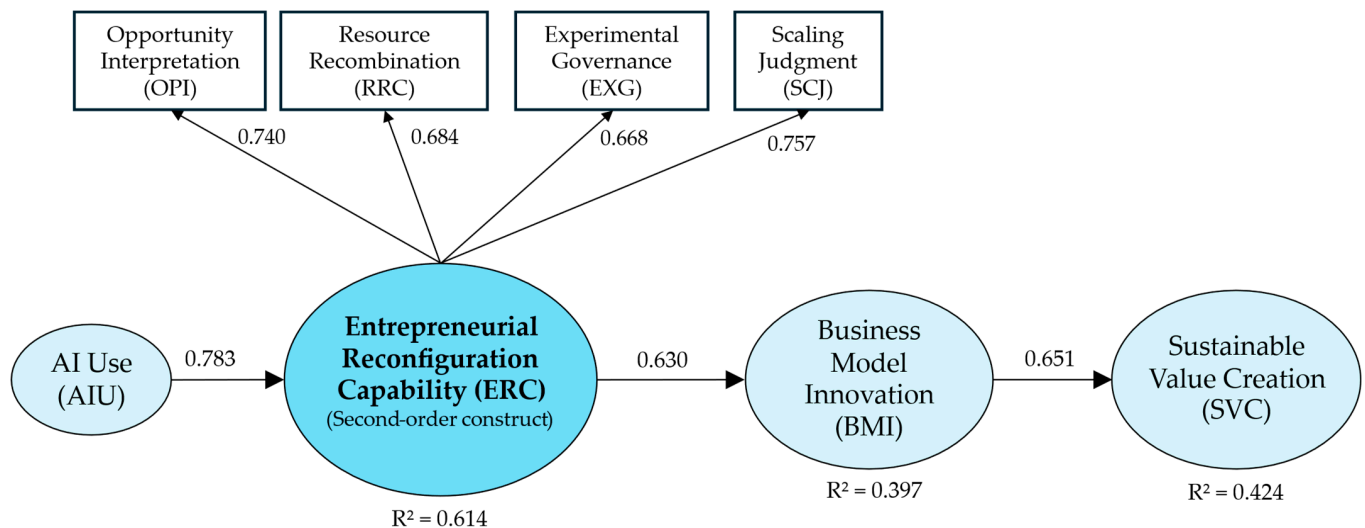


Figure 3. Estimated structural model. The figure presents the PLS-SEM results for the proposed AI Use–ERC–BMI–SVC model, including standardized path coefficients and explained variance for the endogenous constructs.

Table 11 reports the R^2 values for the endogenous constructs. The model shows substantial explanatory power for ERC and moderate explanatory power for BMI and SVC.

Table 11. Explanatory power of the structural model.

Endogenous Construct	R^2	Interpretation
Business Model Innovation (BMI)	0.397	Moderate explanatory power
Entrepreneurial Reconfiguration Capability (ERC)	0.614	Substantial explanatory power
Sustainable Value Creation (SVC)	0.424	Moderate explanatory power

Table 12 presents the effect size assessment. All three structural relationships show large f^2 values, indicating that the paths contribute meaningfully to the explanatory power of the model.

Table 12. Effect size assessment (f^2).

Structural Relationship	f^2	Effect Magnitude
AI Use (AIU) → Entrepreneurial Reconfiguration Capability (ERC)	1.588	Large
Business Model Innovation (BMI) → Sustainable Value Creation (SVC)	0.736	Large
Entrepreneurial Reconfiguration Capability (ERC) → Business Model Innovation (BMI)	0.657	Large

4.3. Mediation Analysis

The mediation analysis results are presented in Table 13. The indirect association between AI Use and BMI through ERC was positive and statistically significant ($\beta = 0.493$, $p < 0.001$). ERC was also indirectly associated with SVC through BMI ($\beta = 0.410$, $p < 0.001$). In addition, the sequential indirect association between AI Use and SVC through ERC and BMI was statistically significant ($\beta = 0.321$, $p < 0.001$).

Table 13. Mediation analysis results.

Effect Type	Path	Standardized Effect (β)	Significance
Indirect effect	AI Use (AIU) $\rightarrow$ ERC $\rightarrow$ Business Model Innovation (BMI)	0.493	$p < 0.001$
Total effect	AI Use (AIU) $\rightarrow$ Business Model Innovation (BMI)	0.493	$p < 0.001$
Indirect effect	ERC $\rightarrow$ Business Model Innovation (BMI) $\rightarrow$ Sustainable Value Creation (SVC)	0.410	$p < 0.001$
Total effect	ERC $\rightarrow$ Sustainable Value Creation (SVC)	0.410	$p < 0.001$
Sequential indirect effect	AI Use (AIU) $\rightarrow$ ERC $\rightarrow$ BMI $\rightarrow$ Sustainable Value Creation (SVC)	0.321	$p < 0.001$
Total effect	AI Use (AIU) $\rightarrow$ Sustainable Value Creation (SVC)	0.321	$p < 0.001$

Note. Table 13 reports the indirect effects associated with the theoretically proposed sequential model. Direct effects from AI Use to Business Model Innovation and Sustainable Value Creation are assessed separately in the alternative model reported in Section 4.4.1.

Overall, the mediation results provide evidence consistent with the proposed sequential mechanism. In the theoretically specified model, AI Use is indirectly associated with BMI through ERC and with SVC through the sequential pathway involving ERC and BMI. Similarly, ERC is indirectly associated with SVC through BMI. However, these indirect effects should be interpreted as theoretically consistent associations rather than as definitive evidence of causal mediation or as proof that ERC is the only possible mechanism linking AI use with BMI.

Taken together, these results support hypotheses H1–H5 and are consistent with the proposed AI Use–ERC–BMI–SVC sequence, while remaining limited to associational evidence. The hypothesis summary is presented narratively to avoid duplicating the structural and mediation results already reported in Tables 10 and 13.

4.4. Robustness and Model Adequacy

Model robustness and adequacy were evaluated using complementary criteria. First, collinearity diagnostics indicated that variance inflation factor (VIF) values were below the recommended threshold, suggesting that multicollinearity was not a relevant concern. Second, the R^2 values indicated substantial explanatory power for Entrepreneurial Reconfiguration Capability (ERC) and moderate explanatory power for Business Model Innovation (BMI) and Sustainable Value Creation (SVC). Third, the f^2 values showed large effects for the three direct structural relationships, indicating that the paths contributed meaningfully to the model's explanatory power.

Predictive relevance was assessed using Q^2 values, reported in Table A6. All endogenous variables showed Q^2 values greater than zero, indicating predictive relevance. The first-order ERC dimensions showed satisfactory values: Experimental Governance ($Q^2 = 0.230$), Opportunity Interpretation ($Q^2 = 0.334$), Resource Recombination ($Q^2 = 0.316$), and Scaling Judgment ($Q^2 = 0.354$). BMI ($Q^2 = 0.305$) and SVC ($Q^2 = 0.150$) also showed predictive relevance. Overall, these results support the adequacy of the model for predicting the key endogenous constructs.

4.4.1. Alternative Model Assessment

Because the original conceptual model specified a sequential mechanism, an additional robustness check estimated a partial mediation model including direct paths from AI Use to BMI and from AI Use to SVC. This assessment examined whether the proposed indirect sequence remained meaningful when theoretically plausible direct effects were included.

The results are reported in Table 14. The direct path from AI Use to BMI was positive and statistically significant, although weak in magnitude ($\beta = 0.171$, $t = 2.767$, $p = 0.006$).

By contrast, the direct path from AI Use to SVC was not statistically significant ($\beta = 0.050$, $t = 1.052$, $p = 0.293$). The indirect effect through ERC and BMI remained statistically significant, as did the sequential indirect effect from AI Use to SVC through ERC and BMI. These results are consistent with a predominantly mediated sequential pattern rather than a purely direct-effects explanation.

Table 14. Alternative model including direct effects.

Path	β	t-Value	p-Value	Interpretation
AI Use $\rightarrow$ Business Model Innovation	0.171	2.767	0.006	Weak but significant direct effect
AI Use $\rightarrow$ Sustainable Value Creation	0.050	1.052	0.293	Non-significant direct effect
AI Use $\rightarrow$ ERC $\rightarrow$ BMI	0.386	8.184	<0.001	Indirect effect retained
AI Use $\rightarrow$ ERC $\rightarrow$ BMI $\rightarrow$ SVC	0.239	6.985	<0.001	Sequential indirect effect retained

Note. The alternative model includes direct paths from AI Use to Business Model Innovation and Sustainable Value Creation while retaining the theoretically proposed indirect sequence through ERC and BMI.

The alternative model suggests that the indirect mechanism through ERC and BMI remains relevant after considering direct paths from AI Use to BMI and SVC. However, because the study is cross-sectional, these results should be interpreted as theoretically consistent associations rather than definitive causal evidence. They support the usefulness of ERC within the proposed model, but do not establish ERC as a distinct organizational capability or rule out alternative capability-based explanations.

4.4.2. Common Method Bias Assessment

Because all variables were measured using self-reported survey data collected from managerial respondents at a single point in time, common method bias was assessed using Harman's single-factor test and full collinearity VIFs.

First, Harman's single-factor test was conducted by entering all measurement items into an exploratory factor analysis without rotation. The first unrotated factor accounted for 41.69% of the total variance, below the commonly used 50% threshold. This result suggests that no single factor explained most of the covariance among the indicators.

Second, full collinearity VIFs were calculated for the latent constructs. As reported in Table 15, all values were below the conservative threshold of 3.3: AI Use (2.642), ERC (3.062), BMI (2.274), and SVC (1.772). These results indicate that common method bias is unlikely to represent a severe threat to the model estimates.

Table 15. Full collinearity VIF assessment.

Construct	Full Collinearity VIF	Assessment
AI Use	2.642	Below 3.3
Entrepreneurial Reconfiguration Capability	3.062	Below 3.3
Business Model Innovation	2.274	Below 3.3
Sustainable Value Creation	1.772	Below 3.3

Note. Full collinearity VIF values below 3.3 indicate that common method bias is unlikely to be a severe concern.

Nevertheless, common method bias cannot be fully dismissed. This issue is especially relevant in SMEs, where decision-making is often centralized in owners or senior managers. Centralization may amplify perceptual consistency because the same respondent evaluates AI use, ERC, BMI, and SVC from a unified managerial perspective. At the same time, it may reduce uninformed responses, since owners and senior managers are typically familiar with strategic decisions, AI-related initiatives, resource allocation, and business model

changes. Thus, while the statistical evidence does not indicate severe common method bias, the findings should still be interpreted cautiously.

4.4.3. Firm-Size Multi-Group Analysis

Given the inclusion of micro, small, and medium-sized enterprises, and the predominance of microenterprises, a multi-group analysis was conducted to assess whether the structural relationships remained stable across firm-size groups. The sample was divided into microenterprises ($n = 292$) and small/medium-sized enterprises ($n = 93$). Small- and medium-sized firms were grouped together because the number of medium-sized firms was limited.

Before the group comparison, measurement invariance was assessed using the MI-COM procedure. The results supported construct comparability across the two groups. PLS-MGA was then used to compare the structural paths between microenterprises and small/medium-sized enterprises. The results are reported in Table 16.

Table 16. PLS-MGA results by firm size.

Structural Path	Microenterprises β	Small/Medium-Sized Enterprises β	Difference	p -Value	Interpretation
AI Use $\rightarrow$ ERC	0.791	0.740	0.051	0.244	Stable
ERC $\rightarrow$ BMI	0.636	0.606	0.030	0.687	Stable
BMI $\rightarrow$ SVC	0.641	0.668	−0.027	0.728	Stable

Note. PLS-MGA compares path coefficients between microenterprises and small/medium-sized enterprises. Significant p -values indicate differences in structural relationships across groups.

The differences in the main structural paths were not statistically significant. The AI Use $\rightarrow$ ERC path showed a small difference between groups ($\Delta\beta = 0.051$, $p = 0.244$), while the ERC $\rightarrow$ BMI path ($\Delta\beta = 0.030$, $p = 0.687$) and the BMI $\rightarrow$ SVC path ($\Delta\beta = -0.027$, $p = 0.728$) also showed non-significant differences. These findings suggest that the proposed mechanism remains stable across firm-size groups in the sampled SMEs.

Overall, the results from the alternative model, common method bias assessment, predictive relevance analysis, and firm-size MGA provide additional evidence of the robustness and internal coherence of the proposed AI Use–ERC–BMI–SVC model. However, this evidence remains associational and should be interpreted within the methodological limits of the cross-sectional design.

5. Discussion

5.1. Main Empirical Insights and Their Interpretation

The main empirical insight of this study is not that AI use directly creates sustainable value in SMEs, but that the results are consistent with a mediated transformation logic. SMEs reporting broader and more embedded AI use also reported stronger Entrepreneurial Reconfiguration Capability (ERC); firms with stronger ERC reported greater Business Model Innovation (BMI); and firms with greater BMI reported stronger Sustainable Value Creation (SVC). This pattern supports the internal coherence of the proposed AI Use–ERC–BMI–SVC sequence and suggests a plausible organizational mechanism through which AI use may become connected to sustainability-oriented outcomes.

The structural and mediation results support this interpretation. AI Use was positively associated with ERC ($\beta = 0.783$, $p < 0.001$), ERC was positively associated with BMI ($\beta = 0.630$, $p < 0.001$), and BMI was positively associated with SVC ($\beta = 0.651$, $p < 0.001$). The indirect associations were also statistically significant: AI Use was indirectly associated with BMI through ERC ($\beta = 0.493$, $p < 0.001$), ERC was indirectly associated with SVC through BMI ($\beta = 0.410$, $p < 0.001$), and AI Use was sequentially associated with SVC

through ERC and BMI ($\beta = 0.321, p < 0.001$). These coefficients should be interpreted as standardized associations rather than causal estimates because the cross-sectional design does not establish temporal ordering or causality.

The positive association between AI Use and ERC suggests that digital technologies may act as enablers of organizational capability development rather than as direct sources of performance. This interpretation is consistent with the dynamic capabilities perspective, which emphasizes that the value of technological resources depends on the firm's ability to integrate, adapt, and reconfigure them [10,29]. In this sense, AI may expand firms' cognitive and operational capacity to identify opportunities, but its transformative potential appears to depend on whether firms actively reinterpret, recombine, and organize its use. However, this relationship should be interpreted carefully because the elevated HTMT value between AI Use and ERC indicates that future research should continue refining the measurement boundary between AI use as a technological input and ERC as an entrepreneurial–organizational capability.

The relationship between ERC and BMI is consistent with the argument that AI-enabled transformation is partly an entrepreneurial process. This finding aligns with digital entrepreneurship research, which highlights how digital technologies support iterative opportunity development [34], and with effectuation theory, which emphasizes experimentation and resource recombination under uncertainty [23]. Thus, SMEs are unlikely to transform through technology per se. Transformation appears to depend on how technology is interpreted, recombined, experimentally governed, and incorporated into new business model configurations.

At the same time, the findings should not be read as excluding alternative capability-based explanations. Dynamic capabilities, digital capability, absorptive capacity, entrepreneurial orientation, and organizational ambidexterity may also explain relevant aspects of AI-enabled transformation. The contribution of ERC is narrower and more specific: it captures the entrepreneurial reconfiguration process through which fragmented AI use may be interpreted, recombined, experimentally governed, and selectively scaled into BMI under uncertainty and resource constraints. Therefore, the results support the usefulness of ERC within the proposed theoretical framing, but they do not establish ERC as a broader theoretical alternative to existing capability-based constructs. Further comparative research is needed to determine whether ERC provides incremental explanatory value beyond alternative constructs and to identify the contextual conditions under which this added value is most relevant.

The positive association between BMI and SVC is consistent with the view that business model innovation is an important mechanism for long-term competitiveness and sustainability [14,30]. The findings suggest that AI-related efficiency gains are not enough; sustainable value creation appears more closely connected to changes in how firms create, deliver, and capture value. This process-based interpretation also challenges deterministic views of technology and is consistent with research suggesting that digital technologies contribute to sustainability when embedded in broader organizational transformation [24,25].

The Ecuadorian context helps explain why this mediated mechanism is especially relevant. SMEs in this setting often face limited digital maturity, restricted access to specialized human capital, weak data infrastructures, and financial constraints. These conditions may reduce the likelihood that AI use alone is directly associated with BMI or SVC. Under such constraints, ERC becomes relevant because it captures how firms reinterpret fragmented AI use, recombine available resources, govern experimentation, and decide which initiatives can be scaled. Nevertheless, the findings are most directly applicable to SMEs operating in similar emerging-economy environments and should not be generalized to firms with

substantially different levels of digital maturity, institutional support, data infrastructure, or organizational resource availability without further validation.

5.2. Theoretical Implications

The empirical findings are relevant to three interconnected research streams: AI adoption in SMEs, dynamic capabilities, and business model innovation. Rather than treating these streams separately, this study connects them through a sequential explanation in which AI use is associated with entrepreneurial reconfiguration, entrepreneurial reconfiguration is associated with business model innovation, and business model innovation is associated with sustainable value creation.

The contribution should, therefore, be interpreted as a bounded theoretical extension rather than as definitive validation of ERC as a universally superior explanatory construct. The study does not claim that established capability-based perspectives are generally insufficient. Rather, it specifies a context-sensitive mechanism through which fragmented AI use may become associated with business model innovation in SMEs through entrepreneurial interpretation, resource recombination, experimental governance, and scaling judgment.

First, the study advances AI-SME research by shifting the analytical focus from adoption to transformation. Prior studies and policy-oriented reports have mainly examined why SMEs adopt digital technologies, which barriers they face, and which organizational or environmental conditions facilitate implementation [2,3,7,8]. The present findings complement this literature by suggesting that AI use is more theoretically meaningful when examined alongside the organizational capabilities that help firms reinterpret AI-enabled possibilities and connect them to business model change. This is especially relevant because AI adoption in SMEs remains uneven and conditioned by digital readiness, data availability, managerial capabilities, and institutional support [12,13].

Second, the study contributes to the dynamic capabilities literature by specifying ERC as a focused and complementary extension of capability-based reasoning. Dynamic capabilities explain how firms sense, seize, and reconfigure resources under changing conditions. ERC does not challenge or replace this broader framework. Instead, it narrows the analytical focus to the AI-contingent entrepreneurial micro-processes through which SMEs reinterpret AI-enabled opportunities, recombine available resources, govern experimentation, and decide which AI-related initiatives should be scaled into business model innovation. Its added value is therefore conditional and process-specific, rather than universal or theoretically substitutive.

Third, the study contributes to the business model innovation literature by positioning BMI as the organizational pathway linking AI-related entrepreneurial capabilities to sustainable value creation. The findings suggest that the association between AI use and sustainability-oriented outcomes is better understood through business model redesign than through technology adoption alone. This interpretation is consistent with arguments that BMI, rather than isolated process improvements, is central to sustained competitive advantage [14–16], and with sustainable BMI research that emphasizes the integration of economic, adaptive, social, and environmental value [30,42,43].

The study also contributes to digital sustainability research by suggesting that the association between AI use and SVC may be indirect and mediated by organizational transformation. This aligns with research emphasizing that digital technologies are more likely to contribute to sustainability when embedded within broader organizational and strategic changes [24,25]. In addition, by treating SVC as a multidimensional outcome, the study connects AI-enabled transformation with broader sustainability and governance debates, where responsible value creation is linked to accountability, transparency, and governance mechanisms [44,45].

Finally, the Ecuadorian SME context contributes to theory development by showing how AI-enabled transformation can be theorized under conditions of constraint. Structural limitations, such as limited resources, weak digital infrastructure, and shortages of specialized human capital, do not necessarily prevent innovation, but may shape the mechanisms through which it occurs. This is consistent with research on entrepreneurial bricolage and resource recombination under constraints [35,36], as well as recent evidence showing that AI adoption in Ecuadorian SMEs remains conditioned by human capabilities, resource alignment, organizational readiness, and heterogeneous adoption patterns across business functions [26,27,46]. In this context, ERC is theoretically relevant as a context-sensitive capability that explains how firms reinterpret, recombine, experiment, and scale AI-enabled possibilities under resource constraints. Nevertheless, further comparative research is needed to determine whether ERC provides stronger explanatory value than alternative capability-based constructs in other empirical settings.

Accordingly, ERC should be understood as a focused conceptual refinement within capability-based reasoning, not as a competing theoretical alternative. Its contribution lies in specifying a particular AI-contingent entrepreneurial reconfiguration mechanism that may be especially useful when AI use is fragmented, experimental, and shaped by resource constraints. This contribution remains bounded by the empirical design and should be interpreted as an initial specification of a complementary construct rather than as definitive evidence that ERC is universally superior to, or theoretically more appropriate than, established capability-based constructs.

5.3. Practical Implications

The findings offer practical implications for SME managers, policymakers, and innovation ecosystems in emerging economies. These implications should be interpreted within the study's empirical scope: SMEs operating in contexts where AI use remains fragmented, experimental, and resource-constrained.

For SME managers, the results suggest that AI should not be evaluated only as a tool for operational efficiency or cost reduction. Managers should also assess whether AI applications help identify market opportunities, redesign customer relationships, improve value delivery, or support new value capture mechanisms. This implication is consistent with the view that digital technologies become strategically relevant when embedded in organizational change and business model transformation rather than treated as isolated technological investments [5,6,14–16]. In practical terms, SMEs should link AI initiatives to explicit business model questions: which customer problem is being reinterpreted, which resources can be recombined, what experiment should be conducted, and which initiative deserves to be scaled.

For internal decision-makers, ERC highlights the importance of controlled experimentation. Rather than adopting AI tools in an isolated or improvised way, firms should establish simple routines for testing AI applications, learning from failures, documenting results, and deciding whether to expand, modify, or discontinue an initiative. This is especially relevant for micro and small firms, where resource constraints make selective scaling more feasible than large-scale digital transformation.

For policymakers, the findings suggest that promoting AI adoption alone may be insufficient. Public programs should combine technological diffusion with capability development, including training in AI-related opportunity identification, data use, experimentation, business model redesign, and digital strategy. This implication aligns with policy-oriented research emphasizing that SME digitalization requires not only access to technology, but also managerial capabilities, advisory support, data infrastructure, and organizational readiness [2,3,12,13]. Policy support should therefore facilitate access to

shared data infrastructure, digital advisory services, innovation vouchers, and collaborative spaces where SMEs can test AI applications before committing scarce resources to broader implementation.

For innovation ecosystems, universities, business associations, technology providers, incubators, and public agencies can help SMEs move from fragmented AI use to business model innovation by providing mentoring, technical support, diagnostic tools, experimentation environments, and sector-specific guidance. Such support is particularly valuable in emerging economies, where firms often lack specialized human capital, structured data, and financial capacity to develop AI-enabled innovation internally.

Overall, the practical implication is not that SMEs should adopt AI more intensively in a generic sense. Rather, AI use becomes more strategically relevant when embedded in entrepreneurial reconfiguration processes that connect technology, resources, experimentation, and business model redesign.

5.4. Limitations and Future Research

Despite its contributions, this study has methodological, conceptual, and contextual limitations. First, the cross-sectional design limits the ability to capture the dynamic nature of AI-enabled transformation and prevents strong causal inference among AI Use, Entrepreneurial Reconfiguration Capability (ERC), Business Model Innovation (BMI), and Sustainable Value Creation (SVC). Although the proposed AI Use–ERC–BMI–SVC sequence is theoretically grounded and statistically supported, the results should be interpreted as theoretically consistent associations rather than definitive causal effects. The design also cannot rule out omitted-variable bias, simultaneity, or reverse causality. Future research should address these issues through longitudinal, panel, quasi-experimental, or experimental designs.

Second, the results support the proposed model but do not definitively validate ERC as a distinct organizational capability in all contexts. ERC was developed deductively and showed acceptable empirical behavior within the model; however, further studies should compare ERC with alternative capability-based constructs, such as dynamic capabilities, digital capability, absorptive capacity, entrepreneurial orientation, and organizational ambidexterity. Such comparisons would help determine whether ERC provides incremental explanatory value beyond established constructs and under which conditions it offers a more appropriate explanation of AI-enabled BMI.

A related measurement limitation concerns discriminant validity between AI Use and ERC. Although the bootstrapped HTMT confidence interval remained below 1.000, and additional evidence from first-order HTMT values, item-content reassessment, Fornell–Larcker results, and cross-loadings supports treating the constructs as empirically close but not operationally redundant, the AI Use–ERC HTMT point estimate was 0.950, exceeding the conservative 0.90 threshold. Therefore, the AI Use–ERC relationship and the sequential mechanism involving ERC should be interpreted with caution. Future research should further validate the distinction between AI Use as a technological input and ERC as an entrepreneurial–organizational capability using alternative samples, multi-source data, longitudinal designs, and competing measurement specifications.

Third, the relationship between ERC and BMI may be more iterative than the cross-sectional model can capture. This study positions ERC before BMI because the theoretical focus is on the capability through which SMEs translate AI-enabled possibilities into business model change. However, BMI may also strengthen ERC over time by creating new routines, learning processes, experimentation practices, and scaling capabilities. Future longitudinal research should examine whether ERC precedes BMI, whether BMI reinforces ERC, or whether both constructs co-evolve during AI-enabled transformation.

Fourth, the use of questionnaire-based self-reported data may introduce common method bias, perceptual consistency, and social desirability bias. Although Harman's single-factor test and the full collinearity VIF assessment did not indicate severe common method bias, these statistical checks do not eliminate the possibility of common method effects. Future studies should complement managerial surveys with objective indicators, archival records, digital trace data, multiple respondents per firm, or longitudinal evidence. In addition, although respondent role was used as an eligibility criterion, the final dataset did not retain a disaggregated respondent-role variable. Future research should retain this information to assess whether respondents' positions influence perceptions of AI use, ERC, BMI, and SVC.

Fifth, the study has a specific geographic, sectoral, and firm-size scope. The sample focuses on Ecuadorian SMEs operating in services, commerce, information technology, and industry, providing a relevant setting for examining AI-enabled transformation amid limited digital maturity, resource scarcity, and uneven institutional support. However, the findings should not be generalized uncritically to all Ecuadorian SMEs, to sectors outside the sampling frame, or to SMEs in other national contexts. Although the sample reflects the structure of the Ecuadorian SME sector, the predominance of microenterprises limits the analysis of firm-size heterogeneity. The PLS-MGA comparing microenterprises with small- and medium-sized enterprises showed stable structural relationships, but future studies should use larger and more balanced samples across firm-size and sectoral categories.

Sixth, although ERC is conceptualized as a multidimensional construct, this study analyzes it primarily as a higher-order capability rather than estimating the separate effects of each dimension. Future research could examine how opportunity interpretation, resource recombination, experimental governance, and scaling judgment contribute differently to BMI and SVC. This would clarify whether all ERC dimensions play equivalent roles or whether some are more influential at specific stages of AI-enabled transformation.

Finally, the Ecuadorian context provides a relevant but bounded setting for examining AI-enabled transformation under resource and institutional constraints. SMEs in developed economies or in emerging economies with stronger innovation ecosystems, better data infrastructures, and more extensive policy support may follow different transformation pathways. Future comparative studies should examine SMEs across countries with different levels of digital maturity, institutional support, innovation ecosystem development, and data infrastructure. They could also extend the model by incorporating moderating variables such as environmental dynamism, digital maturity, institutional support, firm size, sectoral technological intensity, managerial digital orientation, or prior innovation experience.

6. Conclusions

This study examined how AI use is associated with Sustainable Value Creation (SVC) in SMEs through a sequential mechanism involving Entrepreneurial Reconfiguration Capability (ERC) and Business Model Innovation (BMI). The findings show that AI use is positively associated with ERC, ERC is positively associated with BMI, and BMI is positively associated with SVC. The results are also consistent with a sequential indirect pathway in which AI use is associated with SVC through ERC and BMI.

The main conclusion is that AI use alone does not fully explain business model innovation or sustainable value creation in the sampled SMEs. Instead, AI use appears to become more strategically meaningful when firms develop the capability to reinterpret AI-enabled opportunities, recombine available resources, govern experimentation, and scale selected initiatives. In this model, ERC operates as the organizational mechanism linking

AI use with BMI, while BMI is the mechanism most directly associated with sustainable value creation.

Theoretically, the study contributes by moving beyond an adoption-oriented view of AI in SMEs toward a process-oriented explanation of AI-enabled transformation. However, this contribution should be interpreted as theoretically bounded. The findings support the usefulness of ERC within the proposed AI Use–ERC–BMI–SVC framework, but they do not prove that ERC is the only possible mechanism linking AI use with business model innovation or that existing capability-based constructs are insufficient in all contexts. ERC is therefore proposed as a complementary, process-specific construct that extends capability-based reasoning by specifying how SMEs may reinterpret AI-enabled possibilities, recombine constrained resources, govern experimentation, and selectively scale AI-related initiatives into business model change.

The Ecuadorian SME context provides an analytically relevant setting for examining AI-enabled transformation under limited digital maturity, resource scarcity, and uneven institutional support. In such contexts, the value of AI may depend less on the mere adoption of technological tools and more on firms' ability to reinterpret and recombine available resources into new business model configurations. However, this context-specific relevance also limits the transferability of the findings to firms operating under different technological, institutional, and organizational conditions.

These conclusions should be interpreted within the empirical, conceptual, and methodological boundaries of the study. The findings apply primarily to the sampled Ecuadorian SMEs and should not be generalized uncritically to all SMEs or national contexts. Because the study uses cross-sectional survey data and PLS-SEM, the results support theoretically grounded associations but do not establish temporal precedence or definitive causality. Future longitudinal, multi-source, cross-sectoral, and cross-country studies should examine whether AI use contributes over time to the development of ERC, subsequent business model innovation, and sustainable value creation. Future research should also compare ERC with alternative capability-based constructs, such as dynamic capabilities, digital capability, absorptive capacity, entrepreneurial orientation, and organizational ambidexterity, to determine under which conditions ERC provides additional explanatory value.

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Institutional Review Board Statement: This study was conducted using an anonymous survey administered to adult SME owners and managers. It did not involve clinical procedures, biomedical experimentation, intervention, or the collection of sensitive personal data. Participation was entirely voluntary, and respondents were informed about the purpose of the study, the confidential treatment of their responses, and their right to withdraw at any time without consequence. Given the non-clinical, non-interventional, and minimal-risk nature of the research, formal ethical review was not required under the applicable national framework for health research. All procedures were conducted in accordance with internationally recognized ethical principles for research involving human participants, including respect for autonomy, privacy, and confidentiality, as well as voluntary participation. The study was aligned with the ethical principles reflected in the current Declaration of Helsinki.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. Before completing the questionnaire, participants were informed about the purpose of the research, the voluntary nature of participation, the confidentiality of their responses, and their right to withdraw at any time. No personal or identifiable information was collected.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

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Appendix A. Measurement Properties of First-Order Constructs

Table A1. Indicator loadings for first-order constructs.

Construct	Item	Item Label (Short Description)	Loading
AI Use	AIU1	AI across functions	0.890
	AIU2	AI integrated into core processes	0.885
	AIU3	AI supports decision-making	0.874
	AIU4	AI embedded beyond isolated use	0.896
Business Model Innovation	BMI1	Changes in value proposition	0.904
	BMI2	Changes in value delivery	0.888
	BMI3	Changes in value capture	0.883
Experimental Governance	EXG1	Systematic experimentation before scaling	0.878
	EXG2	Trial-and-error implementation	0.864
	EXG3	Learning from AI-related failures	0.861
Opportunity Interpretation	OPI1	AI as source of opportunities	0.893
	OPI2	AI for market/customer opportunities	0.890
	OPI3	AI rethinks value creation	0.881
Resource Recombination	RRC1	Combining AI with existing resources	0.899
	RRC2	Reconfiguring processes with AI	0.891
	RRC3	Creative reuse for AI initiatives	0.897
Scaling Judgment	SCJ1	Evaluating which AI initiatives to scale	0.902
	SCJ2	Judging when to scale AI innovations	0.883
	SCJ3	Prioritizing strategic AI initiatives	0.884
Sustainable Value Creation	SVC1	Improved long-term economic performance	0.903
	SVC2	Greater adaptability to change	0.904
	SVC3	Environmental/social sustainability contribution	0.886

Table A2. Construct reliability and convergent validity for first-order constructs.

Construct	Cronbach’s Alpha (α)	Rho_A	Composite Reliability (CR)	AVE
AI Use (AIU)	0.909	0.910	0.936	0.785
Business Model Innovation (BMI)	0.871	0.872	0.921	0.795
Experimental Governance (EXG)	0.836	0.837	0.901	0.752
Opportunity Interpretation (OPI)	0.866	0.866	0.918	0.789
Resource Recombination (RRC)	0.877	0.877	0.924	0.802
Scaling Judgment (SCJ)	0.869	0.870	0.919	0.792
Sustainable Value Creation (SVC)	0.880	0.885	0.926	0.806

Table A3. HTMT values among first-order constructs.

Construct Pair Compared	HTMT
Business Model Innovation (BMI) and AI Use (AIU)	0.627

Table A3. *Cont.*

Construct Pair Compared	HTMT
Experimental Governance (EXG) and AI Use (AIU)	0.557
Experimental Governance (EXG) and Business Model Innovation (BMI)	0.515
Opportunity Interpretation (OPI) and AI Use (AIU)	0.652
Opportunity Interpretation (OPI) and Business Model Innovation (BMI)	0.541
Opportunity Interpretation (OPI) and Experimental Governance (EXG)	0.424
Resource Recombination (RRC) and AI Use (AIU)	0.633
Resource Recombination (RRC) and Business Model Innovation (BMI)	0.454
Resource Recombination (RRC) and Experimental Governance (EXG)	0.348
Resource Recombination (RRC) and Opportunity Interpretation (OPI)	0.341
Scaling Judgment (SCJ) and AI Use (AIU)	0.671
Scaling Judgment (SCJ) and Business Model Innovation (BMI)	0.557
Scaling Judgment (SCJ) and Experimental Governance (EXG)	0.360
Scaling Judgment (SCJ) and Opportunity Interpretation (OPI)	0.487
Scaling Judgment (SCJ) and Resource Recombination (RRC)	0.432
Sustainable Value Creation (SVC) and AI Use (AIU)	0.443
Sustainable Value Creation (SVC) and Business Model Innovation (BMI)	0.740
Sustainable Value Creation (SVC) and Experimental Governance (EXG)	0.404
Sustainable Value Creation (SVC) and Opportunity Interpretation (OPI)	0.432
Sustainable Value Creation (SVC) and Resource Recombination (RRC)	0.364
Sustainable Value Creation (SVC) and Scaling Judgment (SCJ)	0.398

Table A4. Indicator reliability and significance (bootstrapping results).

Construct	Item	Loading (β)	t-Value	p-Value
AI Use	AIU1	0.890	77.993	<0.001
	AIU2	0.885	70.445	<0.001
	AIU3	0.874	71.361	<0.001
	AIU4	0.896	99.051	<0.001
Business Model Innovation	BMI1	0.904	94.109	<0.001
	BMI2	0.888	77.574	<0.001
	BMI3	0.883	69.565	<0.001
Experimental Governance	EXG1	0.878	64.445	<0.001
	EXG2	0.864	55.658	<0.001
	EXG3	0.861	59.697	<0.001
Opportunity Interpretation	OPI1	0.893	83.428	<0.001
	OPI2	0.890	81.525	<0.001
	OPI3	0.881	70.927	<0.001
Resource Recombination	RRC1	0.899	79.306	<0.001
	RRC2	0.891	76.536	<0.001
	RRC3	0.897	77.277	<0.001
Scaling Judgment	SCJ1	0.902	90.716	<0.001
	SCJ2	0.883	68.963	<0.001
	SCJ3	0.884	72.359	<0.001
Sustainable Value Creation	SVC1	0.903	106.456	<0.001
	SVC2	0.904	93.610	<0.001
	SVC3	0.886	73.140	<0.001

Table A5. Discriminant validity (Fornell–Larcker criterion).

Construct	AIU	BMI	EXG	OPI	RRC	SCJ	SVC
AI Use (AIU)	0.886						
Business Model Innovation (BMI)	0.558	0.892					
Experimental Governance (EXG)	0.486	0.440	0.867				
Opportunity Interpretation (OPI)	0.580	0.471	0.359	0.888			

Table A5. Cont.

Construct	AIU	BMI	EXG	OPI	RRC	SCJ	SVC
Resource Recombination (RRC)	0.566	0.397	0.299	0.297	0.896		
Scaling Judgment (SCJ)	0.598	0.485	0.307	0.423	0.377	0.890	
Sustainable Value Creation (SVC)	0.396	0.651	0.347	0.379	0.321	0.348	0.898

Note. Diagonal elements represent the square root of AVE. Off-diagonal elements represent inter-construct correlations.

Table A6. Predictive relevance (Q^2 values).

Endogenous Construct	Q^2	Interpretation
Experimental Governance (EXG)	0.230	Predictive relevance established
Opportunity Interpretation (OPI)	0.334	Predictive relevance established
Resource Recombination (RRC)	0.316	Predictive relevance established
Scaling Judgment (SCJ)	0.354	Predictive relevance established
Business Model Innovation (BMI)	0.305	Predictive relevance established
Sustainable Value Creation (SVC)	0.150	Predictive relevance established

Table A7. Cross-loadings for AI Use and ERC dimensions at the higher-order level.

Indicator/Dimension	AIU	ERC	BMI	SVC
AI Use (AIU)	1.000	0.783	0.558	0.396
Opportunity Interpretation (OPI)	0.580	0.740	0.471	0.379
Resource Recombination (RRC)	0.566	0.684	0.397	0.321
Experimental Governance (EXG)	0.486	0.668	0.440	0.347
Scaling Judgment (SCJ)	0.598	0.757	0.485	0.348

Note. Bold values indicate the loading of each construct or ERC dimension on its theoretically assigned construct. The results show that the ERC dimensions load more strongly on ERC than on AI Use, BMI, or SVC. AI Use is reported as a first-order construct in the higher-order model.

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