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From Artificial Intelligence Adoption to Business Performance: The Role of AI Capability, Dynamic Capabilities and Responsible AI Governance in Emerging-Market SMEs

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Abstract

Artificial intelligence (AI) is widely expected to improve firm performance, yet evidence that adoption alone creates sustained value remains mixed. This article develops an integrated model explaining how AI adoption translates into performance among small and medium-sized enterprises (SMEs) in emerging economies, and specifies an empirical design to test it. Drawing on the Resource-Based View (RBV), Dynamic Capabilities Theory (DCT), and the Technology–Organization–Environment (TOE) framework, the model positions AI adoption as an antecedent of multidimensional AI capability, which shapes performance through two parallel mechanisms: dynamic capabilities (sensing, seizing, and reconfiguring) and human–AI collaboration. Responsible AI governance is theorized as a boundary condition that strengthens the conversion of AI capability into performance. Nine hypothesis sets are derived, alongside a proposed cross-sectional survey of Ethiopian SMEs analysed via partial least squares structural equation modelling (PLS-SEM) and supplemented by qualitative interviews. The study shifts scholarly attention from adoption as a discrete event to capability orchestration, integrates a micro-level collaboration mechanism, and frames governance as a value-enabling condition rather than a purely compliance-driven constraint. Because no empirical results are reported yet, the model is presented as a structured blueprint for testing.

Keywords: artificial intelligence; AI adoption; AI capability; dynamic capabilities; responsible AI governance; human–AI collaboration; SME performance; emerging economies; resource-based view; technology–organization–environment

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1. INTRODUCTION

Artificial intelligence has transitioned from a specialized technical domain into a central concern of strategic management. Firms now deploy AI across customer analytics, demand forecasting, marketing, recruitment, finance, operations, and—increasingly—generative content creation. Despite rapid uptake, a fundamental question remains unresolved: does adopting AI directly generate superior firm performance, or do performance gains depend on the organizational capabilities cultivated around the technology?

This distinction matters because acquiring software is not the same as transforming how a business creates value. Two enterprises may license identical AI tools; one may simply automate isolated tasks, whereas the other redesigns workflows, sharpens managerial judgment, and builds continuous learning routines. Evidence from small and medium-sized enterprises (SMEs) supports this view. An analysis of 12,108 European SMEs demonstrated that internal digital and innovation capabilities strongly drive AI adoption, whereas external support yields limited results when internal capabilities are weak (Fernandez de Arroyabe et al., 2024).

Against this backdrop, this article asks how, and under what organizational conditions, AI adoption translates into superior SME performance. It proposes an integrated pathway—AI adoption → AI capability → (dynamic capabilities; human–AI collaboration) → performance, moderated by responsible AI governance—and outlines a mixed-methods empirical design to test the model among SMEs in Ethiopia.

2. LITERATURE REVIEW

2.1 Review protocol

The literature review follows a transparent, replicable protocol adapted from PRISMA 2020 guidelines. Systematic searches will cover Scopus, Web of Science, ABI/INFORM, Business Source Premier, and ScienceDirect for publications between 2020 and 2026. Primary Boolean search strings combine four conceptual blocks: ("artificial intelligence" OR "AI adoption" OR "generative AI") AND ("dynamic capabilit*" OR "AI capabilit*" OR "resource-based") AND (SME OR "small and medium" OR "emerging econom*") AND (performance OR "competitive advantage"), complemented by a targeted string covering ("responsible AI" OR "AI governance" OR "human–AI collaboration").

Eligible studies must be peer-reviewed, English-language articles using the firm as the unit of analysis and explicitly examining capability, governance, or performance outcomes. Purely technical computer-science papers, individual consumer-acceptance studies, and non-peer-reviewed commentaries are excluded, though credible grey literature is retained to contextualize the Ethiopian SME environment. Two independent coders will screen titles, abstracts, and full texts, resolving discrepancies through discussion and reporting inter-rater reliability via Cohen's kappa. Screening counts will be documented in a PRISMA flow diagram (Figure 1), and retained studies will be synthesized by theoretical lens, empirical context, sample, methodology, constructs, and key findings (Table 1).

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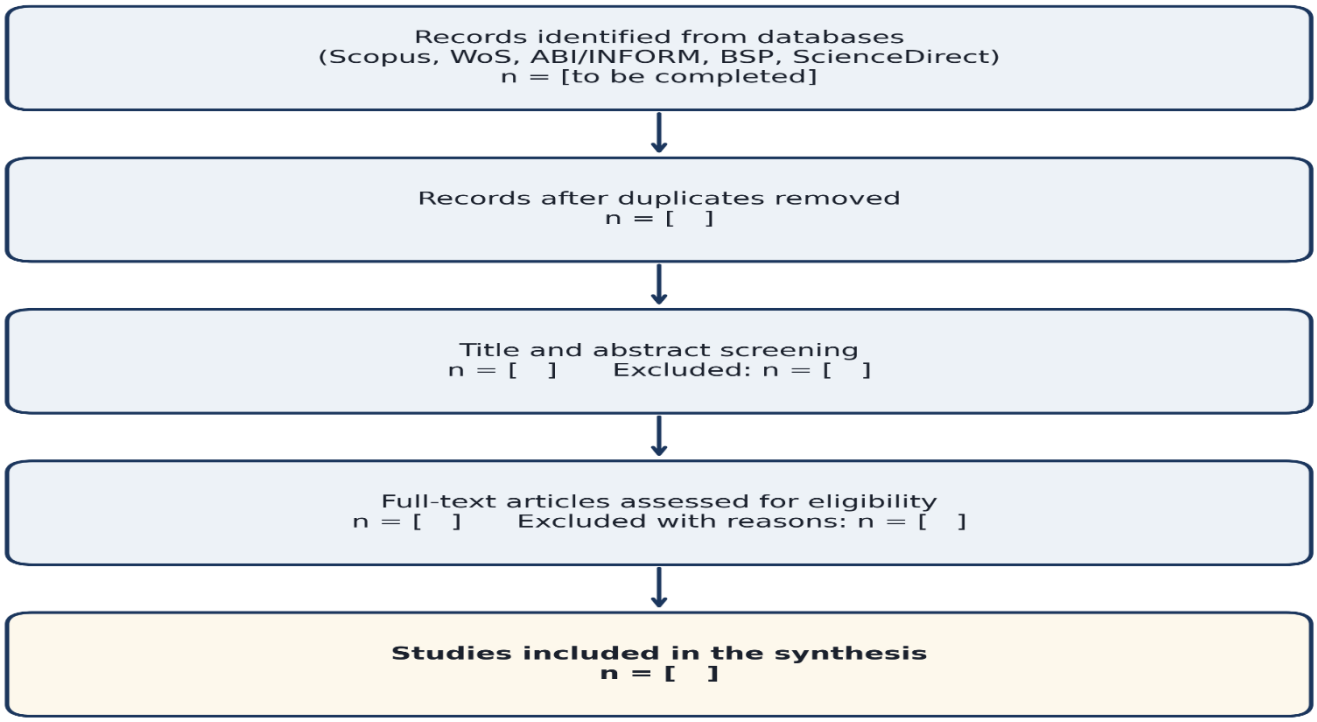


Figure 1. PRISMA 2020 flow template for the literature review (counts to be completed)

2.2 AI adoption and its determinants

Research on organizational AI adoption relies heavily on the Technology–Organization–Environment (TOE) framework (Tornatzky & Fleischer, 1990). Within SME contexts, internal readiness and capability factors consistently outweigh external inducements. Drawing on 12,108 European SMEs, Fernandez de Arroyabe et al. (2024) show that existing digital and innovation capabilities are primary catalysts for AI adoption, while public or external support has muted effects in capability-constrained firms. Similarly, Ul Haq et al. (2026) combine TOE and Resource-Based View (RBV) perspectives in a study of Pakistani manufacturing SMEs, finding significant links among technological readiness, leadership vision, competitive pressure, AI adoption, and firm performance. Reviews of European SMEs further note that adoption scholarship remains skewed toward technologically advanced economies, overlooking the acute resource bottlenecks faced by smaller enterprises. Together, these studies anchor H1a–c while illustrating a recurring limitation: adoption is frequently treated as the final dependent variable rather than the starting point of value creation.

2.3 AI capability and firm performance

A parallel stream of scholarship contends that competitive advantage stems from organizational capability rather than mere technology ownership. Mikalef and Gupta (2021) conceptualize AI capability as a distinct bundle of tangible, human, and intangible resources, demonstrating its positive impact on organizational creativity and firm performance. Investigating 120 Tunisian family firms that adopted AI between 2021 and 2024, Gafsi employs confirmatory factor analysis and structural equation modelling within a dynamic-capabilities lens, showing that AI capabilities significantly boost competitive performance regardless of generational involvement. Complementing this view, research on AI maturity frames maturity as an emergent capability shaped by organizational readiness, technical deployment, and business-model innovation, linking it to operational efficiency, market growth, and financial stability. While these studies substantiate the logic behind H2, inconsistent definitions and operationalizations of AI capability underscore the value of adopting a multidimensional, second-order construct.

2.4 Dynamic capabilities as the conversion mechanism

Dynamic Capabilities Theory (DCT; Teece et al., 1997; Teece, 2007) offers the primary theoretical explanation for how capabilities convert into performance. Wong and Ngai (2025) demonstrate that dynamic capabilities mediate the relationship between AI deployment and operational performance among Chinese telecommunications firms. Likewise, a 2025 University of Pretoria investigation into generative AI reports that dynamic capabilities fully mediate the link between generative AI use and firm performance, concluding that value materializes through capability enhancement and advocating ethical AI governance alongside technical investment. These findings align closely with H3, H5, and H7. Nevertheless, heavy reliance on single-informant perceptual surveys raises concerns regarding common-method inflation in full-mediation models, motivating the procedural and statistical safeguards detailed in Section 9.

2.5 Human–AI collaboration

Empirical work on human–AI collaboration remains comparatively sparse at the organizational level. At the team level, Zercher et al. (2025) examine generative AI as an active team member, documenting meaningful shifts in decision-making routines and decision quality. At the leadership level, a study of 302 Tunisian SME leaders published in the Leadership & Organization Development Journal (DOI: 10.1108/LODJ-10-2025-0887) connects AI utilization with improved decision quality, leadership transformation, and organizational performance. Because validated firm-level scales for human–AI collaboration are still absent from the literature, developing and validating a firm-level measurement instrument forms a core methodological contribution of this study.

2.6 Responsible AI governance

Scholarship on responsible AI governance (RAIG) has evolved from abstract ethical principles toward empirical organizational inquiry. Studying 144 Nordic firms with PLS-SEM, Papagiannidis et al. (2022) reveal that strategically aligned RAIG practices directly strengthen knowledge-management capabilities and indirectly elevate competitive performance, positioning governance as a source of strategic advantage rather than mere red tape. Using a quasi-natural experiment with a difference-in-differences design, Xia et al. (2025) similarly document positive corporate performance effects from responsible AI governance. Furthermore, the Tunisian SME leadership study cited above indicates that a responsible AI climate amplifies the positive link between AI adoption and leadership transformation. Although these findings support the directional logic of H9, prior research has modelled RAIG predominantly as an antecedent or mediator rather than as a moderator of the capability–performance relationship, and rarely within African SMEs.

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2.7 The Ethiopian and wider African SME context

Contextual evidence on AI in Ethiopian and African SMEs remains largely descriptive. Industry reporting by The Reporter Ethiopia on GSMA research highlights structural barriers constraining AI uptake, including limited private-sector engagement, acute AI talent shortages, brain drain, and unreliable electricity grids that restrict high-performance computing. In manufacturing, Tesfaye et al. (2022) outline both growth prospects and infrastructural obstacles to AI adoption in Ethiopia, while Fatawu et al. (2024) synthesize broader opportunities and challenges across African SMEs. No study identified in this review empirically tests an integrated capability, collaboration, and governance model using Ethiopian SME data—defining the exact empirical gap this research addresses.

2.8 Synthesis and positioning

Table 1. Summary of key studies and positioning of the present study

Study	Context	Focus and approach	Limitation relative to this study
Fernandez de Arroyabe et al. (2024)	12,108 European SMEs	Digital and innovation capabilities as adoption drivers	Stops at adoption; no performance mechanism
Ul Haq et al. (2026)	Pakistani manufacturing SMEs	TOE–RBV; adoption, performance, mediation and moderation	No dynamic capabilities, collaboration, or governance
Wong & Ngai (2025)	Chinese telecom firms	Dynamic capabilities mediate AI and operational performance	Single industry and country; no governance
Mikalef & Gupta (2021)	Firms (cross-sector)	AI capability, creativity, and performance	No dynamic capabilities or SME focus
Papagiannidis et al. (2022)	144 Nordic firms	RAIG, knowledge management, competitive performance	Governance not tested as moderator; advanced economy
Zercher et al. (2025)	Teams	Generative AI in team decision-making	Team level, not firm performance
Present study	Ethiopian SMEs	Adoption → capability → DC and collaboration → performance; RAIG moderates	Cross-sectional; perceptual data

Three overarching insights emerge from this synthesis. First, organizational capability—rather than technology possession—is widely recognized as the true locus of value, yet its measurement remains fragmented. Second, dynamic capabilities represent the best-established conversion mechanism, whereas human–AI collaboration remains under-explored at the enterprise level. Third, while responsible governance correlates with stronger performance, its moderating role in resource-constrained African SMEs remains untested. These conclusions directly inform the integrated conceptual model presented in Section 6.

3. PROBLEM STATEMENT AND RESEARCH GAP

Three practical and theoretical problems motivate this investigation. First, technology acquisition does not automatically create organizational capability: an SME may procure AI software while lacking the data infrastructure, technical skills, business processes, and leadership commitment required to exploit it. Second, possessing AI capability does not guarantee superior financial or operational outcomes unless that capability is actively channelled into sensing market shifts, seizing opportunities, and reconfiguring operations. Third, sustainable value creation requires a governance architecture capable of managing privacy, algorithmic bias, transparency, accountability, security, and human oversight.

Four specific research gaps follow from these challenges. First, prior literature frequently examines adoption, capability, and performance in isolation rather than across an end-to-end value chain. Second, although Dynamic Capabilities Theory is increasingly invoked, the precise mechanisms linking AI capability to SME performance require further empirical verification; for instance, Wong and Ngai (2025) demonstrate dynamic-capability mediation in Chinese telecommunications but note single-industry and single-country constraints. Third, responsible AI governance is typically framed as an ethical obligation or regulatory hurdle rather than a strategic condition that shapes value realization. Fourth, empirical evidence remains heavily concentrated in advanced economies or capital-intensive sectors; even emerging-market studies such as Ul Haq et al. (2026) do not jointly integrate dynamic capabilities, human–AI collaboration, and responsible governance.

4. RESEARCH OBJECTIVE AND QUESTIONS

Research Objective: To develop and test an integrated model explaining how AI adoption contributes to SME performance through AI capability, dynamic capabilities, and human–AI collaboration, and how responsible AI governance conditions this relationship.

RQ1: How do TOE-based readiness factors influence AI adoption?

RQ2: How does AI adoption influence AI capability?

RQ3: How does AI capability influence dynamic capabilities and human–AI collaboration?

RQ4: Do dynamic capabilities and human–AI collaboration mediate the relationship between AI capability and SME performance?

RQ5: Does responsible AI governance strengthen the relationship between AI capability and SME performance?

5. THEORETICAL FOUNDATION

5.1 Resource-Based View

The Resource-Based View (RBV) posits that sustained competitive advantage arises from resources that are valuable, rare, inimitable, and organizationally embedded (Barney, 1991). Because off-the-shelf AI software and cloud APIs are commercially accessible to rivals, technical tools alone rarely confer durable differentiation. Instead, competitive advantage emerges from firm-specific combinations of proprietary data, skilled personnel, tailored workflows, and managerial acumen (Mikalef & Gupta, 2021).

5.2 Dynamic Capabilities Theory

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Dynamic Capabilities Theory (DCT) explains how organizations sense emerging opportunities and threats, seize them through timely resource mobilization, and continuously reconfigure their operational asset base (Teece et al., 1997; Teece, 2007). AI reinforces each microfoundation: predictive analytics uncover subtle shifts in customer demand, leadership allocates capital toward high-potential niches, and core products, services, and routines are adapted accordingly.

5.3 Technology–Organization–Environment Framework

The TOE framework (Tornatzky & Fleischer, 1990) accounts for technology adoption across three contextual dimensions: technological (system compatibility, infrastructure reliability, data availability, perceived benefits), organizational (leadership support, financial slack, workforce skills, experimental culture), and environmental (competitive intensity, regulatory frameworks, customer expectations, government incentives). Taken together, TOE explains why SMEs adopt AI, whereas RBV and DCT explain how adoption is transformed into competitive performance.

6. CONCEPTUAL MODEL

Figure 2 illustrates the proposed conceptual model. Dynamic capabilities and human–AI collaboration are specified as parallel mediators linking AI capability to SME business performance. While a serial ordering (dynamic capabilities → collaboration) is not formally hypothesized due to insufficient theoretical justification, it will be evaluated empirically as a competing model during robustness testing.

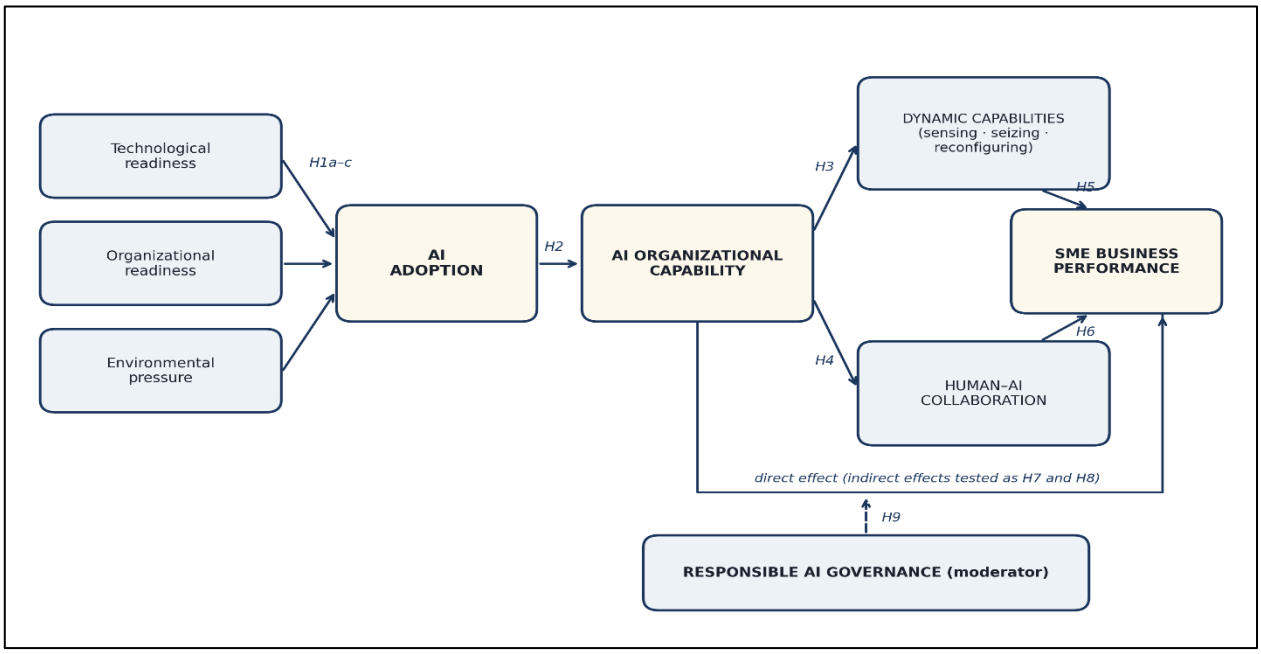


Figure 2. Proposed conceptual model

7. CONSTRUCT DEFINITIONS

Table 2. Constructs and conceptualisation

Construct	Definition and dimensions
AI adoption	Extent to which AI technologies are integrated into core business processes and managerial decision-making.
AI capability	Second-order construct comprising four dimensions: technological (infrastructure, system integration), data (quality, availability, cross-functional integration), human (AI literacy, analytical skills, training), and managerial (AI strategy, resource allocation, change management) capability.
Dynamic capabilities	Second-order construct capturing a firm's capacity for sensing market shifts, seizing opportunities, and reconfiguring organizational assets.
Human–AI collaboration	Extent to which employees and managers jointly execute complementary tasks with AI, pairing algorithmic pattern recognition with human judgment, contextual awareness, and accountability.
Responsible AI governance	Organizational structures, rules, and oversight routines governing accountability, transparency, data privacy, fairness, security, human-in-the-loop supervision, and risk management.
SME performance	Financial (sales growth, profitability) and non-financial (productivity, customer satisfaction, innovation rate, operational efficiency) outcomes relative to key competitors, captured via perceptual scales where audited records are unavailable.

Because AI adoption and AI capability are conceptually adjacent, establishing discriminant validity between them is essential. Adoption reflects the breadth and depth of active tool usage, whereas capability captures the deeper organizational competence required to orchestrate and extract value from those tools (Figure 3).

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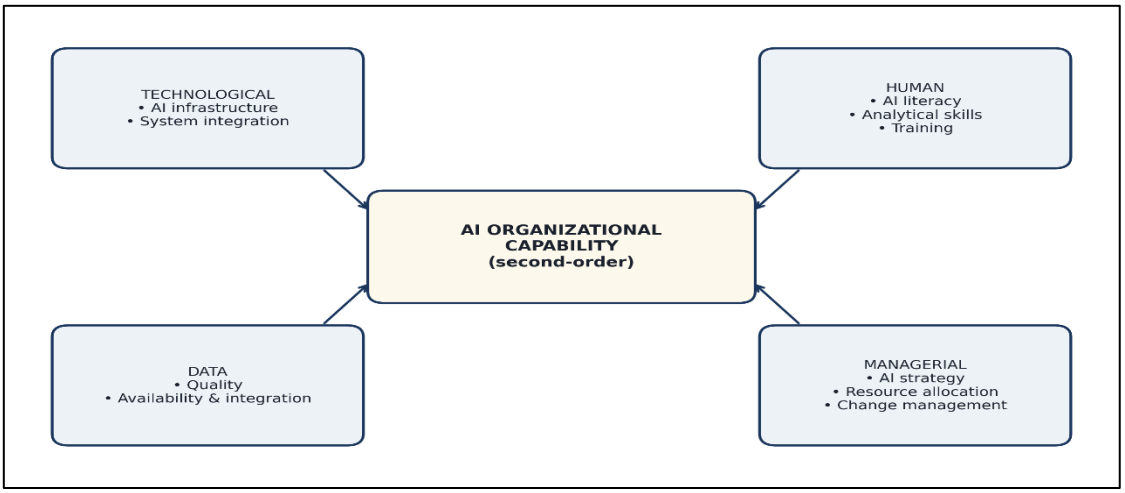


Figure 3. Dimensions of AI organizational capability

8. HYPOTHESIS DEVELOPMENT

H1a–c: Technological readiness (a), organizational readiness (b), and environmental pressure (c) are positively related to AI adoption. Prior TOE scholarship consistently shows that supportive infrastructure, leadership commitment, financial capacity, and external market pressures drive SME adoption decisions (Tornatzky & Fleischer, 1990).

H2: AI adoption is positively related to AI capability. Hands-on integration of AI across business functions fosters technical familiarity, data curation routines, and managerial learning that coalesce into organizational AI capability.

H3: AI capability is positively related to dynamic capabilities. Stronger data-processing and analytical capacity enables SMEs to detect market shifts earlier, commit resources decisively, and reconfigure workflows.

H4: AI capability is positively related to human–AI collaboration. Employee AI literacy, accessible data, and supportive leadership facilitate productive human–machine workflows; team-level evidence confirms that AI alters decision routines and information sharing (Zercher et al., 2025).

H5: Dynamic capabilities are positively related to SME performance.

H6: Human–AI collaboration is positively related to SME performance, as AI generates its highest returns when augmenting rather than merely substituting human domain expertise.

H7: Dynamic capabilities mediate the relationship between AI capability and SME performance, consistent with empirical evidence from telecommunications and service sectors (Wong & Ngai, 2025).

H8: Human–AI collaboration mediates the relationship between AI capability and SME performance.

H9: Responsible AI governance positively moderates the relationship between AI capability and SME performance, such that the positive effect of AI capability on performance is stronger when governance is well developed.

While governance is occasionally dismissed as bureaucratic overhead, clear accountability, human oversight, and risk controls build the internal trust and stakeholder confidence necessary to scale AI beyond isolated pilots. Conversely, a competing perspective suggests that formal governance may impose compliance costs and rigidity on resource-constrained SMEs; thus, the net moderating effect remains an important empirical question. Moderated mediation across the indirect pathways will also be examined as a secondary exploratory analysis.

Table 3. Summary of hypotheses

No.	Relationship	Expected sign	Primary test
H1a–c	Technological, organizational, environmental readiness → AI adoption	+	PLS-SEM path coefficients
H2	AI adoption → AI capability	+	Path coefficient
H3	AI capability → dynamic capabilities	+	Path coefficient
H4	AI capability → human–AI collaboration	+	Path coefficient
H5	Dynamic capabilities → SME performance	+	Path coefficient
H6	Human–AI collaboration → SME performance	+	Path coefficient
H7	AI capability → dynamic capabilities → performance	Mediation	Bootstrapped indirect effect
H8	AI capability → human–AI collaboration → performance	Mediation	Bootstrapped indirect effect
H9	Governance × AI capability → performance	+ (moderation)	Interaction term

9. RESEARCH METHODOLOGY

9.1 Philosophy and design

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Grounded in a post-positivist research philosophy, the study employs an explanatory sequential mixed-methods design (Figure 4). A cross-sectional quantitative survey of Ethiopian SMEs will first test the structural hypotheses, followed by semi-structured qualitative interviews with a purposive subsample of managers to contextualize and explain the statistical patterns.

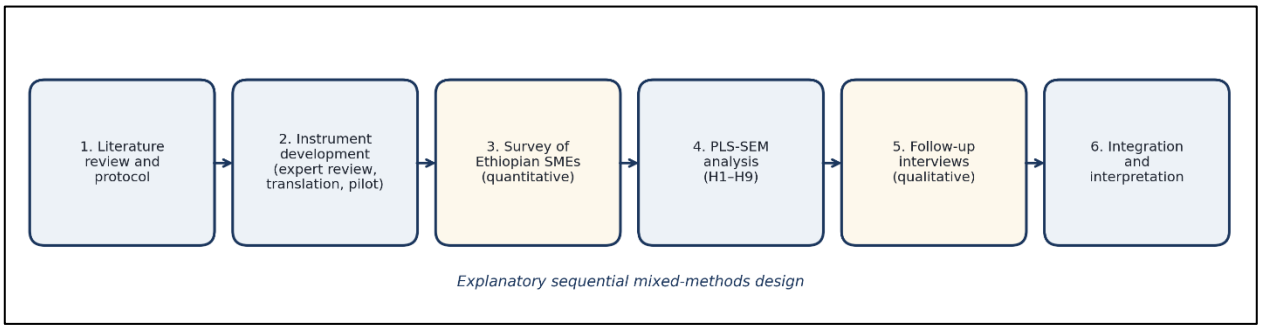


Figure 4. Research design

9.2 Context, population and sampling

The empirical setting comprises SMEs operating in Ethiopia, situated within the broader emerging-economy discourse. Target respondents are senior decision-makers—owners, chief executives, general managers, and functional heads—possessing direct oversight of AI deployment in their firms. A stratified sampling frame drawn from chamber of commerce and trade registry directories will segment firms by industry sector and enterprise size. Minimum sample size requirements will be established via statistical power analysis alongside PLS-SEM benchmarks such as the inverse square root method. Where feasible, a second respondent per enterprise will be surveyed to mitigate single-informant bias.

9.3 Measurement

All latent constructs will be measured using five- or seven-point Likert scales adapted from established instruments, refined through expert panel review, translated into Amharic with independent back-translation, and verified via pilot testing. Control variables include firm size, firm age, industry sector, ownership structure, respondent education level, and prior digital investment. The full draft questionnaire is provided in Appendix A.

9.4 Data analysis

Data analysis will follow a structured eight-stage PLS-SEM workflow (Figure 5): (1) data screening and descriptive profiling; (2) non-response bias checks and common-method-bias diagnostics (Podsakoff et al., 2003); (3) measurement model evaluation for indicator reliability, internal consistency (Cronbach's alpha, composite reliability), and convergent validity (AVE); (4) discriminant validity assessment via the heterotrait–monotrait (HTMT) ratio; (5) structural model estimation examining collinearity (VIF), bootstrapped path coefficients, R^2, f^2, and predictive relevance (Q^2); (6) mediation testing using bootstrapped specific indirect effects; (7) moderation analysis via an orthogonalized or two-stage interaction term; and (8) robustness checks comparing the alternative serial mediation model alongside subgroup and multi-group analyses. PLS-SEM is well suited to the model's higher-order constructs, complex mediation–moderation structure, and predictive focus (Hair et al., 2022), though covariance-based SEM remains a viable complement if global goodness-of-fit indices are prioritized.

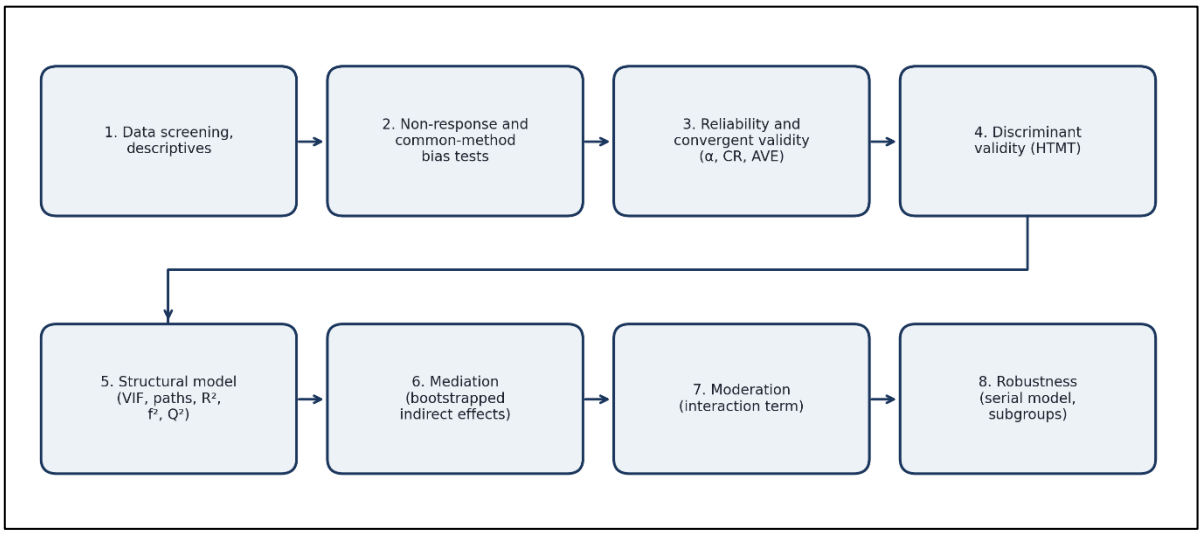


Figure 5. Data analysis workflow (PLS-SEM)

9.5 Ethical considerations

Research execution will adhere strictly to institutional ethics protocols, including formal ethics board clearance, written informed consent, voluntary participation, strict respondent and firm anonymity, and encrypted data storage.

10. EXPECTED CONTRIBUTIONS

Theoretical Contributions: First, the study shifts scholarly attention from passive AI acquisition to the multidimensional organizational capabilities required to extract value. Second, it unpacks the black box of AI value creation by testing dual conversion pathways—macro-level dynamic capabilities and micro-level human–AI collaboration—rather than relying on simplified bivariate AI–performance links. Third, it reframes responsible AI governance as a strategic boundary condition that unlocks commercial scalability rather than merely a compliance requirement. Fourth, it extends an integrated TOE–RBV–DCT framework to an under-researched, resource-constrained African SME setting.

Practical Implications: For SME owners and managers, the framework underscores that AI must be approached as an organizational transformation initiative—requiring coordinated investments in data quality, workforce upskilling, leadership alignment, workflow redesign, human–AI collaboration norms, and governance—rather than a standalone software purchase. Given acute financial, infrastructural, and talent constraints, emerging-

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market SMEs can prioritize modular cloud-based AI services, ecosystem partnerships, incremental deployment, open-source tools, and lightweight governance frameworks rather than attempting to replicate capital-intensive large-enterprise models.

11. LIMITATIONS AND FUTURE RESEARCH

Several methodological boundaries warrant consideration. A cross-sectional survey design constrains strict causal inference; reliance on managerial self-reports introduces potential perceptual subjectivity; and single-country sampling in Ethiopia may limit statistical generalizability across diverse emerging markets. Future investigations can build on this foundation through longitudinal panel designs, multi-country comparative samples, objective financial performance records, formal moderated-mediation testing, and configurational approaches such as fuzzy-set qualitative comparative analysis (fsQCA).

12. CONCLUSION

The competitive payoff of artificial intelligence depends far less on owning advanced algorithms than on an SME's capacity to cultivate, orchestrate, and responsibly govern the organizational capabilities that convert technology into sustained performance. By uniting RBV, DCT, and TOE with human–AI collaboration and responsible governance, this study offers a rigorous, testable roadmap for emerging-market SMEs. Empirical findings will be reported only upon completion of fieldwork and statistical analysis.

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APPENDIX A. SURVEY INSTRUMENT AND INTERVIEW GUIDE

Drafting Note

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All measurement items below are newly drafted to operationalise the constructs defined in the article and are not yet empirically validated. Prior to fieldwork, each construct must be reconciled with published scales, adapted, reviewed by an expert panel, translated into Amharic (and other relevant local languages) with independent back-translation, and pilot tested. Do not describe the scales as "validated" until these steps are completed.

A. Participant Information and Consent

You are invited to participate in an academic study examining how small and medium-sized enterprises use artificial intelligence (AI) and which organizational conditions shape business outcomes. The survey takes approximately 15 minutes to complete. Participation is entirely voluntary, responses are anonymous and reported solely in aggregate form, and you may withdraw at any point prior to submission. All data are stored securely and used exclusively for academic research. By proceeding, you confirm that you are 18 years of age or older and consent to participate. Contact: [researcher email]. Ethics approval reference: [to be inserted].

Operational Definition: Definition of AI: For this study, AI refers to software systems that perform tasks typically requiring human intelligence, including machine-learning analytics, demand forecasting, chatbots, recommendation engines, and generative AI tools (such as text and image generators).

Screening Questions:

(S1) Does your firm use at least one AI tool or application in its operations? [Yes / No — if no, administer the short non-adopter module in Section C8].
(S2) Do you hold a managerial or ownership position with knowledge of how AI is used in the firm? [Yes / No — if no, thank the respondent and conclude].

B. Firm and Respondent Profile (Controls)

#	Question	Response format
P1	Sector of main activity	Manufacturing; trade; services; agribusiness; ICT; construction; other
P2	Number of full-time employees	Exact number, or bands (1–9; 10–49; 50–99; 100–249)
P3	Firm age (years since establishment)	Number
P4	Ownership structure	Sole owner; family; partnership; private company; other
P5	Location (region and city)	Open text
P6	Annual turnover band	Bands in Ethiopian birr [define]
P7	Respondent position and years in post	Open text and number
P8	Respondent education level	Secondary; diploma; bachelor; master; doctorate
P9	Years since first using AI tools; main AI tools used	Number; multi-select list
P10	Share of annual budget spent on digital technology	Bands: <1%; 1–5%; 6–10%; >10%

C. Measurement Items

All items below use a seven-point Likert scale (1 = strongly disagree, 4 = neither agree nor disagree, 7 = strongly agree), unless otherwise noted. Item order should be randomized within blocks, and reverse-worded or attention-check items (e.g., "Select 3 for this item") should be embedded to screen out careless responses.

C1. TOE Antecedents

Code	Item (draft)	Candidate source to adapt
TR1	Our firm has reliable internet, power backup and computing equipment suitable for AI tools.	Tornatzky & Fleischer (1990) TOE logic
TR2	AI tools are compatible with the systems and processes we already use.	[select scale]
TR3	Our firm can access the data needed to run AI applications.	[select scale]
OR1	Top management actively supports the use of AI.	[select scale]
OR2	Our firm can finance the purchase and running costs of AI tools.	[select scale]
OR3	Our organizational culture encourages experimenting with new technology.	[select scale]
EP1	Competitors in our market are using AI.	[select scale]
EP2	Customers or partners expect us to use AI-enabled services.	[select scale]
EP3	Government policy or programmes make it easier to adopt AI.	[select scale]

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C2. AI Adoption

Code	Item (draft)	Candidate source to adapt
AD1	Our firm actively integrates AI into business processes.	[select scale]
AD2	AI supports managerial decision-making in our firm.	[select scale]
AD3	Our use of AI applications has expanded over the past three years.	[select scale]
AD4	AI is used in several functions (for example, marketing, finance, operations).	[select scale]

C3. AI Organizational Capability (second-order: four dimensions)

Code	Item (draft)	Candidate source to adapt
AT1	Our AI tools and infrastructure meet our business needs.	Mikalef & Gupta (2021) [adapt]
AT2	We can integrate AI tools with existing business systems.	Mikalef & Gupta (2021) [adapt]
AD_1	The data we use for AI is accurate and up to date.	Mikalef & Gupta (2021) [adapt]
AD_2	Data from different parts of the firm can be combined for AI use.	Mikalef & Gupta (2021) [adapt]
AH1	Our employees have sufficient AI-related skills.	Mikalef & Gupta (2021) [adapt]
AH2	Our firm provides training so staff can use AI effectively.	Mikalef & Gupta (2021) [adapt]
AM1	Our firm has a clear strategy for how AI will be used.	Mikalef & Gupta (2021) [adapt]
AM2	Managers allocate resources to AI initiatives in line with that strategy.	Mikalef & Gupta (2021) [adapt]
AM3	Our firm manages the organizational change that AI requires.	Mikalef & Gupta (2021) [adapt]

C4. Dynamic Capabilities (second-order: sensing, seizing, reconfiguring)

Code	Item (draft)	Candidate source to adapt
DS1	We quickly detect changes in customer needs.	Wilden et al. (2013); Pavlou & El Sawy (2011)
DS2	We systematically monitor competitors and market trends.	Wilden et al. (2013); Pavlou & El Sawy (2011)
DZ1	We respond rapidly to new market opportunities.	Wilden et al. (2013); Pavlou & El Sawy (2011)
DZ2	We commit resources quickly once an opportunity is identified.	Wilden et al. (2013); Pavlou & El Sawy (2011)
DR1	We can reconfigure resources when market conditions change.	Wilden et al. (2013); Pavlou & El Sawy (2011)
DR2	We readily revise products, services or processes when needed.	Wilden et al. (2013); Pavlou & El Sawy (2011)

C5. Human–AI Collaboration

Code	Item (draft)	Candidate source to adapt
HC1	Employees in our firm work effectively together with AI systems.	New scale; informed by Zercher et al. (2025)
HC2	AI helps employees perform analytical tasks more effectively.	New scale; informed by Zercher et al. (2025)
HC3	Employees know when human judgment should override AI recommendations.	New scale; informed by Zercher et al. (2025)
HC4	Staff and AI tools complement each other’s strengths in our key tasks.	New scale; informed by Zercher et al. (2025)
HC5	Employees feel confident questioning AI outputs.	New scale; informed by Zercher et al. (2025)

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C6. Responsible AI Governance (moderator)

Code	Item (draft)	Candidate source to adapt
RG1	Responsibilities for AI-related decisions are clearly assigned.	Informed by Papagiannidis et al. (2022)
RG2	We can explain to stakeholders how AI is used in our decisions.	Informed by Papagiannidis et al. (2022)
RG3	AI use is subject to appropriate human oversight.	Informed by Papagiannidis et al. (2022)
RG4	We have rules for protecting customer and employee data used by AI.	Informed by Papagiannidis et al. (2022)
RG5	We check AI outputs for errors or unfair outcomes.	Informed by Papagiannidis et al. (2022)
RG6	We regularly assess the risks of our AI applications.	Informed by Papagiannidis et al. (2022)

C7. SME Performance (relative to main competitors over the past three years)

Code	Item (draft)	Candidate source to adapt
PF1	Our sales growth has been better than our main competitors'.	Perceptual performance scales [select]
PF2	Our profitability has been better than our main competitors'.	Perceptual performance scales [select]
PF3	Our productivity has been better than our main competitors'.	Perceptual performance scales [select]
PF4	Our customer satisfaction has been better than our main competitors'.	Perceptual performance scales [select]
PF5	Our rate of introducing new products or services has been better than our main competitors'.	Perceptual performance scales [select]
PF6	Our operational efficiency has been better than our main competitors'.	Perceptual performance scales [select]

C8. Short Module for Non-Adopters (Optional): Respondents answering "No" to screening question S1 complete the technological, organizational, and environmental readiness items (Section C1) alongside open-ended questions on adoption barriers. While excluded from the main structural equation model, these responses provide valuable descriptive benchmarks.

D. Instrument Development Checklist

Step	Validation & Pre-Fieldwork Action
1	Reconcile each construct with a published scale; document exact source citations, retained items, and wording modifications (e.g., Mikalef & Gupta, 2021 for AI capability; Wilden et al., 2013 and Pavlou & El Sawy, 2011 for dynamic capabilities).
2	Convene an expert panel (5–7 academics and industry practitioners) to rate item relevance and compute the content validity index (CVI).
3	Translate the instrument into Amharic with independent back-translation and reconcile semantic discrepancies.
4	Conduct cognitive pretesting with 8–10 SME managers to refine ambiguous phrasing.
5	Execute a pilot study with 30–50 SMEs to evaluate internal consistency and item distributions (excluding pilot cases from the final sample).
6	Implement procedural remedies against common-method bias: separate predictor and outcome blocks, guarantee anonymity, vary scale anchors, and obtain a second respondent per firm where possible.
7	Pre-register the statistical analysis plan, including the competing serial mediation model and subgroup comparisons.

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E. Sampling and Administration Notes

Administration Mode: Face-to-face or telephone-assisted survey administration is recommended to prevent connectivity constraints or digital literacy gaps from skewing sample representation, supplemented by an online link where appropriate.

Target Sample Size: Establish minimum sample size through formal power analysis and PLS-SEM sample-size guidelines, inflating the target to account for anticipated non-response. Document response rates and non-response reasons systematically.

F. Semi-Structured Interview Guide (Explanatory Follow-Up)

1. Describe how your firm first began using AI and what changed operationally or strategically as a result.
2. Which internal resources (skills, data, leadership, financing) mattered most in translating AI adoption into tangible business outcomes?
3. Share a concrete example where AI helped your firm detect or respond rapidly to a market shift.
4. How do employees and AI systems divide or share work in daily operations? Where does human judgment override algorithmic outputs?
5. What rules, checks, or governance practices guide responsible AI use in your firm, and have they accelerated or slowed execution?
6. Which local contextual factors (electricity reliability, internet connectivity, regulation, talent availability) most shape what AI can achieve in your enterprise?
7. Looking at the preliminary survey patterns, which findings surprise you most, and how would you explain them from your practical experience?

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