

Human Capital and Entrepreneurial Antecedents of Sustainable SME Performance: The Mediating Role of AI Adoption and the Moderating Role of Government Support

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Abstract

What causes small and medium-sized enterprises (SMEs) with similar resources to have such a variance in success in harnessing the power of artificial intelligence (AI) for long-term gain? This article presents some initial ideas to answer this question. Among the causes, this work identifies human capital, which denotes the firm's capabilities, and entrepreneurial precursors, which include self-efficacy and orientation and are the motivational and dispositional aspects of the decision maker and the firm's posture. This article's central claim is that these causes do not directly correlate with long-term gain. AI adoption is the mediating mechanism through which the firm's capabilities and the decision maker's disposition are converted into a digital capability, and the extent of this change is determined by the level of government support. The framework is built on the ability-motivation-opportunity synthesis and the microfoundations of dynamic capabilities. It yields seven propositions and an integrated model. The contribution is to reposition AI adoption from a dependent variable, as the adoption literature usually treats it, to a mediating mechanism; to derive the moderating role of government support from a multiplicative interaction logic rather than asserting a direct effect; and to bring the capability-based and agency-based accounts of small firm digital transformation into a single explanatory structure. The article closes with an agenda for empirical testing.

Keywords: *AI Adoption; Entrepreneurial Orientation; Entrepreneurial Self-Efficacy; Government Support; Human Capital; Mediation; SMEs; Sustainable Performance*

Introduction

Small and Medium Enterprises (SMEs) operate at the center of most global economies, where their ability to adopt artificial intelligence (AI) has now become a key indicator of competitiveness. Rational strategic considerations support the hope that the SME sector will benefit from the presence of AI. This expectation is reinforced by previous research showing that the use of machine learning can accurately predict consumer behavior in strategic marketing (Salamiah *et al.*, 2026), as well as the effectiveness of AI-based forecasting models that have been shown to outperform traditional models in projecting SME business performance (Kulal *et al.*, 2026). Despite these clear potential benefits, the extent of AI

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adoption varies considerably across firms. Existing theoretical explanations of this variation fall into two largely separate traditions that have developed with little interaction.

Existing explanations of this variation fall into two largely separate research traditions that have developed with little interaction. The first attributes differences in adoption to variation in the resources the firm possesses. Anchored in the resource-based view and its capability extensions, it identifies human capital and the absorptive capacity it supports as the binding constraint on technology assimilation (Barney, 1991; Dwikat et al., 2023; Díaz-Arancibia et al., 2024). The second attributes the variation to differences in what the decision maker believes and intends. Anchored in entrepreneurship and managerial cognition, it identifies efficacy beliefs and strategic orientation as the proximate drivers of adoption (Mostafiz et al., 2025). Each tradition is consistent and helps to better understand the phenomenon. Neither alone explains why some resource-constrained firms adopt and prosper while some better-endowed firms fail to do so.

This article argues that the two traditions describe complementary inputs to a single process. The more revealing question is not which input matters but how the inputs are converted into performance and under what conditions. The framing is therefore mechanism-forward. It treats human capital as the capability antecedent and the entrepreneurial constructs of self-efficacy and orientation as the entrepreneurial antecedents, and it asks how these antecedents reach sustainable performance. The answer presented here is that they achieve sustainable performance indirectly, through the behavior associated with AI adoption. Adoption is the mechanism that bundles latent capability and disposition into a digital capability with consequences for the firm's economic, social, and environmental outcomes. The completeness of this conversion is, in turn, governed by government support, which sets the opportunity structure within which adopters can realize value.

Positioning the constructs in this way departs from two common practices. The adoption literature frequently terminates at adoption itself, modelling it as the outcome to be explained and leaving its consequences unaddressed (Almashawreh et al., 2024). The framework here instead treats adoption as an intervening variable that transmits the effects of the antecedents. Related literature models government support as a direct cause of adoption or performance (Badghish & Soomro, 2024; Shaban et al., 2025). The framework here instead models it as a contingency that conditions the adoption-performance relationship.

The article offers three contributions. First, by specifying AI adoption as the mediator between two classes of antecedent and sustainable performance, it provides a mechanism-based account of small firm digital transformation rather than a catalogue of predictors. Second, it derives the moderating role of government support from the multiplicative logic of the ability-motivation-opportunity perspective, which yields a theoretically grounded and empirically testable interaction rather than an additional direct path. Third, it assigns human capital and the entrepreneurial antecedents to distinct components of a single ability-motivation-opportunity architecture, thereby integrating the capability-based and agency-based explanations that have developed independently. The remainder of the article proceeds as follows. The conceptual method is explained in section 2. The theory underpinning the development is presented in Section 3. Section 4 reviews the background and the connections between that background and its adoption. The role of AI adoption as a mediator between the variables is specified in Section 5, and the moderating role of government support is specified in Section 6. The integrated model is provided in Section 7, followed by the discussion, research agenda, and conclusion.

To amend the terms used throughout, the study adopts the following working definitions. Artificial intelligence refers to computational systems that perform tasks ordinarily requiring human intelligence, such as prediction, classification, and automated decision-making. AI adoption denotes the organizational decision to acquire, integrate, and routinize such systems within the firm and is treated as a firm-level behavior rather than a single purchase. Human capital denotes the stock of knowledge, skills, and competencies embodied in the firm's people. Government support denotes the funding, training, infrastructure, and regulatory facilitation through which the state shapes the conditions for SME technology adoption. The framework spans two levels of analysis. Human capital, entrepreneurial

orientation, AI adoption, government support, and sustainable performance are firm-level constructs, whereas entrepreneurial self-efficacy is an individual-level attribute of the owner-manager. Placing self-efficacy at the individual level is deliberate and theoretically warranted, because in SMEs the owner-manager is ordinarily the dominant decision maker whose beliefs drive firm-level technology choices; the construct is therefore modelled as an individual antecedent whose effects are realized in firm-level adoption.

Methodology

This article makes a conceptual contribution, and its methodology is reported to allow for the independent evaluation of the design choice, the evidence base, and the procedure for transforming that evidence into propositions.

Research Design

Per Jaakkola (2020), conceptual articles require a clearly stated design and a principled use of theory. Of the four designs distinguished by Jaakkola—namely, theory synthesis, theory adaptation, typology construction, and model building—this study adopts the model-building design, which proposes a reasoned set of relationships among constructs to address a problem that existing theory has not yet resolved, rather than summarizing a single body of work or classifying existing cases. Model building is the appropriate choice here because the problem under study, why comparably resourced SMEs diverge so sharply in the returns they realize from AI, is not answered by any single existing theory and instead requires a new relational structure among established constructs.

The framework specifies partial, or complementary, mediation rather than full mediation. AI adoption is theorized to transmit the dominant share of each antecedent's influence on sustainable performance, while limited direct antecedent-to-performance associations are retained and estimated. The distinction between partial and full mediation is therefore treated as an empirical question to be resolved in testing rather than an assumption imposed in advance.

Model building is uniquely appropriate for this study because the core research question, namely why small and medium-sized enterprises (SMEs) with comparable resource endowments experience vastly divergent returns from artificial intelligence (AI), cannot be answered by any single existing framework. Neither resource-based view (RBV) accounts of static human capital (Barney, 1991) nor pure agency/cognitive accounts of entrepreneurial intention (Bandura, 1997) independently explain the multi-stage path leading to sustainable triple-bottom-line performance.

Literature Search Process

The evidence base was assembled through a structured, though not fully systematic, narrative search, consistent with standard practice for AMS Review-style conceptual model papers (Jaakkola, 2020). Search was conducted primarily through Scopus, Web of Science, and Google Scholar, supplemented by targeted searches within journals that regularly publish SME technology adoption and sustainability research:

1. **Scopus:** Selected for its deep, peer-reviewed coverage in management, strategy, entrepreneurship, and information systems journals.
2. **Web of Science (WoS Core Collection):** Utilized to ensure inclusion of high-impact journals in business and applied economics.
3. **Google Scholar:** Employed as a supplementary database to capture the most recent open access publications, advance online articles, and 2025–2026 studies that Scopus and WoS index with a temporal lag

The search protocol combined the focal constructs using targeted Boolean combinations that were applied as successive, separate searches rather than as a single simultaneously conjoined query. The primary search strings included:

("artificial intelligence" OR "AI" OR "machine learning") AND ("adoption" OR "assimilation" OR "implementation") AND ("SME" OR "small enterprise" OR "MSME")

Each baseline string was systematically intersected with:

AND ("human capital" OR "absorptive capacity" OR "skills")

AND ("entrepreneurial self-efficacy" OR "managerial cognition" OR "self-efficacy")

AND ("entrepreneurial orientation" OR "innovativeness" OR "proactiveness" OR "risk-taking")

AND ("government support" OR "institutional support" OR "public policy")

AND ("sustainable performance" OR "triple bottom line" OR "ESG")

AND ("dynamic capabilities" OR "resource orchestration" OR "ability-motivation-opportunity" OR "AMO")

In practice, the base string on AI adoption in SMEs was executed first to establish the core corpus, and each thematic block above was then intersected with that base string in an independent search. The blocks were not combined with one another in a single query, because requiring every construct to co-occur would have excluded relevant studies that examine only a subset of the constructs.

Search was not restricted to a fixed temporal start date for foundational theoretical frameworks (e.g., Barney, 1991; Lumpkin & Dess, 1996; Appelbaum et al., 2000; Teece, 2007). However, for empirical and applied AI adoption studies, search prioritized literature published between 2020 and 2026, capturing the rapid expansion of SME-level artificial intelligence deployment following the emergence of generative AI and automated decision-making systems.

Inclusion and Exclusion Criteria

To maintain theoretical relevance and empirical coherence, retrieved sources were subjected to strict inclusion and exclusion criteria prior to synthesis:

Inclusion Criteria:

Publication Standard: Published in peer-reviewed academic journals, scholarly edited volumes, or authoritative international policy reports (e.g., OECD, 2025).

- Substantive Construct Fit: Provided substantive theoretical or empirical examination of at least one of the core constructs (human capital, entrepreneurial self-efficacy, entrepreneurial orientation, AI adoption, government support, or sustainable performance).
- SME & Organizational Context: Conducted in an empirical or theoretical setting directly applicable to SMEs, MSMEs, or resource-constrained entrepreneurial ventures, or offered foundational theory with universal firm-level capability relevance.

Exclusion Criteria:

- Narrow Tool Focus: Examined AI solely as a single narrow software utility (e.g., automated email filter) without broader organizational technology assimilation or performance implications.
- Large-Enterprise Dominance: Focused exclusively on multinational corporations or public sector bodies without separable, identifiable SME analytical insights.
- Non-Peer-Reviewed Commentaries: Non-scholarly opinion pieces, editorials, non-peer-reviewed blog posts, or unverified preprints lacking identifiable empirical or theoretical rigor.

Study Selection and Theory Integration Procedure

The study selection and theoretical synthesis proceeded through a rigorous, multi-pass procedure:

Screening Passes:

Pass 1 (Title & Abstract Screening): Initial screening of 142 retrieved articles to determine topical relevance to SME AI adoption and antecedent constructs.

Pass 2 (Full-Text Eligibility): Full-text evaluation of 58 retained articles to verify theoretical alignment and extract empirical relationships involving the focal variables.

Pass 3 (Citation Chaining): Forward and backward citation chaining from foundational and recent anchor studies (e.g., Badghish & Soomro, 2024; Kukanja, 2024; Mostafiz *et al.*, 2025; Shaban *et al.*, 2025; Jamil *et al.*, 2025) to uncover supplementary studies. A final set of 25 core references was retained for synthesis. Table 1 maps each reference to its key finding and its specific contribution to the present framework.

Table 1: Summary of the 25 Core References Synthesised in the Framework, With the Key Statement or Finding Extracted from Each Source and its Contribution to the Present Analysis.

Reference	Key statement or finding	Contribution to the present framework
Almashawreh <i>et al.</i> (2024)	Technological and organizational orientations drive AI adoption in Jordanian SMEs; the analysis stops at adoption.	Motivates repositioning AI adoption as a mechanism rather than a terminal outcome.
Appelbaum <i>et al.</i> (2000)	Ability-motivation-opportunity (AMO) model: performance is a joint, multiplicative function of ability, motivation, and opportunity.	Supplies the organizing architecture and the multiplicative interaction logic for the moderation.
Badghish & Soomro (2024)	TOE study of AI adoption for sustainable performance in Saudi SMEs; models government support as a direct driver.	Foil is used to treat government support as a moderator rather than a direct cause.
Bandura (1997)	Self-efficacy theory of human agency.	Theoretical basis for entrepreneurial self-efficacy as a motivational antecedent.
Barney (1991)	Resource-based view: valuable, rare, inimitable resources yield sustained advantage.	Grounds human capital as the capability antecedent; it is retained as a background lens.
Becker (1964)	Human capital theory: knowledge and skills as value-creating investments.	Defines the human-capital construct.
Chen <i>et al.</i> (1998)	Develops and validates an entrepreneurial self-efficacy measure distinguishing entrepreneurs from managers.	Provides the construct definition of entrepreneurial self-efficacy.
Cimino <i>et al.</i> (2025)	Extended dynamic-capability framework for AI adoption and SME sustainability.	Rival parsimonious specifications are used as a basis for contrasting the decomposed model.
Dwikat <i>et al.</i> (2023)	Competent human capital and strategic flexibility raise sustainable performance in Palestinian manufacturing SMEs.	Empirical support shows that human capital drives SME sustainable performance.
Eisenhardt & Martin (2000)	Dynamic capabilities are identifiable processes; they critique the static RBV.	Justifies moving beyond static RBV to an agentic conversion mechanism.
Elkington (1997)	Triple bottom line: economic, social, and environmental performance.	Defines the sustainable-performance outcome.
Jaakkola (2020)	Four designs for conceptual articles, including model building.	Methodological warrant for the model-building design.
Jamil <i>et al.</i> (2025)	AI adoption and technological readiness raise sustainable performance through employee capacity building in Pakistani SMEs.	Key empirical support for AI adoption as a mediator and for the intermediate-capability path.
Kukanja (2024)	EO, self-efficacy, and perceived performance shape AI-adoption attitudes in hospitality SMEs; some EO effects are weak or negative.	Evidence of non-uniform antecedent effects; supports partial mediation and dimensional refinement.

Kulal et al. (2026)	AI-driven forecasting outperforms traditional models in projecting MSME business performance.	Recent evidence of AI's performance relevance for SMEs.
Lumpkin & Dess (1996)	Clarifies entrepreneurial orientation as innovativeness, proactiveness, and risk-taking.	Provides the construct definition of entrepreneurial orientation.
MacInnis (2011)	Framework for conceptual contributions in management.	Criteria for deriving falsifiable, bounded propositions.
Mostafiz et al. (2025)	Entrepreneurial cognition shapes AI-adoption intention, contingent on ecosystem resources and bricolage.	Support for the agency account: managerial beliefs drive adoption.
OECD (2025)	Policy analysis of AI adoption by SMEs, including barriers, cybersecurity, and support instruments.	Evidence base for government-support relevance and boundary risks.
Salamiah et al. (2026)	Machine learning predicts consumer behavior for MSME strategic marketing.	Recent evidence of AI's strategic value for SMEs.
Shaban et al. (2025)	Government support moderates the effect of AI capability on organizational performance in SMEs.	Direct empirical warrant for the moderation proposition.
Sirmon et al. (2007)	Resource orchestration: managers structure, bundle, and deploy resources to create value.	Theoretical basis for AI adoption as an orchestrating behavior.
Soulami et al. (2024)	AI adoption in the workplace induces technostress and displacement concerns.	Evidence base for the dark-side and boundary-risk discussion.
Teece (2007)	Microfoundations of dynamic capabilities: sensing, seizing, reconfiguring.	Identifies AI adoption as a capability-generating action.
Zihan & Makhbul (2024)	Green HRM raises sustainable performance through green innovation.	Supports the social and environmental dimensions of sustainable performance.

Four-Step Theory Integration Procedure:

Construct Mapping to AMO Framework: Each antecedent construct was mapped onto the Ability-Motivation-Opportunity (AMO) architecture (Appelbaum et al., 2000). Human capital was operationalized as *Ability*; entrepreneurial self-efficacy and orientation were operationalized as dual dimensions of *Motivation*; and government support was operationalized as *Opportunity*.

- **Mechanism Mapping to Resource Orchestration:** The behavioral connection between antecedents and sustainable performance was theorized using the microfoundations of dynamic capabilities (Teece, 2007) and resource orchestration (Sirmon et al., 2007). This framework provided the theoretical warrant for positioning AI adoption as an orchestrating behavior (bundling and deploying latent human and entrepreneurial assets into dynamic capabilities) rather than a simple terminal outcome.
- **Derivation of Multiplicative & Boundary Logic:** Based on the multiplicative interaction logic of the AMO model ($\text{Performance} = f(A \times M \times O)$), government support was positioned as a moderating boundary condition on the adoption–performance relationship rather than an additive direct antecedent.
- **Falsifiable Proposition Derivation:** Each proposition (P1 through P7) was developed to satisfy MacInnis's (2011) criteria for conceptual contribution, ensuring each proposition is clearly differentiated from direct-effect models, bounded by explicit scope conditions, and formulated with sufficient relational precision to be tested via structural equation modeling (PLS-SEM or CB-SEM).

Theoretical Foundation

The framework outlines a model using the ability-motivation-opportunity (AMO) perspective, which discusses performance and discretionary behavior as the outcome of the three aforementioned constructs (Appelbaum *et al.*, 2000; Agirre-Aramburu *et al.*, 2024). The ability component deals with knowledge and skills to perform actions. Motivation deals with the inclination to perform actions, and the opportunity component deals with the conditions that enable the expression of ability and motivation. This perspective fits the issue at hand because it treats the constructs as interrelated and inseparable. Performance is the result of the synthesis of the three. Therefore, this perspective holds that if a particular construct is weak, it will, to some extent, limit what the other two can contribute.

This perspective distinguishes itself from other approaches that treat the antecedents as additive. The constructs of this paper align directly with the AMO framework. Human capital represents the ability construct, as it encapsulates the skills needed to assimilate new technology. The entrepreneurial traits represent the motivation construct, as entrepreneurial self-efficacy contributes to belief and entrepreneurial orientation represents the innovativeness, proactive behavior, and risk-taking the firm is willing to undertake. Government support fills the opportunity construct, as it establishes the environment in which the firm operates. This approach creates the structural framework of the model and allows for the separation of the constructs into ability and entrepreneurial classes while preserving the distinction between the ability and motivational components.

The AMO perspective describes discretionary behavior as the pathway from ability and motivation to performance, but it does not specify which kind of behavior is critical in a given context. To cover that, the framework relies on the microfoundations of dynamic capabilities (Teece, 2007; Cimino *et al.*, 2025) and of resource orchestration (Sirmon *et al.*, 2007). This work argues that resources alone don't yield performance; managers must structure, bundle, and deploy them into market-rewarded capabilities. In this case, AI adoption is orchestrating action. This behavior converts human capital and entrepreneurial precursors into a digital capability that influences performance. The two theoretical streams therefore speak to each other: the AMO model supplies the broad architecture and the interaction logic, while the microfoundations of dynamic capabilities identify AI adoption as the mechanism. The resource-based view is retained as a background lens rather than a focal one, given the limits of its static formulation in addressing the agency and active conversion that this framework places at the center (Eisenhardt & Martin, 2000).

The Antecedents of AI Adoption

This section develops the two antecedent classes and their relationships to AI adoption. Human capital is treated first as the capability antecedent, after which entrepreneurial self-efficacy and entrepreneurial orientation are treated together as the entrepreneurial antecedents, in keeping with their shared status as motivational forces within the AMO architecture.

Human Capital

Human capital, the stock of knowledge, capabilities, and competencies embedded in the people of the firm, is a long-recognized driver of value and an advantage that is difficult to imitate (Becker, 1964; Barney, 1991). Its importance is even greater in SMEs, because their lean structures mean each individual's contribution is more consequential for whether new technology is absorbed (Dwikat *et al.*, 2023; Syed, 2025). In the AMO architecture, human capital corresponds to the ability component, shaping whether the firm can identify which AI applications are relevant, judge which candidates are worth pursuing, and fold them into existing routines without disruption large enough to cancel the benefit.

The link that explains adoption runs through absorptive capacity. Firms with a stronger endowment of capabilities are better positioned to interpret the technical and commercial relevance of AI, to select use cases that fit their operations, and to reduce the implementation friction that often pushes less capable firms back. SME-focused evidence supports this view, indicating that capability and readiness conditions determine whether AI becomes embedded in practice or remains a trial that is later

abandoned (Jamil *et al.*, 2025). When human capital is limited, the firm often lacks the interpretive and integrative capability needed to make effective use of AI, so even where adoption occurs, it tends not to persist.

Proposition 1. Human capital is positively associated with AI adoption in SMEs, meaning that firms with more accumulated know-how, skills, and competencies are more likely to adopt and also embed AI into everyday work.

Entrepreneurial Antecedents: Self-Efficacy and Orientation

The entrepreneurial antecedents comprise two distinct constructs that share a motivational character. Entrepreneurial self-efficacy is the strength of an individual's belief that they can handle entrepreneurial tasks and roles (Chen *et al.*, 1998), and it draws on self-efficacy theory as an account of human agency (Bandura, 1997). Entrepreneurial orientation is a firm-level disposition toward innovativeness, proactiveness, and risk-taking that steers strategic choice (Lumpkin & Dess, 1996; Escob Barragan & Becker, 2025). One resides in the decision maker and the other in the firm's strategic posture, yet both occupy the motivation position in the AMO architecture, because each shape whether the actor is prepared to commit to uncertain, resource-intensive action.

AI adoption is precisely such an action. It requires committing real resources, disrupting routine work, and accepting technical uncertainty, all under conditions where outcomes are difficult to forecast. Decision makers with higher entrepreneurial self-efficacy tend to frame these conditions as workable rather than as a deterrent and are therefore more likely to initiate adoption. Recent work on entrepreneurial cognition supports this reasoning, showing that entrepreneurs' belief systems shape their intention to adopt AI, particularly where institutional certainty is thin and personal conviction must substitute for it (Mostafiz *et al.*, 2025). The dimensions of entrepreneurial orientation run along related but parallel paths: innovativeness makes the firm more receptive to the experimentation that early deployment requires, proactiveness pushes action ahead of competitors, and a measured tendency toward risk helps the firm sustain the decision when information remains incomplete. Both constructs are non-uniform in their effects. Some self-efficacy dimensions show modest effects, and some orientation dimensions are weakly or even negatively related to adoption when managers assess the maturity of current AI applications against their priorities (Kukanja, 2024).

Proposition 2. Entrepreneurial self-efficacy is positively associated with AI adoption in SMEs, such that decision makers with stronger belief in their entrepreneurial capability are more likely to initiate and sustain adoption.

Proposition 3. Entrepreneurial orientation is positively associated with AI adoption in SMEs, such that firms exhibiting greater innovativeness, proactiveness, and calculated risk-taking are more likely to adopt AI.

The Mediating Role of AI Adoption

Sustainable performance is conceptualized through the triple bottom line, encompassing economic, social, and environmental dimensions rather than financial return alone (Elkington, 1997). This framework is particularly well suited to the SME context, because the value of AI extends beyond cost reduction to include resource efficiency, improved working conditions, and reduced environmental impact, all of which shape the firm's long-term viability (Zihan & Makhbul, 2024). Adoption works along the economic dimension through automation, forecasting, and data-informed decision-making; it also taps the social dimension by relieving people from repetitive tasks and redirecting effort toward higher-value activities, and it meets the environmental dimension via predictive and optimization uses that lower waste across energy, materials, and inventory. Most SME papers report that adoption tends to improve those ends, but usually by strengthening intermediate capabilities first, not by jumping straight to performance without an in-between move (Jamil *et al.*, 2025).

Proposition 4. AI adoption is positively linked with the sustainable performance of SMEs across economic, social, and environmental dimensions.

The analytical heart of the entire framework lies in the mediating statement, which the article title essentially implies. The factors listed in Section 4 connect to the result in Section 5, but not through straightforward direct paths; instead, they operate via adoption. That aligns with resource orchestration thinking: human capital and entrepreneurial disposition are like latent potential, and they become actualized only when the firm does the bundling and deployment activities (Sirmon *et al.*, 2007; Cimino *et al.*, 2025).

SMEs increasingly pursue AI adoption to enhance the intelligence and responsiveness of their industries and services. In this sense, adoption itself is the act, while enhanced organizational intelligence is the objective it is intended to achieve. The antecedents primarily influence sustainable performance by impacting adoption. A firm rich in human capital that refuses to adopt loses the capability that the human capital has to be expressed at scale, and a firm with highly self-efficacious, entrepreneurial decision-makers that fail to translate the disposition into adoption loses its motivational advantage. This is consistent with evidence that the impact of firm endowments on SME performance goes through technology adoption; the intermediate path through capability building accounts for much of the impact, and it explains the otherwise puzzling finding that direct paths from antecedents to adoption are weak in some contexts, as the impact of untranslated motivation has no performance consequence. (Jamil *et al.*, 2025)

Proposition 5a. AI adoption mediates the relationship between human capital and sustainable performance in SMEs.

Proposition 5b. AI adoption mediates the relationship between entrepreneurial self-efficacy and sustainable performance in SMEs.

Proposition 5c. AI adoption mediates the relationship between entrepreneurial orientation and sustainable performance in SMEs.

Two points qualify this mediating claim. First, the mediation proposed is partial rather than full: although AI adoption is expected to carry most of the influence of the antecedents, each antecedent may retain a modest direct association with sustainable performance, so that both the indirect paths and the residual direct paths are shown in Figure 1 and estimated in testing. Second, because the antecedents operate at different levels, the indirect effect of entrepreneurial self-efficacy runs from an individual-level belief to firm-level performance through a firm-level behavior, which an empirical test should model accordingly.

The Moderating Role of Government Support

Government support encompasses financial assistance, training programs, infrastructure development, and regulatory frameworks that collectively shape the conditions under which SMEs adopt new technologies. While existing research often treats such support as a direct driver of technology adoption or firm performance (Badghish & Soomro, 2024), this framework assigns it a distinct function. Within the AMO model, government support corresponds to the "Opportunity" element, shaping how ability and motivation are realized rather than replacing them. As such, the article positions it not as a primary driver but as a moderator of the adoption process.

This conceptualization stems from the multiplicative logic central to the AMO framework described in Section 3, where performance emerges from the interplay of ability, motivation, and opportunity. In this view, the benefits of adopting AI are not automatic but depend on the opportunities available to firms. When government support is strong, through accessible funding, technical resources, and supportive infrastructure, it helps SMEs overcome structural constraints that might otherwise limit their capacity to fully leverage new technologies. Even firms with high capability and willingness to adopt may struggle to realize the full value of AI if they must independently navigate implementation challenges and bear associated costs. The AMO model's multiplicative structure captures this nuanced role of support more effectively than institutional theories, which merely acknowledge contextual influences. Empirical findings further reinforce this view, showing that government support amplifies the positive impact of organizational capabilities on performance when using AI (Shaban *et al.*, 2025).

Proposition 6: Government support strengthens the positive relationship between AI adoption and sustainable performance in SMEs, meaning this link is more pronounced when support is more readily available.

Extending this reasoning to indirect pathways leads to an expectation of moderated mediation. If government support influences the effectiveness of the adoption-performance link, then the overall indirect effect of each antecedent on sustainable performance will also vary depending on the level of support. Specifically, the mediating role of AI adoption in transmitting the effects of human capital, entrepreneurial self-efficacy, and entrepreneurial orientation should be more significant in environments with greater institutional backing. This final layer makes the mediation process contingent upon the broader opportunity structure.

Proposition 7: Government support moderates the indirect effects of human capital, entrepreneurial self-efficacy, and entrepreneurial orientation on sustainable performance via AI adoption, such that these indirect relationships are stronger when support levels are higher.

The Integrated Conceptual Framework

Figure 1 presents the integrated framework and corresponds directly to the seven propositions. Human capital is shown on the left as the capability antecedent (Ability), while entrepreneurial self-efficacy and entrepreneurial orientation are grouped as the entrepreneurial antecedents (Motivation). Both classes of antecedent predict AI adoption, which occupies the center of the model as the mediating mechanism (Propositions 1, 2, and 3). AI adoption predicts sustainable performance across its economic, social, and environmental dimensions (Proposition 4) and transmits the indirect effects of the antecedents (Propositions 5a, 5b, and 5c). Consistent with the partial-mediation specification, each antecedent also retains a direct path to sustainable performance, shown as the thin dashed arrows. Government support enters from above as the moderator, conditioning the conversion of adoption into performance and, by extension, the indirect paths (Propositions 6 and 7). The figure therefore renders the mechanism-forward logic of the framework: the antecedents on the left reach the outcome on the right chiefly through the adoption behavior at the center, and only to the extent that the opportunity structure permits.

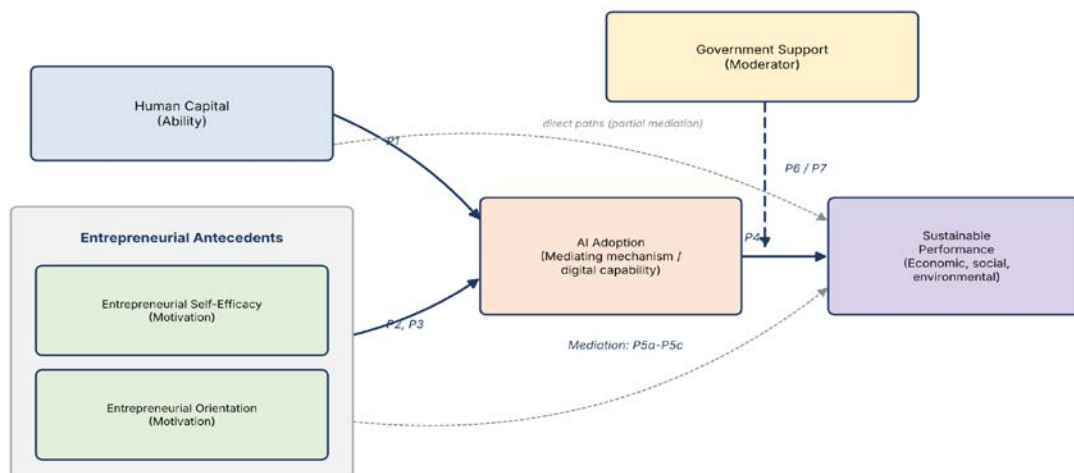


Figure 1: Integrated conceptual framework.

Human capital (the capability antecedent) and the entrepreneurial antecedents of entrepreneurial self-efficacy and entrepreneurial orientation (the motivational antecedents) influence sustainable performance through the mediating mechanism of AI adoption, with government support functioning as the moderator. Solid arrows denote direct paths; the dashed arrow denotes moderation.

Discussion

Theoretical Contributions & Critical Comparison with Prior Studies

The conceptual framework advances discourse across three major management conversations, offering distinct theoretical refinements over existing models:

Reframing AI Adoption from Terminal Outcome to Mediating Mechanism: Thus, the adoption is typically modeled as the last dependent variable to be explained in research on technology adoption (Badghish & Soomro 2024). For example, Almashawreh *et al.* (2024) illustrate that tech and ORI spur adoption; however, they conclude their analysis at the stage of adoption. This research builds on this notion by suggesting that adoption is not the ultimate outcome of value creation (Sirmon *et al.*, 2007); rather, it functions as an intervening orchestration mechanism that transforms the latent potential of human capital and entrepreneurial behavioral dispositions into economic, social, and environmental performance outcomes (Jamil *et al.*, 2025).

Reconciling Resource-Based Capability and Entrepreneurial Agency: General SME literature has divided mainly into two lines of research: on the one hand, resource-based capability accounts (Barney, 1991; Dwikat *et al.*, 2023) and agency/cognitive explanations (Mostafiz *et al.*, 2025). The model, by combining capital (Ability) and the two nests of entrepreneurial self-efficacy/orientation (Motivation), within a single AMO structure (Appelbaum *et al.*, 2000), shows how capability without motivational agency results in “idle potential,” while Agency without HC produces “faulty implementation.” Critical comparison with alternative models: This framing differs from dynamic capability models (Cimino *et al.*, 2025). A business model is a system of interrelated activities through which an organization creates, delivers, and captures value (Teece, 2010). While Cimino *et al.* (2025) provide parsimony, the present study’s decomposition offers diagnostic precision by distinguishing between what an SME possesses in terms of knowledge and capabilities (human capital) and what its owner-manager perceives, believes, and intends (self-efficacy and entrepreneurial orientation). This distinction enables researchers to identify more precisely the specific points at which adoption barriers or bottlenecks occur.

Grounding Contingency Logic via Multiplicative AMO Architecture: In the existing literature, government support is often seen as a direct instrument to take up technology or firm performance (e.g. Badghish & Soomro 2024; Shaban *et al.* 2025). In comparison, the framework of this study situates government support as an opportunity boundary condition (moderator) that acts upon the interaction logic of the AMO perspective (Appelbaum *et al.*, 2000). As Shaban *et al.* (2025) note, institutional support (a.k.a. government backing) compounds the performance dividends of capabilities: this model formalizes the concept via proving government support moderates how quickly adopted AI tools translate into long-term, sustainable performance, a moderated-mediation relationship. Consistent with Section 5, this mediation is specified as partial rather than full: each antecedent is expected to retain a limited direct association with sustainable performance alongside the dominant indirect pathway through AI adoption.

Rival Specifications

The proposed framework is positioned against three rival specifications that empirical work should estimate alongside it. The first is a direct-effects model, in which human capital and the entrepreneurial antecedents act on sustainable performance without passing through AI adoption; the present framework predicts that this model will understate the role of adoption and leave the conversion mechanism unexplained. The second is a full-mediation model, in which the antecedents affect performance only through adoption; the framework departs from this model by specifying partial mediation and retaining direct paths. The third is the parsimonious dynamic-capability model of Cimino *et al.* (2025), which treats AI adoption as a dynamic capability without separating the capability base from the motivational base; the present decomposition is more demanding but yields greater diagnostic precision about where adoption barriers arise. Distinguishing the proposed model from these three rivals is what renders its propositions falsifiable.

Adverse Effects, Dark Side, and Boundary Risks of AI Adoption in SMEs

A critical limitation of mainstream adoption literature is its implicit "pro-innovation bias", the optimistic assumption that technology adoption is an unalloyed good that automatically yields superior outcomes. In reality, AI adoption introduces substantial dark-side risks and organizational frictions that can attenuate or reverse the performance dividends theorized in Proposition 4.

Workforce Disruption, Technostress, and Job Displacement Fears

Workplace-level empirical evidence reveals that AI adoption often triggers acute employee stress, anxiety over job displacement, and perceived loss of autonomy (Soulami *et al.*, 2024). In SMEs, where workforce buffer capacity is minimal and formal change management processes are absent, these psychological frictions can lead to active or passive resistance, reducing workplace morale and degrading social performance even if operational throughput improves.

Algorithm Aversion and Managerial Cognition Crises

When owner-managers experience AI errors or unpredictable system outputs, they are susceptible to algorithm aversion, a disproportionate drop in trust following a visible system mistake (Mostafiz *et al.*, 2025). In owner-managers with high entrepreneurial self-efficacy (Proposition 2), encountering unexplainable AI errors can shatter efficacy beliefs, causing managers to abandon or underutilize adopted AI systems (Kukanja, 2024).

Cybersecurity Vulnerabilities and Data Privacy Exposure

SMEs expanding their reliance on AI often ingest sensitive customer and operational data without adequate cybersecurity safeguards (OECD, 2025). Unlike large enterprises with dedicated IT security departments, SMEs face severe exposure to data breaches, algorithmic bias liabilities, and regulatory penalties, which directly threaten long-term economic and reputational sustainability.

Theoretical Implication: These adverse mechanisms suggest that adoption occurrence alone is insufficient; adoption governance and adoption quality act as crucial secondary qualifiers of the adoption–performance relationship.

Specific Implications for SME Practice

The model suggests that unless investments in human capital and entrepreneurial posture are actualized through AI adoption, they will not translate into sustainable performance for SME owner-managers. To make this conversion and minimize the dangers of the dark side, managers need to take three concrete steps:

Connect AI Skills Training to Specific Implementation Ownership

Managers should assign specific AI implementation responsibilities to named staff with defined bi-weekly review milestones instead of sending staff to generic AI training sessions. Dormant human capital, not a dynamic absorption capability, is unassigned knowledge.

Pilot in Phases with Well-Defined Course Corrections

To avoid algorithm aversion (Kukanja, 2024), managers can "start slow" by deploying AI systems to support low-stakes backend operations (e.g., first inventory predictions) and build towards customer-facing activities. Defining mistakes early on as a necessary part of the calibration process can help maintain entrepreneurial self-efficacy.

Plan and Pay for Change Management and Communication

Managers should budget time and money for internal communications to mitigate employee concerns about being replaced (Soulami *et al.*, 2024) and build processes collaboratively so that AI is used to support employees, not take away their sense of control.

Implications for Policy and Technology Providers

For Public Policymakers

The moderating logic of government support (Propositions 6 and 7) carries a direct policy message: government intervention is most effective when it targets the returns to adoption rather than merely promoting adoption awareness.

Shift from Blanket Subsidies to Co-Funded Implementation Grants

Instead of funding general AI awareness seminars for non-adopting firms, governments should disburse co-funded vouchers disbursed post-adoption for technical auditing, algorithm verification, and custom integration (Shaban *et al.*, 2025).

Establish Subsidized Cybersecurity and Privacy Audits

To alleviate SME data privacy vulnerabilities highlighted in Section 8.2 (OECD, 2025), state agencies should sponsor cybersecurity compliance certifications tailored for small businesses using cloud-based AI tools.

Provide Sector-Specific Digital Literacy Programs

Training initiatives should focus on building integrative absorptive capacity within traditional SME sectors rather than generic coding skills.

For AI Technology Vendors

Advice to Vendors of AI Technologies: If you sell to the SME market, understand that reducing the barrier to adoption behavior doesn't just mean improving base model accuracy. Additional steps include building in XAI functionality and error-logging dashboards as part of the SME-facing user interface to help prevent algorithm aversion and selling your product alongside "ready-to-go" implementation services, data privacy documentation, and user onboarding programs.

Limitations and Future Research

As a conceptual contribution, the framework is subject to several limitations that qualify its claims and, in doing so, define the agenda for the empirical work that should follow. The limitations are organized around the nature of the contribution, the specification of the model, and the provenance of its constructs. The future research directions are then mapped onto these limitations so that each weakness is matched to a concrete design that would address it.

Limitations

Non-empirical status. The framework is theoretical rather than tested, so the direction, sign, and magnitude of every proposition are argued rather than demonstrated. The relationships are plausible on the strength of the ability-motivation-opportunity logic and the supporting literature, but until the model is estimated on primary data, the propositions remain conjectures, and alternative patterns, including null or negative associations for particular dimensions, cannot be ruled out.

The partial-mediation assumption. The model specifies partial, complementary mediation, retaining direct antecedent-to-performance paths alongside the dominant indirect path through AI adoption. This specification is itself a theoretical claim that could be mis-specified. It is possible that mediation is closer to full in some settings or that the direct paths dominate where adoption is superficial, so the mediation structure should be treated as a hypothesis to be adjudicated rather than a settled feature of the model.

Omitted contingencies. For parsimony the framework holds constant several variables that plausibly shape the relationships. Firm size within the SME band, industry sector, the type and maturity of the AI applications adopted, and firm age are not modelled, yet each could condition both the antecedent-to-adoption links and the adoption-to-performance link. Their omission means the framework describes a general tendency rather than a fully specified contingency model, and estimates obtained without controlling for them may be confounded.

Static framing. The logic of the model is cross-sectional. It does not represent the time lag between AI adoption and the realization of sustainable performance, nor the feedback loops through which early performance gains replenish human capital, raise entrepreneurial self-efficacy, and attract further government support. Because digital transformation unfolds over time, a static reading risks understating these dynamic and recursive effects.

The dark side sits outside the testable model. The workforce, cognitive, and cybersecurity risks discussed earlier qualify the optimistic reading of the adoption-performance link, but they are presented as narrative caveats rather than as formal propositions. As a result, they are not currently part of the structure that empirical work would estimate, which leaves the model vulnerable to the pro-innovation bias it sets out to resist.

Construct provenance. The core constructs, including the resource-based view, self-efficacy, entrepreneurial orientation, and the ability-motivation-opportunity perspective, were developed and validated largely in Western and often large-firm contexts. Transferring them to resource-constrained SMEs in emerging economies is reasonable but not costless, since measurement equivalence and the meaning of the constructs across institutional and cultural settings cannot be assumed and should be established rather than taken for granted.

Future Research Directions

Empirical validation against rival models. The immediate priority is to estimate the framework on primary SME data using partial least squares structural equation modelling, which suits the latent constructs and the moderated-mediation structure. The test should not fit the proposed model in isolation but should compare it against the three rival specifications identified earlier, namely the direct-effects model, the full-mediation model, and the parsimonious dynamic-capability model, so that the contribution is established by relative fit rather than by assertion.

Longitudinal and dynamic designs. To address the static framing, panel and longitudinal designs should model the lag between adoption and sustainable performance and test the feedback loops through which performance feeds back into the antecedents. Such designs would convert the cross-sectional logic into a genuinely dynamic account and allow the durability of the government-support moderation to be assessed over time.

Configurational and multilevel analysis. Because the ability-motivation-opportunity logic is multiplicative, fuzzy-set qualitative comparative analysis offers a natural complement to structural equation modelling, identifying the combinations of human capital, motivation, and government support that are jointly sufficient for high sustainable performance. In parallel, multilevel designs should model entrepreneurial self-efficacy at the owner-manager level and the remaining constructs at the firm level, addressing the cross-level structure that a single-level estimation obscures.

Finer measurement and fuller contingency. Entrepreneurial orientation and entrepreneurial self-efficacy should be disaggregated to their dimensions, since evidence suggests the components do not act uniformly on adoption, and sustainable performance should be decomposed so that its economic, social, and environmental effects are estimated separately and their differing sensitivity to government support is exposed. Firm size, sector, AI type and maturity, and firm age should be included as controls or moderators so that the general tendency is refined into a specified contingency model.

Formalizing the dark side and widening the context. Future models should bring the workforce, cognitive, and cybersecurity risks inside the testable structure, for example, by specifying adoption quality and adoption governance as moderators of the adoption-to-performance path, so that the conditions under which adoption fails to convert into performance are modelled rather than merely noted. Finally, comparative designs across countries and institutional regimes would test the generalizability of the constructs and the moderating role of government support where its level and form vary and would establish the measurement equivalence that the construct-provenance limitation calls into question.

Conclusion

This article set out to explain why SMEs of comparable means differ so markedly in their ability to convert artificial intelligence into sustainable performance and to do so in a way that narrows the long-standing division between capability-based and agency-based accounts. It has argued that human capital and the entrepreneurial antecedents of self-efficacy and orientation reach sustainable performance not directly but through the mediating mechanism of AI adoption, that government support sets the strength of this conversion as a moderating boundary condition, and that the conversion process carries risks to workforce well-being that a purely performance-oriented reading of the model would miss. By grounding the model in the ability-motivation-opportunity perspective and the micro foundations of dynamic capabilities, the framework integrates two explanatory traditions, reframes adoption from outcome to mechanism, and derives a contingency that observation alone could not supply. The contribution is offered as a foundation for empirical inquiry and as an illustration of how a disciplined conceptual design, positioned against rival specifications and alert to its own optimistic assumptions, can bring coherence to a domain in which the evidence remains dispersed.

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Conflict of Interest

The author states that there are no conflicts of interest related to anyone in this study. This research was conducted independently, without any financial, commercial, or personal connections that could affect the findings or interpretation of the results. All procedures were carried out transparently and in accordance with applicable academic and ethical standards.

AI Assistance Declaration

The authors affirm that they did not use any artificial intelligence (AI) tools in generating, analyzing, or writing this manuscript. The authors conducted all aspects of the research, including data collection, interpretation, and manuscript preparation, without the assistance of AI-based technologies. Next, the authors take full responsibility for the integrity, validity, and originality of this work and state that it has not been affected by the use of AI-assisted tools in a way that reduces the accuracy, transparency, or originality of the research.

CRedit Authorship Contribution Statement

DY: Conceptualization, Methodology, Software, Formal Analysis, Writing - Original Draft Preparation, Writing - Review & Editing. SMK: Methodology, Validation, Formal Analysis, Writing - Original Draft Preparation, Writing - Review & Editing. RW: Methodology, Validation, Formal Analysis, Investigation, Writing - Original Draft Preparation, Writing - Review & Editing.

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