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When Does AI Capability Convert to Advantage? A Complementarity-Gated Framework for Startups in Resource-Constrained Economies

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Abstract

Purpose: This paper develops a conceptual framework linking artificial intelligence (AI) capability, competitive advantage, and startup performance in emerging economies, addressing the limited and fragmented understanding of how AI capability translates into venture outcomes in resource-constrained contexts.

Design/methodology/approach: The paper employs a structured review of empirical and theoretical literature, grounded in the resource-based view (RBV) and the dynamic capabilities perspective. It synthesizes evidence across studies to identify points of convergence, divergence, and unresolved tension, and on this basis derives a set of testable propositions.

Findings: The review suggests that AI capability is a multidimensional construct whose translation into competitive advantage is conditional rather than automatic: it depends on complementary resources such as digital skills, infrastructure, organizational and absorptive capacity, and strategic alignment that are systematically scarce in emerging-economy startups. The paper advances a framework in which competitive advantage mediates the AI capability–performance relationship, but in which that mediating pathway is itself gated by the availability of complementary resources, making the capability–advantage link contingent on context rather than a general regularity.

Originality: The paper's contribution is not that AI capability requires complements, a point established in prior literature, but that it formalizes *where* complementarity binds: not on the path from advantage to performance, where most mediation literature locates contingency, but on the prior path from capability to advantage itself. It specifies this as three concrete, measurable gating conditions, digital infrastructure, founder AI literacy, and ecosystem support, rather than treating resource scarcity as unmodeled context. This repositions AI capability from a resource assumed to convert into advantage into one whose conversion is itself the object of theoretical and empirical explanation, with the moderated pathway as the paper's central, testable claim.

Keywords: Artificial intelligence capability; competitive advantage; startup performance; resource-based view; dynamic capabilities; emerging economies; Tanzania

1. Introduction

Artificial intelligence has moved from a specialized technical domain to a general-purpose capability that firms of varying size and maturity now seek to harness for competitive ends. Contemporary evidence indicates that AI adoption is expanding across firm populations, although adoption remains uneven across regions, sectors, and firm sizes. National and cross-national assessments document both the accelerating diffusion of AI and the persistence of substantial gaps between leading and lagging economies in the resources required to deploy it productively. For emerging economies in particular, the promise of AI is accompanied by structural constraints, including limited digital infrastructure, skills shortages, and affordability barriers, that shape what adoption can realistically achieve.

Against this backdrop, a growing body of management research treats AI not merely as a technology to be adopted but as an organizational capability to be built. The conceptualization of an AI capability, understood as the firm's ability to marshal AI-related tangible, human, and intangible resources toward business value, has provided a foundation for empirical work linking such capability to organizational creativity and firm performance [1]. This capability framing aligns naturally with the resource-based view (RBV), which holds that resources that are valuable, rare, inimitable, and organizationally embedded can underpin sustained competitive advantage [2], [3]. It also connects to the dynamic capabilities perspective, which emphasizes the firm's capacity to sense, seize, and reconfigure resources in changing environments [4], [5], [6].

Startups warrant attention as a distinct focal group rather than as small versions of established firms. Early-stage ventures face the liability of newness, operate under acute resource constraints, and concentrate strategic and technical decision-making in founders and small teams, conditions that sharply differentiate how they can acquire and deploy an AI capability. Whereas large enterprises can absorb the cost of dedicated AI units and tolerate uncertain returns, startups must convert limited AI investments into competitive position quickly or not at all. This makes the relationship between AI capability and performance both more consequential and more conditional for startups, and it is the reason this paper centers the startup segment rather than the broader firm population.

Despite this conceptual progress, a deeper theoretical problem remains unresolved. The dominant treatment of AI capability, inherited from the resource-based view, frames it as a resource that is valuable across contexts: build the capability, and competitive advantage follows. Yet a parallel and older lineage in the strategy literature holds that the value of a resource is not intrinsic but contingent on the complementary assets required to deploy it [7], and that firms differ in their capacity to absorb and exploit a new technology according to their prior knowledge and resources [8]. These two views are in tension. If AI capability yields advantage only in combination with complements: digital skills, reliable infrastructure, organizational routines, strategic alignment, then in settings where those complements are scarce, the capability–advantage relationship cannot be assumed to hold as it does in resource-rich economies. This tension is nowhere sharper than in emerging-economy startups, which face acute and systematic scarcity of precisely these complementary resources, yet it is precisely there that the relationship is least studied: for Tanzania and the broader East African region, evidence on AI capability in entrepreneurial ventures is effectively absent, even as the regional startup ecosystem expands.

This paper develops a conceptual framework that resolves this tension by reframing AI capability as a conditional rather than a uniformly valuable resource. Its central theoretical claim is that competitive advantage mediates the relationship between AI capability and startup performance, but that this mediating pathway is itself gated by the availability of complementary resources, such that the capability–advantage link is strong where these complements are present and weak or absent where they are not. This differs from the dominant treatment in the AI capability literature, which generally acknowledges the importance of complementary resources but incorporates them as antecedents of AI capability, parallel organizational capabilities, or broad contextual conditions. Consequently, AI capability remains implicitly treated as a resource that naturally generates competitive advantage once assembled. The present framework advances a different theoretical position by arguing that the conversion of AI capability into competitive advantage is itself the phenomenon requiring explanation. Rather than treating complementary resources as peripheral contextual conditions, it positions them as gating mechanisms that determine whether AI capability can become a strategic resource in the first place. The theoretical contribution therefore lies not in recognizing that complementary resources matter, but in relocating their explanatory role to the capability–competitive advantage relationship itself. By specifying complementarity as operating on a single, identifiable pathway rather than diffusely across the model, the framework offers a parsimonious and testable explanation for why ventures with comparable AI capability may realize markedly different competitive outcomes in resource-constrained environments.

Existing AI-capability literature, including the frameworks this paper builds on, treats AI capability as a resource that converts into competitive advantage once assembled. This paper argues that assumption is theoretically incomplete: AI capability converts into advantage only under specific complementarity conditions, and where those conditions are absent, the relationship should be expected to weaken or fail rather than merely attenuate. The framework's task is to specify those conditions precisely enough to be tested, not to assert their existence in general terms.

The remainder of the paper proceeds as follows. The next section sets out the theoretical foundation, integrating the RBV and dynamic capabilities perspectives with the AI capability construct. The paper then describes the structured review approach used to assemble and screen the literature. Subsequent sections synthesize the evidence thematically: the conceptualization and dimensionality of AI capability; the link between AI capability and competitive advantage; the link between competitive advantage and performance; and the state of evidence in African and emerging-economy contexts. The paper then articulates the research gap, presents the conceptual framework and propositions, and concludes with a discussion of implications and an agenda for empirical research.

2. Theoretical Foundation

2.1. The Resource-Based View

The resource-based view provides the primary theoretical lens for this paper. Its central proposition is that firms are heterogeneous bundles of resources, and that competitive advantage arises when a firm controls resources that are simultaneously valuable and rare, and that competitors cannot readily imitate or substitute [2]. Wernerfelt [3] first articulated the firm as a collection of resources whose strategic value depends on the difficulty rivals face in acquiring or replicating them. Subsequent formalization through the VRIO logic, assessing whether a resource is valuable, rare, costly to imitate, and supported by organizational arrangements to exploit it, offered managers and researchers a structured way to evaluate the competitive implications of a given resource [9].

Empirical and conceptual work in the RBV tradition has consistently emphasized that resource possession alone is insufficient; advantage depends on organizational capacity to deploy resources effectively. Comparative analyses of the VRIO framework, including work conducted in African settings, suggest that the organizational dimension, the firm's structures and routines for exploiting a resource, is often decisive in converting potential into realized advantage [10]. This emphasis is directly relevant to AI, where access to tools does not guarantee value; the surrounding human, organizational, and strategic resources determine outcomes.

2.2. The Dynamic Capabilities Perspective

Because AI environments evolve rapidly, the static reading of the RBV is usefully complemented by the dynamic capabilities perspective. Teece et al. [6] defined dynamic capabilities as the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments. Teece [5] later elaborated the microfoundations of these capabilities through the activities of sensing opportunities and threats, seizing them through investment and commitment, and reconfiguring the asset base to maintain fit. Eisenhardt and Martin [4] clarified that dynamic capabilities consist of identifiable and often best-practice organizational processes, and that in high-velocity environments they take a more experiential and situational form.

For AI capability, the dynamic capabilities lens explains why advantage from AI is rarely automatic or permanent. Firms must continually sense new AI applications, commit resources to integrate them into products and processes, and reconfigure routines as the technology and the competitive landscape shift [11]. This perspective also rationalizes the mediation logic developed below: AI capability contributes to performance to the extent that it is mobilized through capability-driven processes that establish and renew a competitive position, rather than through mere possession of AI tools.

2.3. Complementary Assets and Absorptive Capacity

The conditional view of AI capability advanced in this paper rests on two further strands of theory that qualify the resource-based view. The complementary-assets perspective holds that the returns to a technology accrue not to the technology itself but to the co-specialized assets required to deploy it commercially, so that the same technology yields advantage for firms holding the relevant complements and little for those without them [7]. The absorptive-capacity perspective adds that firms differ in their capacity to recognize, assimilate, and apply new technology as a function of their prior related knowledge, an asymmetry that systematically favors firms already rich in relevant resources [8]. Together these perspectives imply that AI capability is not a uniformly valuable resource but a conditional one: its conversion into competitive advantage depends on complementary resources and absorptive capacity that vary across firms and, critically, are systematically scarce in resource-constrained settings. This is the theoretical foundation for treating the AI capability–competitive advantage link as contingent rather than automatic, and for the moderating conditions specified later in the framework.

2.4. AI Capability as a Strategic Resource

Building on the information systems and IT-capability literature, recent scholarship conceptualizes AI capability as a firm-level construct rather than a property of individual technologies. The foundational logic parallels earlier work on IT capability, which showed that firms able to combine IT resources with complementary human and organizational assets achieved superior performance, whereas commoditized technology alone did not [12]. Extending this reasoning, Mikalef and Gupta [1] conceptualized, measured, and empirically tested an AI capability construct, demonstrating its association with organizational creativity and firm performance. Complementary theoretical work frames AI capability as resting on the orchestration of tangible resources such as data and infrastructure, human resources such as technical and managerial skills, and intangible resources such as organizational change capacity and a supportive culture [13], [14].

Synthesizing across these accounts, this paper treats AI capability as multidimensional, comprising at least four interrelated components relevant to startups. The human dimension covers AI-related skills, talent, and managerial understanding; in a startup, this may be as basic as a founder who can specify an AI feature to a developer or evaluate a vendor's tool. The infrastructure dimension covers access to data, computing, and AI-enabled tools; for a startup this typically means cloud-based and subscription AI services rather than owned infrastructure. This venture-level infrastructure dimension is conceptually distinct from the digital-infrastructure moderator introduced in Section 7.2: the former concerns the AI-specific resources a venture has assembled (its tools, data, and computing access), while the latter concerns the external operating environment, electricity reliability, connectivity, and affordable computing, within which that assembly and its use occur. A venture can possess a well-assembled AI-capability infrastructure dimension (e.g., a functioning cloud AI subscription) while operating in an external environment of unreliable electricity and connectivity that constrains how consistently that capability can be deployed; the framework's moderator captures precisely this external constraint, not the venture's internal resource assembly. The strategic dimension covers the alignment of AI initiatives with the venture's competitive logic; in a startup this is visible in whether AI is directed at the core value proposition or adopted ad hoc. The innovation dimension covers the use of AI to generate new products, services, and processes; for a startup this often means embedding AI directly into the product offered to customers. This multidimensional conceptualization is consistent with the capability framings advanced in the AI and IT literatures and provides the basis for the propositions developed later.

3. Review Approach

This paper employs a structured literature review designed to assemble, screen, and synthesize evidence relevant to the relationship among AI capability, competitive advantage, and venture performance, with particular attention to emerging-economy and African contexts. The approach is systematic in its screening and documentation while remaining interpretive in its synthesis, consistent with the paper's aim of building a conceptual framework rather than producing a meta-analytic estimate.

Literature was identified through targeted searches of major scholarly databases and publisher platforms, including Scopus-indexed outlets accessed via Elsevier ScienceDirect, Emerald Insight, Springer, Wiley, Taylor and Francis, and MDPI, supplemented by Google Scholar for breadth and by authoritative institutional sources for contextual and infrastructural evidence. Search terms combined the core constructs (for example, “artificial intelligence capability,” “AI adoption,” “competitive advantage,” “firm performance,” “SME performance,” and “startup performance”) with method and context qualifiers (for example, “PLS-SEM,” “mediation,” “emerging economy,” and country names including Tanzania, Kenya, Ghana, Nigeria, Egypt, and South Africa). The search emphasized the period from 2019 to 2026 for AI-specific empirical evidence, while retaining foundational theoretical and methodological sources irrespective of date. Illustrative search strings included combinations such as (“artificial intelligence capability” OR “AI capability”) AND (“competitive advantage” OR “firm performance” OR “startup performance”); (“AI adoption” AND “SME” AND (“emerging economy” OR “developing country”)); and (“artificial intelligence” AND (“Tanzania” OR “Kenya” OR “Nigeria” OR “sub-Saharan Africa”)). Searches were conducted between April and June 2026. In approximate terms, the searches and subsequent citation snowballing retrieved on the order of 550 to 600 records; after removal of duplicates and screening of titles and abstracts against the inclusion criteria stated above, approximately 230 sources were reviewed in full, of which the 34 most directly relevant to the framework's constructs and propositions are cited in the manuscript. These figures are stated as good-faith approximations consistent with the integrative character of the review rather than as audited counts from a formally logged protocol. This corpus spans peer-reviewed empirical studies, foundational theoretical and methodological works, and institutional or policy documents, and was assembled through structured searches across these databases rather than through a single reproducible systematic-search protocol. The corpus was not formally coded by source type, but its composition falls into three broad categories, of which peer-reviewed empirical studies testing components of the capability–advantage–performance relationship constituted the largest single share, followed by foundational theoretical and methodological works underpinning the resource-based, dynamic-capabilities, complementary-assets, and absorptive-capacity perspectives, with the remainder comprising contextual, institutional, and policy sources documenting infrastructural, regulatory, and ecosystem conditions in Tanzania and comparable emerging economies. Empirical studies were the primary basis for the thematic contrasts identified in Section 4 (for example, direct versus conditional effects, and full versus partial mediation), foundational works supplied the theoretical constructs integrated in Section 2 and formalized in Section 7, and contextual sources informed the boundary conditions and moderators specific to resource-constrained settings.

Records were screened against inclusion criteria prioritizing relevance to the focal constructs, transparency of method and measurement, and credibility of the publication outlet. Sources were classified by their role in the review: empirical studies suitable for evidence synthesis; theoretical and methodological anchors; and contextual or policy sources used to characterize the emerging-economy and regional setting. Duplicate records and items outside the scope of the focal relationships were removed. Because the corpus deliberately combined peer-reviewed empirical studies with institutional reports and policy documents, the review distinguishes throughout between claims supported by empirical research and claims drawn from contextual or policy material. Where individual sources appeared in outlets with limited peer-review standing, they were retained only as supporting or contextual evidence and were not used to anchor central inferences. The synthesis that follows is organized thematically rather than study-by-study, comparing findings across studies, identifying convergence and divergence, and surfacing the gaps that motivate the conceptual framework.

4. Thematic Synthesis and Critical Assessment of the Literature

The literature relevant to this paper can be organized around four analytical questions: how AI capability is conceptualized and measured; whether and how it relates to competitive advantage; whether competitive advantage transmits capability effects to performance; and how this evidence base maps onto African and emerging-economy contexts. Rather than reporting studies sequentially, the synthesis below foregrounds points of convergence, points of divergence, and the unresolved tensions that motivate the conceptual framework. Particular attention is paid to inconsistencies in findings, to studies reporting weak, partial, or conditional effects, and to the contextual and methodological reasons these differences arise.

4.1. Conceptualizing and Measuring AI Capability: Convergence on Construct, Divergence on Measurement

There is broad convergence that AI capability should be theorized as a firm-level organizational capability rather than as the presence of particular technologies. Mikalef and Gupta [1] provide the most influential operationalization, calibrating a multidimensional AI capability measure and linking it to organizational creativity and firm performance, and subsequent applications in public and private settings report broadly consistent positive associations [14]. This capability framing inherits the central lesson of the earlier IT-capability literature, in which the combination of technological, human, and organizational resources, rather than technology alone, distinguished higher-performing firms [12].

Beneath this convergence, however, lies a genuine divergence in measurement that the descriptive literature tends to understate. Studies differ in the number and labeling of AI capability dimensions, in whether the construct is modeled reflectively or formatively, and in whether it is treated as first- or second-order. These are not cosmetic differences: they affect which relationships are estimable and how results should be compared across studies. The absence of a single validated measurement standard means that the apparently consistent positive findings rest on heterogeneous instruments, which weakens any claim that effect sizes are directly comparable across contexts. This measurement heterogeneity is itself a reason that downstream findings on performance effects diverge, and it has direct implications for any new empirical instrument, which must justify its dimensional structure rather than assume it.

4.2. AI Capability and Competitive Advantage: A Relationship That Is Conditional, Not Automatic

A second body of work links AI capability to competitive advantage. The weight of evidence supports a positive relationship: AI strengthens innovation-related capabilities and supports the reconfiguration of processes through which advantage is established [15], [16], and in marketing and tourism settings AI capability has been associated with sustainable competitive advantage [17]. Yet the more careful studies do not report this relationship as automatic. Alhelal *et al.* (2025) find that the effect of AI on competitive advantage operates through digital culture and digital skills rather than directly, implying that firms lacking these complements may realize little advantage from AI investment. Evidence from European SMEs similarly indicates that AI adoption raises growth outcomes primarily where complementary digital resources such as IoT and big-data analytics are already present [18], and SME-focused work reports effects that are contingent on organizational and environmental conditions [19], [20].

The contradiction worth naming is between studies that present AI capability as a relatively direct driver of advantage and those that show its effects are heavily conditioned by complementary resources. The reconciliation favored here, consistent with the dynamic capabilities perspective, is that AI capability is better understood as a higher-order enabler whose competitive payoff depends on the firm's surrounding human, cultural, and strategic resources. This reading has sharp implications for resource-constrained contexts: where complementary resources are scarce, as is common among emerging-economy startups, the AI-capability-to-advantage relationship may be attenuated rather than simply replicated at a lower level. The divergence between studies reporting direct effects and those reporting conditional effects is plausibly attributable to differences in model specification and setting rather than to contradictory underlying mechanisms: studies conducted in tourism and marketing contexts, where digital infrastructure is comparatively less binding, more often report direct effects, whereas studies in manufacturing and cross-national SME samples, where complementary resource availability varies more sharply, more often detect conditional or attenuated effects. A further likely factor is model specification itself: studies that do not include complementary-resource variables cannot, by construction, detect the conditioning they may be missing, so the appearance of a direct effect in some studies may partly reflect omitted-variable structure rather than a genuinely unconditional relationship.

4.3. Competitive Advantage and Performance: Strong Mechanism, Narrow Evidentiary Base

The third and most central body of evidence concerns competitive advantage as the mechanism transmitting capability into performance. Here the convergence is theoretically reassuring but the evidentiary base is narrower than the volume of studies suggests. Multiple structural-equation studies report that competitive advantage mediates the relationship between upstream capabilities and firm performance [21], [22], [23]. Critically, however, several of these report partial rather than full mediation, and at least one reports mediation alongside necessary-condition logic in which competitive advantage is required but not sufficient [24]. The distinction between full and partial mediation is frequently glossed over in descriptive reviews, yet it is theoretically consequential: partial mediation implies that AI capability retains a direct performance effect not captured by competitive advantage, which is precisely why the framework developed below retains a direct path alongside the indirect one. The split between full and partial mediation findings likely reflects, in part, differences in how broadly competitive advantage is operationalized across studies: measures that capture a narrower set of positional dimensions leave more of AI capability's performance effect unexplained, and therefore mechanically yield partial rather than full mediation, while broader competitive-advantage measures absorb more of that effect. Industry and firm-type differences across the underlying samples, particularly the concentration in Southeast Asian micro and small enterprises noted above, may compound this pattern, since the relative importance of positional advantage versus direct capability effects on performance need not be constant across institutional and market settings.

A second limitation of this evidentiary base is its striking geographic concentration. A large share of the competitive-advantage mediation evidence originates from a small number of national contexts, with Indonesian micro, small, and medium enterprises particularly heavily represented (for example, [21], [23]). This concentration raises a genuine external-validity question that the existing literature rarely confronts: it is not established that a mediation structure observed repeatedly in Southeast Asian SMEs generalizes to African startups operating under different institutional, infrastructural, and market conditions. The mechanism may well hold, but its strength, and the relative size of direct versus indirect effects, is an empirical question that the current evidence cannot answer for the African context.

It is precisely here that the most relevant African evidence enters. Kiyabo and Isaga [25], studying SMEs in Tanzania's welding industry, found that competitive advantage mediated the relationship between strategic entrepreneurship and SME performance, using structural-equation methods. This finding is doubly important. Substantively, it demonstrates that the competitive-advantage mediation mechanism operates in the Tanzanian SME setting, not only in Southeast Asia. Methodologically, it establishes the feasibility of variance-based structural modeling with Tanzanian SME respondents. What it does not do is test AI capability as the antecedent, leaving the specific relationship of interest to this paper unexamined even as it lends credibility to the mechanism.

4.4. Performance as a Multidimensional, Perceptual Construct

Across these literatures, performance is consistently treated as multidimensional, and frequently measured perceptually. The foundational treatment distinguishes financial from broader operational and strategic dimensions and warns against single-indicator measurement [26], while validation work shows that subjective managerial assessments correlate meaningfully with objective indicators [27]. This justification is not a mere methodological convenience in the present context: startups in emerging economies typically cannot or will not provide audited financial data, making perceptual multidimensional measurement the only feasible approach. The convergence in this literature is strong enough that the main risk is not measurement choice but construct contamination, namely the danger of defining performance dimensions so broadly that they overlap with the competitive-advantage mediator. Maintaining conceptual separation between advantage and performance is therefore essential to any test of the mediated model.

5. Startups, and Digital Entrepreneurship in Africa and Tanzania

The synthesis above establishes that the AI-capability, competitive-advantage, and performance relationships have been studied almost entirely outside Africa, and almost never in the startup segment. This section examines the African and, specifically, the Tanzanian evidence in greater depth, because the contribution of this paper rests on a precise characterization of what is and is not known in this context.

5.1. The African Evidence Base

Research on AI in African firms is expanding but remains dominated by studies of adoption, readiness, and sectoral application rather than tests of the capability-advantage-performance mechanism. Evidence from South African retailers links the tangible, human, and intangible dimensions of big-data analytics capability to organisational performance [28], echoing the complementary-resources logic seen in the global literature. Sector-specific evidence from Kenya similarly associates AI adoption with financial performance in the financial services industry [29]. Such studies vary widely in method and outlet quality, however, and few model an intervening competitive-advantage mechanism. National AI strategies in Egypt [30] and Rwanda [31] signal rising policy commitment, yet policy ambition has outpaced firm-level empirical evidence, particularly for early-stage ventures. The recurring theme across this body of work is structural: African firms operate under infrastructure limitations, digital-skills shortages, and affordability constraints that condition whether AI capability can be built at all, and these constraints are precisely the complementary-resource deficits that the global literature identifies as decisive for converting AI into advantage. Recent ecosystem data from Tanzania make the scarcity of these complements concrete. The national power-outage rate stands at 41% of weeks, rising to between 47% and 67% in regions outside Dar es Salaam against 23% within it, such that hardware-oriented founders outside the capital report spending USD 1,200 to USD 4,500 per month on diesel backup, equivalent to between 8% and 30% of operating cost [32]. Internet penetration of the adult population remains at 47%, and the ecosystem exhibits a documented misalignment between graduate skill profiles and startup demand, particularly in software engineering, product management, and data science [32]. These conditions illustrate, in a concrete national setting, the systematic scarcity of precisely the infrastructural and human complements on which the conversion of AI capability into competitive advantage is argued here to depend.

This pattern reframes the African context not as a smaller version of the settings studied elsewhere, but as a qualitatively different one in which the boundary conditions identified in passing by global studies become first-order determinants. An African startup may possess a nominal AI capability, in the sense of access to generative AI tools or analytics platforms, while lacking the digital culture, skilled personnel, reliable infrastructure, and strategic alignment that the evidence suggests are necessary to translate that capability into competitive advantage. The implication is that models developed and validated in high-resource settings cannot be assumed to transfer; the relative magnitudes of direct and mediated effects, and the role of contextual moderators, must be established rather than imported.

5.2. The Tanzanian Context: Ecosystem without Evidence

Tanzania presents a context in which the entrepreneurial and digital ecosystem is increasingly well documented even as the focal relationships remain untested. Ecosystem mapping and status reporting describe an expanding population of technology-oriented startups concentrated in Dar es Salaam, with smaller clusters in Arusha and other urban centers, supported by a growing but still nascent network of incubators, hubs, and innovation-support organizations. Analyses of the national innovation system and of digital transformation document both the rapid diffusion of mobile-enabled services and the persistent gaps in infrastructure, electricity reliability, internet affordability, and advanced digital skills that shape what ventures can realistically deploy. Together, these sources establish that Tanzania has a real and growing startup ecosystem operating under pronounced resource constraints, which is the setting in which questions about AI capability become both pertinent and distinctive.

Empirical management research in this setting, however, has only begun to approach the focal relationships. Utonga et al. [33] provide directly relevant evidence, demonstrating with structural-equation methods that digital technology adoption improves the performance of small and medium-sized enterprises in the Tanzanian fruit juice processing industry. This study is valuable on two counts: it confirms that digital technologies can yield measurable performance benefits among Tanzanian SMEs, and it demonstrates the feasibility of the analytical approach in this context. Yet it addresses digital technology adoption in the aggregate rather than AI capability specifically, it is situated in a single processing industry rather than the broader startup population, and it does not model competitive advantage as a mediating mechanism. Alongside Kiyabo and Isaga [25], which establishes the mediating role of competitive advantage for a strategic-entrepreneurship antecedent, these two Tanzanian studies bracket the relationship of interest without testing it: one demonstrates the mediator mechanism with a non-AI antecedent; the other demonstrates a digital-technology performance effect without the mediator. The specific model integrating AI capability, competitive advantage, and multidimensional startup performance remains unexamined in the Tanzanian and wider East African context.

6. Research Gap

The critical synthesis and contextual review converge on three interlocking gaps. The first is a mechanism gap. Although the resource-based view and dynamic capabilities reasoning imply that competitive advantage should mediate the effect of AI capability on performance, the AI literature frequently models direct effects, the mediation evidence that exists is dispersed across heterogeneous antecedents, and the recurring finding of partial rather than full mediation indicates that both direct and indirect pathways require explicit specification rather than an either-or treatment.

The second is a contextual gap. The mediation evidence is concentrated in a narrow set of national settings, with Southeast Asian SMEs heavily overrepresented, while the structural realities of emerging-economy startups, namely infrastructure limitations, skills shortages, and affordability constraints, are treated as background rather than as theorized boundary conditions. Because the global literature itself identifies complementary resources as decisive, these constraints are likely to alter the strength and structure of the focal relationships in the African context, not merely their level.

The third is a precise empirical gap. Across the literature reviewed, no study tests the relationship among AI capability, competitive advantage, and startup performance in Tanzania or the wider East African region. The two most relevant Tanzanian studies bracket but do not test this model: Kiyabo and Isaga [25] establish the mediating mechanism with a different antecedent, and Utonga *et al.* [33] establish a digital-technology performance effect without the mediator. This convergence of a mechanism gap, a contextual gap, and a specific empirical gap defines the contribution space for the conceptual framework and the empirical program developed below.

Addressing these gaps requires more than applying established capability theory to a new empirical setting; it requires a theoretical account of why the capability–advantage relationship should be expected to differ in kind, not merely in degree, where complementary resources are systematically scarce. This is the task the framework below undertakes.

7. Conceptual Framework and Propositions

Integrating the theoretical foundation and the thematic synthesis, this section advances a conceptual framework in which AI capability influences startup performance both directly and, more substantially, indirectly through competitive advantage. The framework is grounded in RBV logic, whereby a valuable and difficult-to-imitate resource yields advantage, and in dynamic capabilities reasoning, whereby advantage is established and renewed through the firm's sensing, seizing, and reconfiguring activities. AI capability is modeled as a multidimensional second-order construct encompassing human, infrastructure, strategic, and innovation dimensions. Competitive advantage is modeled as the mediating mechanism, capturing the venture's differentiation, responsiveness, and operational efficiency defined positionally, that is, relative to rivals. To preserve conceptual separation from the outcome construct, competitive advantage is specified as a relative, positional capability, whereas startup performance is specified as a set of absolute outcomes; in particular, relative operational efficiency as a component of advantage is kept distinct from absolute operational performance as a component of the outcome. Startup performance is modeled as a multidimensional outcome spanning market, operational, innovation, and financial performance, measured perceptually in line with established practice.

The framework is presented schematically in Figure 1. AI capability is positioned as the exogenous construct; competitive advantage as the mediator; and startup performance as the endogenous outcome. Solid paths represent the hypothesized structural relationships to be tested in subsequent empirical work.

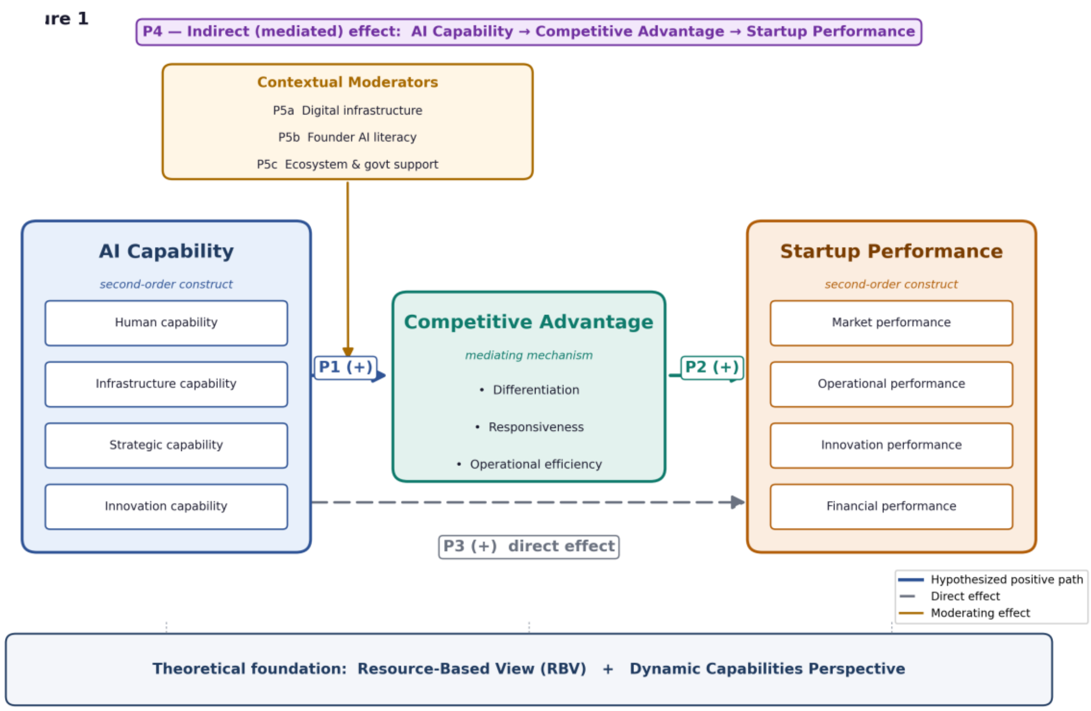

Figure 1. Conceptual framework: AI capability, competitive advantage, and startup performance.

Source: Authors' own work.

Propositions 1 through 4 establish the baseline capability–advantage–performance logic on which the framework's central contribution, the moderated pathway specified below, depends.

7.1. Proposition Development

AI capability and competitive advantage. Drawing on the RBV, a well-developed AI capability constitutes a valuable and difficult-to-imitate resource bundle that enables a venture to differentiate its offerings, respond more rapidly to market signals, and operate more efficiently than rivals. The dynamic capabilities perspective adds that these advantages are realized as the venture senses AI-enabled opportunities and reconfigures its processes accordingly. Empirical evidence across SME, marketing, and sustainability contexts supports a positive association between AI capability and competitive advantage [15], [16], [17]. Accordingly:

> **Proposition 1. AI capability positively influences the competitive advantage of startups in emerging economies.**

Competitive advantage and startup performance. A central tenet of the RBV is that advantage, once established, manifests in superior performance. Empirical work consistently links competitive advantage to firm performance and, more specifically, models competitive advantage as a mediator transmitting the effects of upstream capabilities [21], [22], [23]. Evidence from the Tanzanian SME context supports the advantage-performance link for a strategic-entrepreneurship antecedent [25]. Accordingly:

> **Proposition 2. Competitive advantage positively influences the multidimensional performance of startups in emerging economies.**

Direct effect of AI capability on performance. Beyond its effect through competitive advantage, AI capability may influence performance directly, without passing through the venture's competitive position. Certain AI applications yield automated operational adjustments, such as reduced processing time, lower error rates, or decreased labor cost, that improve performance outcomes regardless of whether they alter the firm's standing relative to rivals. Because these efficiency gains can accrue even when they are equally available to competitors and therefore confer no positional advantage, a purely mediated specification would misattribute them. This is also consistent with the recurring empirical finding of partial rather than full mediation, which implies a residual direct path. Studies report direct associations between AI capability and performance outcomes [1], [14]. Accordingly, the framework retains a direct path alongside the mediated one:

> **Proposition 3. AI capability positively influences the multidimensional performance of startups in emerging economies.**

Mediating role of competitive advantage. The framework's central claim is that competitive advantage mediates the relationship between AI capability and performance. RBV and dynamic capabilities reasoning jointly imply that capability improves performance primarily as it is converted into a defensible competitive position. Evidence that AI-capability effects on performance operate substantially through intermediate mechanisms supports a mediated structure [34], as does the broader body of competitive-advantage mediation studies. Accordingly:

> **Proposition 4. Competitive advantage mediates the positive relationship between AI capability and the multidimensional performance of startups in emerging economies.**

7.2. Contextual Moderators

The reframing of AI capability as a conditional resource places complementary resources at the theoretical center of the framework rather than at its margins. If the conversion of AI capability into competitive advantage depends on complements that are systematically scarce in emerging-economy startups, then the factors governing the availability of those complements are not peripheral boundary conditions but the core mechanism determining whether the capability–advantage relationship holds at all. The framework therefore formalizes three such factors as moderators on the path from AI capability to competitive advantage, each representing a category of complementary resource whose presence or absence gates the relationship. In high-resource settings these complements can be treated as background; in emerging-economy startup contexts they vary substantially across ventures and therefore function as first-order moderators. Consistent with this reasoning, the framework formally incorporates three contextual moderators on the path from AI capability to competitive advantage. These are selected because they are theoretically grounded in the dynamic capabilities and resource-complementarity literatures. Specifically, complementary-assets theory identifies the category of resource that matters: co-specialized assets external to the core capability, without which value cannot be captured. Absorptive-capacity theory identifies the mechanism: the capacity to recognize and apply a technology's potential, through which those assets take effect. Digital infrastructure and ecosystem support instantiate the former, and founder and managerial AI literacy instantiates the latter. They are also empirically salient in the African and Tanzanian context documented above, and parsimonious enough to remain testable. The framework deliberately formalizes a small number of strong moderators rather than an exhaustive list, since over-specification would compromise both conceptual clarity and the feasibility of subsequent empirical estimation.

Other plausible moderators, including organizational culture, firm size, entrepreneurial orientation, and absorptive capacity, were considered and deliberately excluded or subsumed rather than overlooked. Absorptive capacity is treated as the theoretical mechanism underlying the framework's moderators rather than as a separate moderator itself, since infrastructure, literacy, and ecosystem support are the concrete, measurable conditions through which absorptive capacity is realized in a resource-constrained startup.

Organizational culture and entrepreneurial orientation, while relevant to capability deployment generally, are firm-level dispositions rather than complementary resources whose scarcity is systematically documented in the emerging-economy context this paper addresses, and their inclusion would extend the framework beyond the specific gap identified. Firm size and sector are retained as controls rather than moderators because the theoretical claim concerns the availability of complements, not firm characteristics that may correlate with but do not constitute that availability. The three moderators retained are those for which both a clear theoretical mechanism and a documented empirical basis in the emerging-economy startup context jointly exist.

The three moderators that follow correspond to three categories of complementary resource: physical and technological (digital infrastructure), individual and cognitive (founder and managerial AI literacy), and institutional and collective (ecosystem support).

Digital infrastructure. The capacity to build and deploy AI capability depends on reliable access to electricity, connectivity, computing, and data. Where infrastructure is constrained, as is common across emerging-economy startup ecosystems, the conversion of AI capability into competitive advantage is likely to be weakened, because the venture cannot consistently operate the systems on which AI-enabled differentiation, responsiveness, and efficiency depend. Where infrastructure is robust, the same level of AI capability should yield greater competitive advantage. Accordingly:

> **Proposition 5a. Digital infrastructure positively moderates the relationship between AI capability and competitive advantage, such that the relationship is stronger when digital infrastructure is more developed.**

Founder and managerial AI literacy. In early-stage ventures, the founder and core management team are the primary locus of strategic and technical decision-making. The dynamic capabilities perspective emphasizes managerial sensing and seizing as micro foundations of capability deployment; in the AI context, the founder's understanding of what AI can and cannot do shapes whether AI resources are directed toward genuine sources of advantage or dissipated. This is distinct from the human dimension of AI capability described above. The capability dimension concerns venture-level technical and managerial competence already embedded in the team and its practices. Founder and managerial AI literacy, as a moderator, concerns something different: the strategic judgment that determines how effectively that assembled competence, and the AI capability built upon it, is converted into competitive positioning. Higher founder and managerial AI literacy should therefore strengthen the translation of AI capability into competitive advantage. Accordingly:

> **Proposition 5b. Founder and managerial AI literacy positively moderates the relationship between AI capability and competitive advantage, such that the relationship is stronger when AI literacy is higher.**

Ecosystem and government support. Startups do not build capability in isolation; they draw on incubators, innovation hubs, financing, training, and enabling policy. The Tanzanian and broader African evidence documents an expanding but uneven support ecosystem and growing policy attention through national AI strategies. Where such support is accessible, ventures are better able to acquire complementary resources and absorb the costs and risks of AI deployment, strengthening the path from capability to advantage. Accordingly:

> **Proposition 5c. Ecosystem and government support positively moderates the relationship between AI capability and competitive advantage, such that the relationship is stronger when supportive ecosystem and policy resources are more accessible.**

These moderators are specified on the AI-capability-to-competitive-advantage path because the synthesis indicates that the principal contingency lies in whether AI capability can be converted into a competitive position, rather than in whether an established competitive advantage yields performance. The framework treats venture-level characteristics such as startup age and industry sector as control variables rather than focal moderators, to be accounted for in empirical estimation without expanding the theoretical model beyond what the evidence supports. Figure 1 presents the full framework, including the direct, mediated, and moderated relationships.

8. Discussion

This paper has developed a conceptual framework linking AI capability, competitive advantage, and startup performance, grounded in the resource-based view and the dynamic capabilities perspective and informed by a structured review of the literature. Three contributions follow. First, the framework clarifies the mechanism through which AI capability affects performance, positioning competitive advantage as the central mediating construct rather than treating AI capability as a direct driver of outcomes. This integration responds to the dispersed and inconsistent treatment of mediation in the AI literature and aligns the model with the theoretical logic of the RBV, in which advantage is the proximate source of superior performance.

The principal theoretical contribution of this paper is not the introduction of additional moderators into an established AI capability model. Rather, it reconceptualizes where complementarity operates within the resource-conversion process. Existing AI capability frameworks, including the influential work of Mikalef and Gupta [1] and its subsequent applications, conceptualize AI capability as a strategic resource whose assembly from tangible, human, and intangible components constitutes the primary explanatory task. Although these studies acknowledge the importance of complementary organizational resources, they generally treat them as antecedents of capability, parallel organizational capabilities, or broader contextual conditions, leaving the conversion of AI capability into competitive advantage largely implicit. The present framework challenges this assumption by arguing that AI capability possesses no inherent strategic value independent of complementary resources. Instead, complementary resources determine whether AI capability can be transformed into competitive advantage at all. Consequently, the capability–advantage relationship becomes the primary theoretical phenomenon requiring explanation rather than an assumed outcome of capability accumulation. This perspective distinguishes capability assembly from capability conversion as analytically separate processes and predicts that ventures with comparable levels of AI capability may realize systematically different competitive outcomes because they differ in the complementary resources required to convert capability into advantage. By relocating complementarity to the capability–competitive advantage relationship itself, the framework offers a more precise explanation of why AI capability produces uneven competitive outcomes across resource-constrained startup environments.

Second, the paper foregrounds context. By synthesizing evidence on AI in African and emerging-economy settings alongside the structural constraints documented in infrastructure, skills, and affordability, the framework situates AI capability within the realities that shape its development and payoff for resource-constrained ventures. This contrasts with the implicit assumptions of much of the AI-capability literature, which is grounded in settings of high digital maturity. The framework's attention to boundary conditions invites a more contingent theorization of AI-enabled competition in emerging economies.

Third, the paper identifies and specifies a precise empirical gap. The review found no study testing the AI capability, competitive advantage, and startup performance relationships in Tanzania or the broader East African region. The framework and propositions provide the basis for an empirical program to address this gap. Such a program would be well suited to variance-based structural equation modeling, given the multidimensional and partly latent nature of the constructs and the model's mediation structure. Established guidance on partial least squares structural equation modeling, discriminant validity assessment, common-method-bias evaluation, and mediation analysis provides a methodological foundation for this work [30], [31], [32], [33],[39].

8.1. Implications for Theory and Practice

For theory, the framework's contribution is to reconceptualize AI capability as a conditional rather than a uniformly valuable resource. By integrating complementary-assets and absorptive-capacity logic with the resource-based view, it specifies the conditions under which AI capability converts into competitive advantage and the conditions under which that conversion fails, thereby explaining why a capability–advantage relationship documented in resource-rich settings cannot be assumed to transfer to resource-constrained ventures. This moves the theoretical question from whether AI capability matters to when and for whom it matters, and offers a testable account of the moderating conditions that govern the relationship.

For incubators, accelerators, and innovation hubs, the moderating role of founder AI literacy implies that capability-building support, mentorship, technical training, and structured guidance on where AI can credibly create value, may generate greater returns than facilitating tool access alone. Programs that raise founders' capacity to direct AI toward genuine sources of advantage address the precise contingency the framework identifies.

For policymakers and government agencies, the prominence of digital infrastructure and ecosystem support as moderators indicates that interventions in connectivity, electricity reliability, affordable data, and enabling policy are not peripheral to AI-driven entrepreneurship but are preconditions for it. National AI strategies in the region will be more effective where they prioritize stable electricity supply, affordable cloud and connectivity access, founder-focused AI literacy training, and startup-support policy, because these are precisely the complementary resources the framework identifies as gating whether AI capability converts into competitive advantage rather than remaining unrealized potential. For investors, the framework offers a lens for due diligence: assessing not only whether a venture uses AI, but whether it possesses the surrounding capabilities and contextual support to translate that use into sustained competitive advantage.

8.2. Limitations and Future Research

As a conceptual contribution, the paper is subject to the limitations inherent in literature-based theorization. The structured review, while systematic in its screening and documentation, was interpretive in its synthesis and did not constitute a fully reproducible systematic review with meta-analytic pooling. The corpus combined peer-reviewed empirical studies with contextual and policy sources of varying provenance; central inferences were anchored in peer-reviewed evidence, but the heterogeneity of sources warrants caution. The mediation evidence drawn upon is concentrated in a limited set of national contexts, and its generalizability to emerging-economy startups remains to be established empirically. Future research should test the proposed framework using primary data from startups in Tanzania and comparable East African settings, examine the contextual moderators outlined above, and refine the measurement of AI capability for resource-constrained ventures. Comparative studies across emerging economies would further clarify the boundary conditions under which AI capability yields competitive advantage and performance.

9. Conclusion

Artificial intelligence is increasingly understood as a strategic organizational capability rather than a discrete technology, and its competitive implications are mediated by the advantage it helps create. This paper has synthesized the evidence on AI capability, competitive advantage, and venture performance, and has developed a conceptual framework and propositions positioning competitive advantage as the mechanism through which AI capability shapes multidimensional startup performance. By situating this model in the realities of emerging-economy startup ecosystems, and by identifying the absence of evidence in the Tanzanian and East African context, the paper establishes both a theoretical contribution and a clear agenda for empirical research. This paper argues that AI capability should not be viewed as a strategic resource whose competitive value is automatically realized once assembled. Instead, AI capability becomes strategically valuable only when complementary resources enable its conversion into competitive advantage. By shifting theoretical attention from capability accumulation to capability conversion, the framework offers a new explanation for why ventures with similar AI capability frequently achieve markedly different competitive outcomes in resource-constrained environments.

10. References

[1] P. Mikalef and M. Gupta, ‘Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance’, Information & Management, vol. 58, no. 3, p. 103434, Apr. 2021, doi: 10.1016/j.im.2021.103434.

[2] J. Barney, ‘Firm Resources and Sustained Competitive Advantage’, Journal of Management, vol. 17, no. 1, pp. 99–120, Mar. 1991, doi: 10.1177/014920639101700108.

[3] B. Wernerfelt, ‘A Resource-Based View of the Firm’, Strategic Management Journal, vol. 5, no. 2, Art. no. 2, 1984.

[4] K. M. Eisenhardt and J. A. Martin, ‘Dynamic Capabilities: What Are They?’, Strategic Management Journal, vol. 21, no. 10/11, pp. 1105–1121, 2000.

[5] D. J. Teece, ‘Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance’, Strategic Management Journal, vol. 28, no. 13, pp. 1319–1350, Dec. 2007, doi: 10.1002/smj.640.

[6] D. J. Teece, G. Pisano, and A. Shuen, ‘Dynamic Capabilities and Strategic Management’, Strategic Management Journal, vol. 18, no. 7, Art. no. 7, 1997.

[7] D. J. Teece, 'Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy', Research Policy, vol. 15, no. 6, pp. 285–305, Dec. 1986, doi: 10.1016/0048-7333(86)90027-2.

[8] W. M. Cohen and D. A. Levinthal, 'Absorptive Capacity: A New Perspective on Learning and Innovation', Administrative Science Quarterly, vol. 35, no. 1, p. 128, Mar. 1990, doi: 10.2307/2393553.

[9] J. B. Barney and W. S. Hesterly, Strategic Management and Competitive Advantage: Concepts. Pearson Prentice Hall, 2008.

[10] N. Cardeal, 'Valuable, rare, inimitable resources and organization (VRIO) resources or valuable, rare, inimitable resources (VRI) capabilities: What leads to competitive advantage?', Afr. J. Bus. Manage., vol. 6, no. 37, Sep. 2012, doi: 10.5897/AJBM12.295.

[11] D. J. Teece, 'Hand in Glove: Open Innovation and the Dynamic Capabilities Framework', Strategic Management Review, vol. 1, no. 2, pp. 233–253, Jun. 2020, doi: 10.1561/111.00000010.

[12] A. S. Bharadwaj, 'A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation1', MIS Quarterly, vol. 24, no. 1, pp. 169–196, Mar. 2000, doi: 10.2307/3250983.

[13] P. Mikalef, S. O. Fjørtoft, and H. Y. Torvatn, 'Developing an Artificial Intelligence Capability: A Theoretical Framework for Business Value', in Business Information Systems Workshops, vol. 373, W. Abramowicz and R. Corchuelo, Eds, in Lecture Notes in Business Information Processing, vol. 373. , Cham: Springer International Publishing, 2019, pp. 409–416. doi: 10.1007/978-3-030-36691-9_34.

[14] P. Mikalef et al., 'Examining how AI capabilities can foster organizational performance in public organizations', Government Information Quarterly, vol. 40, no. 2, p. 101797, Apr. 2023, doi: 10.1016/j.giq.2022.101797.

[15] Y. Gao, S. Liu, and L. Yang, 'Artificial intelligence and innovation capability: A dynamic capabilities perspective', International Review of Economics & Finance, vol. 98, p. 103923, Mar. 2025, doi: 10.1016/j.iref.2025.103923.

[16] S.-L. Wamba-Taguimdje, S. F. Wamba, J. R. K. Kamdjoug, and C. E. T. Wanko, 'Impact of Artificial Intelligence on Firm Performance: Exploring the Mediating Effect of Process-Oriented Dynamic Capabilities', in Digital Business Transformation, vol. 38, R. Agrifoglio, R. Lamboglia, D. Mancini, and F. Ricciardi, Eds, in Lecture Notes in Information Systems and Organisation, vol. 38. , Cham: Springer International Publishing, 2020, pp. 3–18. doi: 10.1007/978-3-030-47355-6_1.

[17] A. A. Alhelal, A. A. Alshiha, and B. S. Al-Romeedy, 'AI-Driven Sustainable Competitive Advantage in Tourism and Hospitality: Mediating Roles of Digital Culture and Skills', Sustainability, vol. 17, no. 19, p. 8903, Oct. 2025, doi: 10.3390/su17198903.

[18] L. Ardito, R. Filieri, E. Raguseo, and C. Vitari, 'Artificial intelligence adoption and revenue growth in European SMEs: synergies with IoT and big data analytics', Internet Research, vol. 35, no. 4, pp. 1508–1534, Nov. 2025, doi: 10.1108/INTR-02-2024-0195.

[19] A. Cimino, V. Corvello, C. Troise, A. Thomas, and M. Tani, 'Artificial Intelligence Adoption for Sustainable Growth in SMES : An Extended Dynamic Capability Framework', Corp Soc Responsibility Env, vol. 32, no. 5, pp. 6120–6138, Sep. 2025, doi: 10.1002/csr.70019.

[20] F. Ul Haq, N. M. Suki, H. Zaigham, A. Masood, and A. Rajput, 'Exploring AI Adoption and SME Performance in Resource-Constrained Environments: A TOE–RBV Perspective with Mediation and Moderation Effects', Journal of Digital Economy, p. S2773067025000330, Jul. 2025, doi: 10.1016/j.jdec.2025.07.002.

[21] C. A. Gunawan and G. Ongkowijoyo, 'Assessing the Mediating Role of Competitive Advantage: The Influence of Innovation Capabilities and Strategic Flexibility on Firm Performance in East Java's F&B Industry Post COVID-19', Dinasti International Journal of Economics, Finance & Accounting, vol. 6, no. 1, pp. 516–534, Mar. 2025, doi: 10.38035/dijefa.v6i1.4004.

[22] M. Novitasari and D. Agustia, 'Competitive advantage as a mediating effect in the impact of green innovation and firm performance', Business: Theory and Practice, vol. 24, no. 1, pp. 216–226, May 2023, doi: 10.3846/btp.2023.15865.

[23] Z. Zahara, M. Muslimin, A. Rumijati, and Z. T. Rony, 'Competitive Advantage as Mediating Role to Enhance MSMES Performance', Journal of Small Business Strategy, vol. 34, no. 2, Sep. 2024, doi: 10.53703/001c.121131.

[24] E. A. Gani, C. Herdinata, and L. Dewi, 'Digital Transformation on Competitive Advantage through Customer Experience in Indonesian Companies', JIMKES, vol. 13, no. 6, pp. 4321–4334, Nov. 2025, doi: 10.37641/jimkes.v13i6.3978.

[25] K. Kiyabo and N. Isaga, 'Strategic entrepreneurship, competitive advantage, and SMEs' performance in the welding industry in Tanzania', J Glob Entrepr Res, vol. 9, no. 1, p. 62, Dec. 2019, doi: 10.1186/s40497-019-0188-9.

[26] N. Venkatraman and V. Ramanujam, 'Measurement of Business Performance in Strategy Research: A Comparison of Approaches', The Academy of Management Review, vol. 11, no. 4, p. 801, Oct. 1986, doi: 10.2307/258398.

[27] J. Dawes, 'The Relationship between Subjective and Objective Company Performance Measures in Market Orientation Research: Further Empirical Evidence', 1999, [Online]. Available: http://marketing-bulletin.massey.ac.nz/v10/mb_v10_n3_dawes.pdf

[28] D. Welbotha and C. van den Berg, 'Big Data Analytics Capabilities and the Organisational Performance of South African Retailers', South African Computer Journal, vol. 36, no. 2, 2024, doi: 10.18489/sacj.v36i2.17937.

[29] F. M. Omambia, 'Artificial Intelligence (AI) And Financial Performance of the Financial Service Industry in Kenya', AJOCS, vol. 6, no. 4, pp. 86–94, Jul. 2025, doi: 10.59413/ajocs/v6.i4.8.

[30] National Council for Artificial Intelligence, 'Egypt National Artificial Intelligence Strategy: Second Edition (2025–2030)', Ministry of Communications and Information Technology (MCIT), Cairo, Egypt, 2025. [Online]. Available: https://ai.gov.eg/SynchedFiles/en/Resources/AIstrategy%20English%2016-1-2025-1.pdf

[31] D. Hanyurwimfura, 'Rwanda: Advancing Science Through the Development of Artificial Intelligence', in Preparing National Research Ecosystems for AI: Third Edition, D. Castle, V. McBride, and J. Randles, Eds, International Science Council, 2026. [Online]. Available: https://council.science/wp-content/uploads/2026/02/Rwanda-AI.pdf

[32] Tanzania Startup Association, 'Tanzania Startup Ecosystem Status Report 2025', Tanzania Startup Association, Dar es Salaam, Annual Ecosystem Report, 2025. [Online]. Available: https://www.tsa.co.tz

[33] D. Utonga, C. S. Tundui, and E. Mkuna, 'Harnessing performance through digital technology adoption: an empirical analysis of SMEs in the Tanzanian fruit juice processing industry', Cogent Business & Management, vol. 13, no. 1, p. 2612771, Dec. 2026, doi: 10.1080/23311975.2026.2612771.

[34] Md. A. I. Gazi et al., 'AI Capability and Sustainable Performance: Unveiling the Mediating Effects of Organizational Creativity and Green Innovation with Knowledge Sharing Culture as a Moderator', Sustainability, vol. 16, no. 17, p. 7466, Aug. 2024, doi: 10.3390/su16177466.

[35] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, 'When to use and how to report the results of PLS-SEM', EBR, vol. 31, no. 1, pp. 2–24, Jan. 2019, doi: 10.1108/EBR-11-2018-0203.

[36] P. M. Podsakoff, S. B. MacKenzie, J.-Y. Lee, and N. P. Podsakoff, 'Common method biases in behavioral research: A critical review of the literature and recommended remedies.', Journal of Applied Psychology, vol. 88, no. 5, pp. 879–903, 2003, doi: 10.1037/0021-9010.88.5.879.

[37] E. Roemer, F. Schuberth, and J. Henseler, 'HTMT2–an improved criterion for assessing discriminant validity in structural equation modeling', IMDS, vol. 121, no. 12, pp. 2637–2650, Nov. 2021, doi: 10.1108/IMDS-02-2021-0082.

[38] X. Zhao, J. G. Lynch, and Q. Chen, 'Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis', J Consum Res, vol. 37, no. 2, pp. 197–206, Aug. 2010, doi: 10.1086/651257.

[39] J. Henseler, C. M. Ringle, and M. Sarstedt, 'A new criterion for assessing discriminant validity in variance-based structural equation modeling', J. of the Acad. Mark. Sci., vol. 43, no. 1, pp. 115–135, Jan. 2015, doi: 10.1007/s11747-014-0403-8.

[40] K. Abrokwah-Larbi and Y. Awuku-Larbi, 'The impact of artificial intelligence in marketing on the performance of business organizations: evidence from SMEs in an emerging economy', JEEE, vol. 16, no. 4, pp. 1090–1117, Jun. 2024, doi: 10.1108/JEEE-07-2022-0207.