Journal of
Information Technology,
Cybersecurity, and Artificial Intelligence

(RESEARCH ARTICLE)

# When Everyone Has the Same AI: Competitive Advantage for Startups under Generative AI Commoditization

Mwita Joseph James Wanyancha
*Department of Innovation and Entrepreneurship Management, School of Business Studies and Humanities, The Nelson Mandela African Institution of Science and Technology, Arusha, Tanzania.*
*Email: wanyancham@nm-aist.ac.tz*
*ORCID: https://orcid.org/0009-0009-7416-9531*

Journal of Information Technology, Cybersecurity, and Artificial Intelligence, 2026, Volume 3, Issue 4,, Pages 15-29

DOI: https://doi.org/10.70715/jitcai.2026.v3.i4.085

**Abstract**

Generative artificial intelligence (AI), delivered through general-purpose foundation models accessible on demand at low cost, has become available to firms of all sizes. This accessibility challenges the dominant view in which AI capability, built from scarce data, infrastructure, and talent, is a source of competitive advantage: when the same frontier capability can be rented by any firm, the model satisfies neither the rarity nor the inimitability conditions that the resource-based view requires of an advantage-conferring resource. This paper develops a conceptual framework explaining where competitive advantage resides once generative AI becomes, in effect, a shared utility. Engaging the precedent of the information-technology commoditization debate, it argues that generative AI differs in kind: it commoditizes capability rather than infrastructure, displacing advantage from the technology to the complements it cannot replicate. The paper names this regularity the advantage-relocation mechanism, the displacement of advantage, when a capability-like technology is commoditized, toward co-specialized complements such as proprietary data, domain judgment, customer relationships, and the orchestration capability that converts a common model into a distinctive value proposition. Integrating the resource-based view, complementary-assets theory, absorptive capacity, and dynamic capabilities, and stated at the level of the firm with resource-constrained startups as its sharpest boundary condition, the framework yields a set of falsifiable propositions concerning the relocation of advantage, the role of absorptive capacity in differentiating firms that use identical models, and the accelerated erosion of AI-derived advantage. It contributes a strategic account of competitive advantage under technological commoditization and an agenda for empirical testing.

**Keywords:** *Generative AI; Competitive advantage; Commoditization; Complementary assets; Absorptive capacity; Orchestration capability; Startups.*

## 1. Introduction

Generative artificial intelligence (AI) has diffused into business practice with a speed that has few precedents. Foundation models, large general-purpose systems such as those underlying widely used conversational assistants, can now be accessed by any firm through an application programming interface or a consumer subscription, at a cost trivial relative to the investment once required to build advanced AI capability in-house. This accessibility is the defining strategic fact of the current moment: a two-person venture and a multinational can, in principle, invoke the same frontier model on the same terms.

This fact sits awkwardly with the prevailing account of AI and competitive advantage. A substantial literature, grounded in the resource-based view (RBV), frames AI as an organizational capability that firms build from tangible resources such as data and computing, human resources such as technical talent, and intangible resources such as a supportive culture, and that yields advantage for the firms able to assemble this bundle [1]. The logic is sound when the capability is scarce. But the RBV is equally clear that a resource confers sustained advantage only when it is valuable, rare, and costly to imitate [2], [3]. A capability that any competitor can rent on demand is, by construction, neither rare nor costly to imitate. The commoditization of the underlying model therefore threatens to dissolve precisely the advantage that the capability view attributes to it.

Recent empirical work has begun to document this shift. Firm-level evidence from innovative SMEs finds that internal capability-building ceases to predict technology adoption once external sourcing and complementary collaboration are accounted for, suggesting that advantage increasingly rests on complements rather than on internally held capability [4]. In parallel, studies of generative-AI adoption report an emerging "generative-AI divide," in which access to the technology is broadly distributed but effective use is gated by resource, positional, and skill-related factors [5], [6]. Concurrent strategy research has likewise turned to how firms might configure sustainable competitive advantage from AI through business-model and workflow reconfiguration rather than through the technology itself [7], [8]. Yet this emerging literature has not been integrated into a coherent theoretical account of *where* advantage resides once the underlying model is commoditized, the gap this paper addresses.

The strategy field has confronted a structurally similar moment before. Two decades ago, Carr (2003) argued that information technology, having become a ubiquitous and standardized infrastructure, had ceased to offer competitive differentiation and had become a commodity input akin to electricity. The claim provoked vigorous rebuttal, much of which held that IT continued to confer advantage where it was combined with distinctive organizational complements rather than deployed in isolation. The generative AI moment rhymes with this debate, but it is not identical to it, and the difference is consequential: where Carr's IT was largely back-office infrastructure, generative AI is a general-purpose, capability-like technology that performs cognitive work once thought to require scarce human or organizational capability. The commoditization of a capability, rather than of an infrastructure, raises the strategic stakes and is the puzzle this paper addresses.

The question is especially acute for startups. Early-stage ventures have been among the most enthusiastic adopters of generative AI, precisely because it lowers barriers that once favored incumbents: a small team can now access capabilities in software development, content generation, analysis, and customer interaction that previously required substantial headcount and capital [9]. Yet this same accessibility means that whatever a startup can do with a foundation model, its rivals can do too. The strategic problem for the founder is therefore sharper than for the incumbent: if the AI confers no durable edge, where is the venture's defensible advantage to be found?

Accordingly, this paper addresses the following research question: when generative AI is commoditized and equally accessible to all competitors, where does a firm's defensible competitive advantage reside? The question is examined with reference to startups, for which the commoditization of capability is most consequential, but it is posed at the level of the firm and bears on any organization whose competitive position has rested on privileged access to advanced AI capability.

This paper develops a conceptual framework to answer that question. Its central argument is that generative AI does not abolish competitive advantage but relocates its sources. When the model is commoditized, advantage migrates to complementary assets the model cannot replicate or equalize proprietary or hard-to-access data, accumulated domain judgment, customer relationships and trust, and the organizational capability to orchestrate AI into a coherent and distinctive value proposition. The model becomes table stakes; the advantage lies in what surrounds it. The paper grounds this argument in the resource-based view, complementary-assets theory, absorptive capacity, and the dynamic capabilities perspective, and it engages the information-technology commoditization debate as both precedent and foil.

The contribution is threefold. First, the paper provides a strategic account of competitive advantage under conditions of technological commoditization, extending the RBV to a setting in which the focal technology is deliberately non-rare, and clarifying what is genuinely new about the generative AI case relative to the earlier IT debate. Second, it specifies the mechanisms through which advantage relocates, advancing testable propositions concerning complementary assets, the differentiating role of absorptive capacity among firms using identical models, and the accelerated erosion of AI-derived advantage. Third, it draws out implications for the actors who must navigate this shift, including startups in resource-constrained settings for whom the relocation of advantage carries distinct risks and opportunities. The remainder of the paper proceeds as follows: the next section establishes the theoretical foundation; the third reviews and synthesizes the evidence on generative AI and competitive advantage; the fourth develops the framework and propositions; and the fifth discusses implications and an agenda for research. As a theory-building conceptual paper, it advances and integrates existing theory to explain an emerging phenomenon rather than testing hypotheses on primary data.

## 2. Theoretical Foundation

### 2.1. Methodological Approach

This paper is a conceptual, theory-building contribution developed through an integrative review of the strategic-management and information-systems literature rather than a systematic or quantitative review. The integrative approach is appropriate where the aim is not to catalogue a settled body of evidence but to synthesize fragmented and fast-moving work into a coherent theoretical account of an emerging phenomenon. Source selection proceeded purposively in three strands: foundational strategy theory establishing the conditions for competitive advantage (the resource-based view, complementary-assets theory, absorptive capacity, and dynamic capabilities); the historical debate on the commoditization of information technology, engaged as both precedent and foil; and recent peer-reviewed and authoritative work, published between 2023 and 2026, on generative AI and its strategic, firm-level, and developing-economy implications. Within each strand, priority was given to peer-reviewed journal articles and to established theoretical anchors, with working papers and practitioner sources used to characterize the contemporary phenomenon rather than to carry theoretical weight.

Theoretical consistency was established by organizing the four theories around a single analytical spine: each is introduced to address a distinct link in one causal chain, from the commoditization of the model (resource-based view), to the relocation of advantage toward complements (complementary-assets theory), to the differential capacity of firms to exploit a common model (absorptive capacity), to the renewal of advantage under rapid technological change (dynamic capabilities). The propositions were then derived deductively from this integrated logic so that each follows from a stated theoretical premise and is, in principle, empirically falsifiable. This design ensures internal coherence among the constructs and traceability from theory to proposition.

### 2.2. The Resource-Based View and the Conditions for Advantage

The resource-based view holds that competitive advantage derives from resources and capabilities that are valuable, rare, costly to imitate, and organizationally exploited [2], [3]. The framework's diagnostic power lies in its conditions: a resource that is valuable but common confers competitive parity, not advantage, because rivals possess it equally; a resource that is valuable and rare but easily imitated confers only temporary advantage, eroding as competitors replicate it. Sustained advantage requires that a resource resist imitation and substitution over time. This logic is the analytical foundation of the present paper, because it implies a precise test for whether any given technology can be a source of advantage, and generative AI, in its commoditized form, fails that test at the level of the model itself.

### 2.3. AI as Capability: The Dominant View and Its Boundary Condition

A productive stream of research has applied capability logic to AI, conceptualizing AI capability as a firm-level construct assembled from data and infrastructure, human and managerial skills, and intangible organizational resources, and linking it to creativity and performance [1], [10]. This view has been generative, and it remains valid under its implicit boundary condition: that building the capability is itself difficult and unevenly distributed. The IT-capability literature on which it builds established exactly this point, showing that information technology raised performance not in isolation but when combined with complementary human and organizational assets that were themselves scarce [11], [12]. The arrival of foundation models accessible on demand violates the boundary condition for the model component of AI capability: the technical core that once had to be built can now be rented. The capability view is not thereby refuted, but its locus shifts, from the model to the complements, which is the move this paper develops.

### 2.4. Complementary Assets and the Locus of Value Capture

Complementary-assets theory provides the mechanism for that shift. Teece (1986) argued that the returns to an innovation accrue not to the innovation itself but to the holders of the co-specialized complementary assets required to commercialize it, particularly when the innovation is easily imitated and the complements are tightly held. Applied to generative AI, the theory yields a direct prediction: as the model becomes imitable and widely accessible, value capture migrates to whoever controls the scarce complements with which the model must be combined to create value, such as proprietary data, distribution, customer relationships, and domain expertise. The model is the imitable innovation; the complements are where advantage is captured. This is the theoretical core of the paper's argument and distinguishes it from accounts that treat AI adoption as itself advantage-conferring.

### 2.5. Absorptive Capacity and the Capacity to Exploit Common Technology

If two firms access the identical model, what distinguishes the value they extract from it? Absorptive capacity offers the answer: the ability to recognize the value of new information, assimilate it, and apply it is a function of prior related knowledge and is unevenly distributed across firms [13]. A common technology does not produce common outcomes, because firms differ in their capacity to absorb and deploy it. In the generative AI context, this capacity manifests as the judgment to direct the model toward valuable problems, to evaluate and correct its output, and to integrate it into workflows, an emerging managerial competence rather than a feature of the model. Absorptive capacity thus explains why identical access yields divergent results, and it is the conceptual basis for the paper's proposition concerning orchestration capability.

### 2.6. Dynamic Capabilities under Rapid Technological Change

Finally, the dynamic capabilities perspective frames advantage as the capacity to sense, seize, and reconfigure resources in fast-moving environments [14], [15], [16], a capacity shown to matter specifically in emerging technology markets [17], [18]. Generative AI is a paradigm of such an environment: model capabilities advance on a timescale of months, and any advantage derived from a particular model or application is liable to rapid erosion as the frontier moves and rivals adopt the same advance. This perspective grounds the paper's proposition that AI-derived advantage is faster-eroding than advantage from more durable resources, and that the relevant capability is less a one-time build than a continuous process of reconfiguration and learning.

## 3. Generative AI and Competitive Advantage: A Critical Synthesis

This section synthesizes the emerging evidence on generative AI and competitive advantage, organized around three questions: whether the commoditization claim holds; where, if the model confers no advantage, advantage is observed to relocate; and what the IT-commoditization debate teaches about the present case. The synthesis foregrounds points of consensus, tension, and unresolved dispute rather than cataloguing studies.

### 3.1. The Commoditization Claim and Its Precedent

The proposition that a ubiquitous general-purpose technology ceases to confer advantage is not new. Carr (2003) argued that information technology had become an infrastructural commodity whose universal availability neutralized its strategic value, advising firms to manage it for cost and risk rather than advantage. The claim was widely contested; critics countered that IT continued to enable advantage where embedded in distinctive processes and complementary capabilities, and that the commodity was the input, not the use to which it was put. With two decades' hindsight, the reconciliation is now broadly accepted: the technology layer commoditized while the differentiating value moved to complements and integration [19], [20]. The generative AI debate recapitulates this structure, and recent analyses explicitly frame foundation-model access as the new table stakes whose universal availability shifts advantage to what surrounds it. The precedent is instructive but not dispositive, because generative AI differs from Carr's IT in a way that sharpens rather than dissolves the strategic question, as the next subsection argues.

### 3.2. What Is Genuinely New: The Commoditization of Capability, Not Infrastructure

Carr's IT was largely infrastructure: networks, storage, and standardized enterprise software that supported business processes without themselves performing cognitive work. Generative AI is different in kind. It is a general-purpose technology that performs tasks, drafting, analyzing, coding, designing, that previously required scarce human capability, and it does so as a rentable service. The commoditization therefore reaches not an input to capability but a substantial portion of capability itself, including capabilities that were historically a startup's scarce advantage over better-resourced rivals. This is why the generative AI case is strategically more radical than the IT case: it compresses the value of certain human and organizational capabilities even as it leaves the complementary assets surrounding them untouched. Evidence that generative AI raises the productivity of less-experienced and lower-skilled workers more than that of experts is consistent with this compression, indicating that the technology narrows capability differences that once underpinned advantage [21]. The strategic implication is not that advantage disappears but that it is squeezed out of the commoditized capability and into the non-commoditized complements, which is precisely the relocation this paper theorizes.

### 3.3. Where Advantage Relocates: Data, Domain, Relationships, and Orchestration

A convergent body of recent work, though dispersed across academic and practitioner sources, locates post-commoditization advantage in a recognizable set of complements. The most discussed is proprietary data: because foundation models are trained on broadly available corpora, firm-specific data that rivals cannot access is argued to be a durable differentiator [22]. Yet this claim is contested, and the disagreement is theoretically important. A skeptical line argues that data is less defensible than commonly assumed, exhibiting diminishing returns and being frequently replicable, so that data alone is not a reliable barrier to entry [23]. The reconciliation favored here is that raw data is a weak moat but data embedded in a proprietary feedback loop, continuously generated through customer interaction and difficult to replicate, is a strong one, consistent with the complementary-assets logic that prizes co-specialized, hard-to-trade resources. Beyond data, a second locus is domain-specific judgment and tacit expertise: generic model deployments are observed to underperform in specialized contexts precisely because they lack the contextual knowledge that distinguishes expert practice, relocating advantage to firms possessing that expertise, consistent with the absorptive-capacity premise that the value of a new technology depends on prior specialized knowledge [13], [24]. A third locus is the orchestration capability to integrate models into distinctive workflows and value propositions, an organizational competence rather than a property of the model, and one consistent with the foundational finding that technology pays off through complementary organizational assets [12], [17]. The consensus across these strands is that advantage survives commoditization but only by residing in complements the model does not supply.

This argument must engage a genuine counter position: that the model itself can remain a source of differentiation through fine-tuning, retrieval augmentation, proprietary model layers, or vertically integrated domain-specific systems. The objection has force, but it does not overturn the argument; rather, it confirms it. Each of these mechanisms differentiates not because the base model is rare, it is not, but because it is combined with a scarce complement: proprietary data in the case of fine-tuning and retrieval augmentation, and domain integration capability in the case of vertical systems. The apparent exception is therefore an instance of the rule. What differentiates is never the commoditized model alone but the co-specialized complement with which it is fused, which is precisely the relocation this paper theorizes.

### 3.4. Market Structure: Commoditization at the Application Layer, Concentration at the Model Layer

A complete account must be distinguished between two layers. At the level of foundation-model provision, evidence points toward concentration rather than commoditization: the capital, data, and compute required to train frontier models are formidable, and analyses warn of market concentration among a small number of model providers [25], [26]. Consistent with the strategic salience of this divide, firm-value studies find that the equity market rewards firms positioned to benefit from generative AI, indicating that investors already price differential exposure to the technology rather than treating mere adoption as value-neutral [27]. At the level of model use by ordinary firms, by contrast, access is cheap and broadly equal, which is the commoditization that motivates this paper. The two observations are consistent: the providers of the commoditized utility may themselves enjoy concentrated market power, much as electricity is a commodity to its users while its generation is concentrated. For the startup using AI rather than building it, the operative condition is commoditized access, and it is the strategic consequence of that condition for the using firm, not the market structure of the providers, that this paper theorizes.

## 4. Conceptual Framework and Propositions

The framework integrates the foregoing into a single account of competitive advantage under generative AI commoditization. Its premise is that the foundation model is a commoditized resource available to all firms on comparable terms, and therefore, by the resource-based view's own criteria, not a source of sustained advantage at the level of the model. Its central claim, which the paper terms the *advantage-relocation mechanism*, is that the commoditization of the model displaces competitive advantage from the technology to the complementary assets and deployment capabilities that surround it: advantage relocates to complementary assets, the capacity to exploit a common model differentiates firms, and AI-derived advantage erodes faster than advantage from more durable resources. Although the mechanism is examined here for startups, where its effects are sharpest, it is stated at the level of the firm: it applies wherever a previously scarce, advantage-conferring capability becomes commoditized, with the startup case serving as the most acute boundary condition rather than the limit of the argument. Figure 1 presents the framework: the commoditized model layer at the base, the complementary assets through which advantage is captured, the orchestration capability that combines them, and the accelerated erosion that conditions the whole. Figure 2 contrasts the pre-commoditization and post-commoditization loci of advantage. Table 1 summarizes the loci of advantage before and after commoditization.

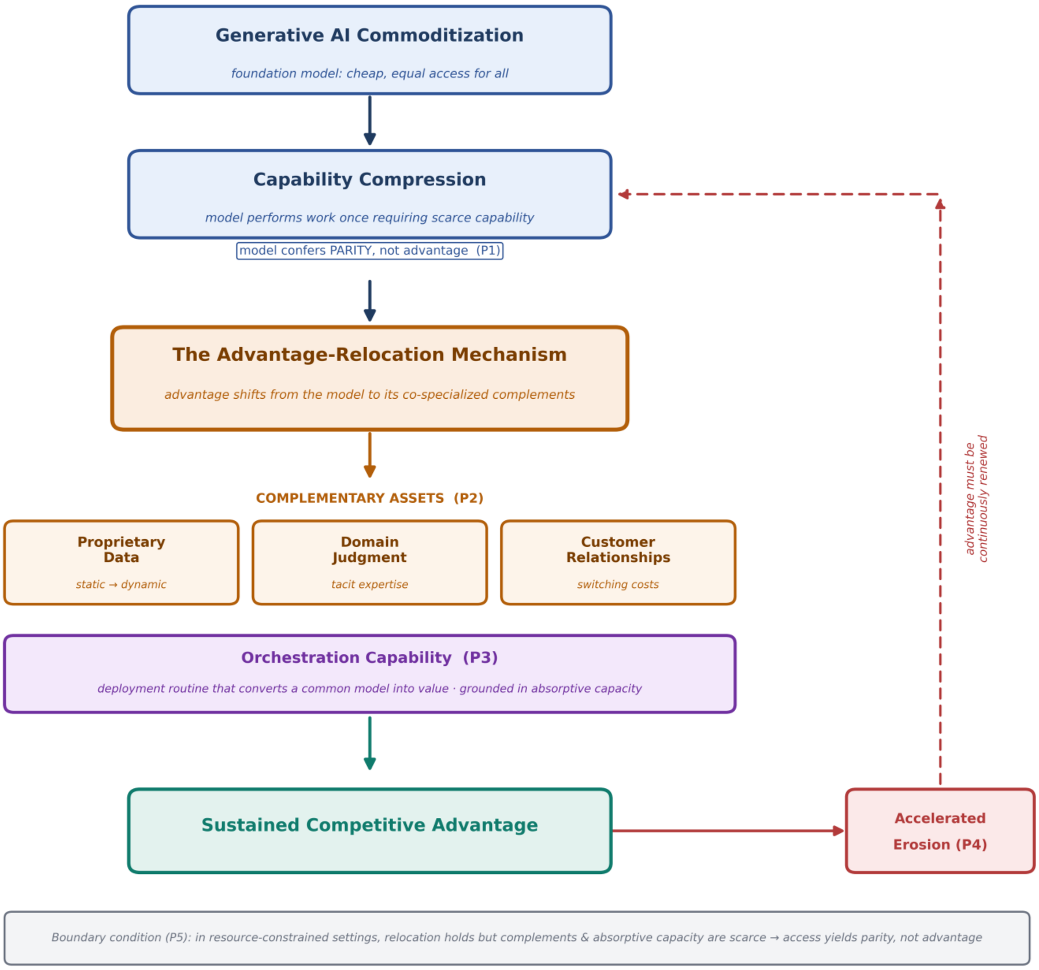


***Figure 1:*** *Competitive advantage under generative AI commoditization: the model as table stakes and the relocation of advantage to complementary assets and orchestration capability.*

***Source:*** *Author's own work.*

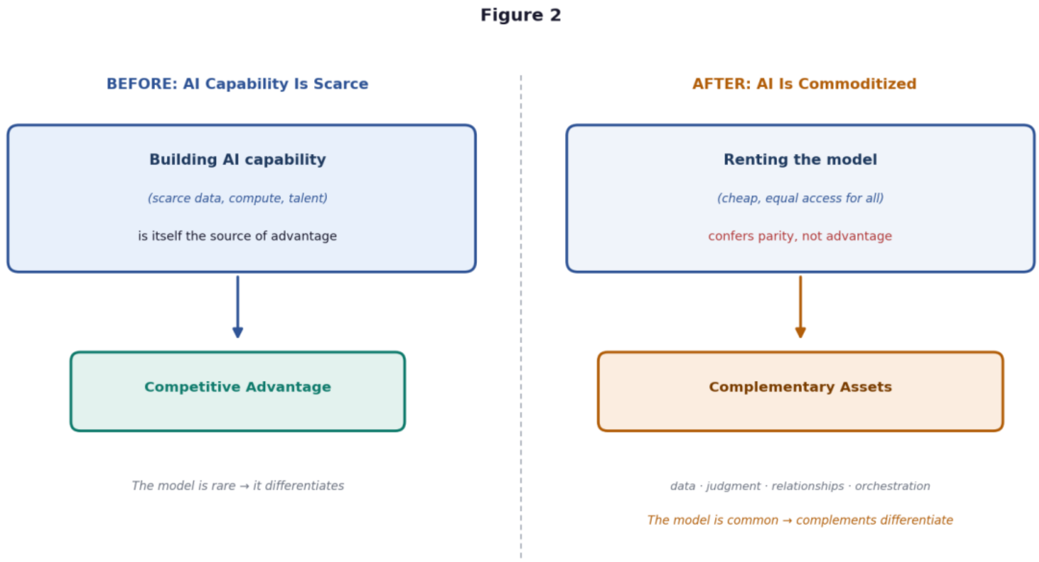


***Figure:*** *The relocation of advantages: before and after generative AI commoditization.*

***Source:*** *Author's own work.*

**Table 1:** Loci of competitive advantage before and after generative AI commoditization.

| Locus | Before commoditization (AI scarce) | After commoditization (AI common) | Why it resists commoditization | Theoretical basis |
|---|---|---|---|---|
| **The AI model** | Source of advantage — building the capability is scarce and hard | Table stakes — confers parity, not advantage | Does not resist; now rentable by all | RBV rarity/inimitability [2] |
| **Proprietary data** | One input among many | Primary differentiator when embedded in feedback loops | Co-specialized, continuously generated, hard to trade | Complementary assets [28] |
| **Domain judgment** | Embodied in scarce expert talent | Differentiators as generic deployments underperform in specialized contexts | Tacit, slow to accumulate, context-bound | Absorptive capacity [13] |
| **Customer relationships** | Distribution and trust advantage | Source of switching costs and proprietary-data generation | Relational, time-dependent, non-transferable | Complementary assets [28] |

| Locus | Before commoditization (AI scarce) | After commoditization (AI common) | Why it resists commoditization | Theoretical basis |
|---|---|---|---|---|
| **Orchestration capability** | Implicit in AI capability | Distinguishes firms with identical model access | Organizational competence at point of use | Dynamic capabilities [15] |

***Source:*** *Author's own work.*

### 4.1. The Commoditized Model and the Erosion of Model-Level Advantage

The framework's point of departure is that the foundation model, accessible to any firm on comparable terms, fails the rarity and inimitability conditions for sustained advantage [2]. Adoption of a foundation model may be necessary for competitive parity, and a firm that fails to adopt may suffer disadvantages, but adoption cannot by itself confer advantage when rivals adopt the same model. This is the generative AI analogue of the IT-commoditization thesis [29], sharpened by the observation that the technology compresses capability differences across firms and workers [21]. Accordingly:

> **Proposition 1: Once foundation-model access is widely and cheaply available, variation across startups in which model they adopt is unrelated to variation in their competitive advantage; differences in advantage instead track differences in complementary assets, not differences in model access or choice.**

### 4.2. The Relocation of Advantage to Complementary Assets

If the model confers parity, advantage must reside elsewhere. Complementary-assets theory locates it in the co-specialized resources with which the model must be combined to create value and which rivals cannot readily access or replicate: proprietary data embedded in feedback loops, domain-specific judgment, and customer relationships and trust [22], [24], [28]. These complements satisfy the conditions the model fails, being valuable, rare, and costly to imitate, and they are therefore where advantage is captured under commoditization. Accordingly:

> **Proposition 2: Under generative AI commoditization, sustained competitive advantage derives from complementary assets the model cannot replicate, particularly proprietary data embedded in feedback loops, domain-specific judgment, and customer relationships, rather than from the model itself.**

A qualification specific to early-stage ventures must be addressed, since it appears to threaten the argument with circularity: if advantage derives from proprietary data embedded in feedback loops, yet such loops require a user base a startup does not yet possess, then the startup seems unable to begin. The resolution lies in distinguishing two forms of data advantage. *Dynamic* feedback loops, in which customer interaction continuously regenerates proprietary data, are indeed a consequence of scale and accrue over time. But *static* proprietary data, a founder's distinctive historical dataset, privileged access to a domain, or a hard-to-assemble initial corpus, is available at inception and independent of scale. Static data, together with domain judgment and nascent relationships, constitutes the entry endowment that lets a venture create initial value from a commoditized model; the dynamic loop is then built upon that endowment as the venture acquires users. The complementary assets of Proposition 2 therefore operate sequentially for startups: static endowments bridge the cold-start gap, and dynamic loops compound the advantage thereafter. This sequence is itself a testable feature of the framework.

### 4.3. Orchestration Capability as a Differentiator among Equal-Access Firms

Propositions 2 and 3 refer to analytically distinct constructs that are easily conflated, and the distinction must be stated precisely. Proposition 2 concerns *asset stocks*, the data, expertise, and relationships a firm possesses, whose competitive value derives from their scarcity and inimitability. Proposition 3 concerns deployment *capability*, the organizational competence to convert a commonly available model into value, which has effect even where asset stocks are equal. The two are related but not identical, and the relation is precise: absorptive capacity is the cognitive *baseline*, the firm's stock of prior related knowledge that determines what it can in principle assimilate [13], whereas orchestration capability is the behavioral *routine* through which that baseline is enacted, the recurring organizational practice of directing the model toward valuable problems, evaluating and correcting its output, and integrating it into distinctive workflows. Orchestration capability is thus defined here as the dynamic capability *specialized to the commoditized model*: sensing where it can create value, seizing that value through workflow integration, and reconfiguring practice as the model frontier advances, locating it within the micro foundations of dynamic capabilities [15]. This anchoring distinguishes it from absorptive capacity, which it draws upon but is not reducible to: two firms with identical absorptive capacity and identical model access can still diverge in outcomes according to the routines through which they deploy the model. Orchestration capability is best understood as a *specific, lower-order* expression of dynamic capability rather than a synonym for it. Whereas dynamic capabilities are the firm's general-purpose capacity to sense, seize, and reconfigure resources across any domain of change [15], orchestration capability is that capacity specialized to a single object, the commoditized foundation model, and enacted as a concrete operational routine: prompt and task design, evaluation and correction of model output, and integration of the model into workflows [8]. Two implications follow. First, the construct is bounded: it predicts performance specifically in AI-mediated activities and need not correlate with a firm's dynamic capability in domains where AI is not deployed, which renders it empirically distinguishable rather than a relabeling. Second, it is a routine and therefore observable and accumulable, in contrast to the broader, more dispositional dynamic-capability construct from which it descends. Orchestration capability is thus a discriminable sub-capability, not a renaming of dynamic capabilities. Because orchestration operates at the point of use and is available in principle even to firms lacking proprietary data, it is especially salient for resource-constrained startups. Accordingly:

> **Proposition 3: Among startups with equal access to identical foundation models and equivalent complementary-asset stocks, those with greater orchestration capability, the routinized practice of directing, evaluating, and integrating model output, achieve superior competitive outcomes; orchestration capability is empirically distinguishable from generic dynamic capability in that it predicts performance specifically in AI-mediated tasks and not in tasks where AI is not deployed.**

### 4.4. The Accelerated Erosion of AI-Derived Advantage

Whatever advantage a startup derives from a particular AI application is exposed to unusually rapid erosion, and the mechanism is specific rather than general. Three forces compress the durability of AI-derived advantage. First, model improvements diffuse simultaneously to all users: when the underlying foundation model advances, every firm renting it inherits the gain at once, so any advantage premised on model capability is completed away the moment the frontier moves. Second, the learning curves that ordinarily protect an advantage collapse, because generative AI lowers the experience and skill thresholds for performing tasks, narrowing the gap between novice and expert users and shortening the time a rival needs to match a capability [21]. Third, the barriers to imitating an AI-based application are low: applications built on a shared model are readily observed and reproduced, and the model itself supplies no proprietary protection [15], [30]. Together these forces make advantage under generative AI less a defensible position to be held than a lead to be continuously renewed, placing a premium on the dynamic capability of reconfiguration and on the speed of organizational learning rather than on any static capability. Accordingly:

> **Proposition 4a: Competitive advantage derived from a given generative-AI application erodes more rapidly than advantage derived from the firm's complementary assets, because model-level gains diffuse simultaneously to all adopters while complementary assets do not.**

> **Proposition 4b: Consequently, among AI-using startups, sustained advantage is associated with the rate at which a firm renews its position, the speed of learning and reconfiguration, rather than with the size of any static AI capability it holds at a point in time.**

### 4.5. Boundary Conditions: Resource-Constrained and Emerging-Economy Startups

The relocation of advantage has a distinct character for startups in resource-constrained and emerging-economy settings, and stating this scope condition sharpens rather than localizes the framework. Commoditized access is, in one respect, equalizing: a venture in such a setting can now invoke the same model as a Silicon Valley competitor, lowering a barrier that once excluded it [9], [31]. But the framework implies that this equalization is confined to the model layer and does not extend to the complements where advantage now resides. Where the complementary assets and absorptive capacity required to exploit the model, digital skills, reliable infrastructure, and domain integration, are scarce, commoditized access yields parity without advantage, and the binding constraint shifts from acquiring AI to building the complements around it. Empirical evidence from low-resource settings is consistent with this implication: generative AI tools, though accessible, are taken up and converted into value unevenly, gated by digital literacy and infrastructure rather than by access to the tools themselves [32]. The global pattern of generative AI adoption similarly reveals a widening rather than narrowing divide in effective use, even as nominal access broadens [33]. Accordingly:

> **Proposition 5: For resource-constrained and emerging-economy startups, commoditized AI access lowers entry barriers at the model layer but confers durable advantage only where complementary assets and absorptive capacity are present; where these are absent, access yields competitive parity rather than advantage.**

## 5. Discussion

This paper has argued that generative AI, by commoditizing the foundation model, does not eliminate competitive advantage for startups but relocates its sources from the model to the complements the model cannot supply. Three contributions follow. First, the paper extends the resource-based view to a setting its standard application does not contemplate, one in which the focal technology is deliberately non-rare, and shows that the framework's own conditions, far from being rendered obsolete, precisely predicts the relocation of advantage to scarce complements. Second, by engaging the information-technology commoditization debate as both precedent and foil, the paper clarifies what is genuinely new about the generative AI case, the commoditization of capability rather than infrastructure, and thereby guards against the misreading that the argument is the earlier debate restated. Third, the framework specifies testable mechanisms, the relocation of advantage to complementary assets, the differentiating role of orchestration capability among equal-access firms, and the accelerated erosion of AI-derived advantage, that convert a broad intuition into a research agenda.

The argument reframes a common claim about generative AI and startups. It is frequently observed that generative AI levels the playing field, allowing small ventures to access capabilities once reserved for the well-resourced [9]. The framework qualifies this claim in a specific way: the leveling is real but confined to the commoditized model layer, and it is precisely because the model is leveled that advantage migrates to the unleveled complements. The accessibility that empowers the startup also strips the startup's AI use of durable distinctiveness, returning the strategic question to where it always resided, in the venture's data, judgment, relationships, and capacity to learn. Generative AI thus changes the tools of competition without changing its underlying logic.

### 5.1. Theoretical Contributions

The paper makes three theoretical contributions that go beyond applying existing theory to a new technology. First, it identifies a boundary condition of the resource-based view that the AI-capability literature has left implicit. That literature treats AI capability as advantage-conferring [1]; the present analysis shows this holds only while the capability is scarce, and that commoditization of the model voids the rarity condition on which the claim depends. The contribution is not that complements matter, which is established, but that generative AI *relocates the binding constraint* within the resource bundle, from the technology to its complements, an inversion the capability view does not anticipate. The paper names this displacement of the *advantage-relocation mechanism*: the regularity by which commoditization of a capability-like technology shifts the locus of advantage from the technology to its co-specialized complements. Naming the mechanism is intended not to claim a new grand theory but to give regularity a referent that future empirical work can test and cite.

Second, the paper refines the commoditization thesis itself. Carr's (2003) argument concerned infrastructure that supported work; the analysis here distinguishes the commoditization of *capability*, technology that performs work once requiring scarce human or organizational competence. This distinction is consequential rather than semantic: infrastructure commoditization erodes a cost advantage, whereas capability commoditization erodes a *competence* advantage, compressing the very capability differences that the resource-based view treats as sources of advantage, a compression for which there is emerging evidence [21]. The generative AI case is therefore not the IT debate restated but a distinct theoretical situation in which a commoditized resource is capability-like.

Third, the paper specifies a mechanism, not merely a direction. It is not enough to say advantage moves to complements; the analysis identifies *which* complements, why each resists commoditization, and through what capacity, absorptive capacity expressed as orchestration, firms with equal access diverge. This mechanism is rendered as testable propositions, converting a widely shared intuition that generative AI changes competition into a falsifiable account of how it does so.

### 5.2. Relation to Recent Empirical Evidence

Although this paper is conceptual, recent empirical findings lend convergent support to its central mechanism and help to delimit its scope. Most directly, firm-level evidence from a large panel of innovative SMEs shows that internal capability-building ceases to predict technology adoption once external acquisition and complementary collaboration are accounted for, with advantage tracking complements, particularly customer collaboration, rather than internally held capability [4]. This is precisely the relocation the present framework predicts: as the capability layer becomes commoditized or source able, the locus of advantage shifts to the surrounding complements. The framework offered here supplies the theoretical account that such empirical work has thus far lacked, explaining *why* internal capability loses its differentiating power and *where* advantage migrates as a result.

The framework's boundary condition (Proposition 5) is likewise corroborated. Studies of generative-AI uptake document an emerging "generative-AI divide," in which nominal access is widely distributed but effective use is stratified by resource, positional, and skill-related factors [5], [6], and evidence from resource-constrained micro-firms shows that converting accessible generative AI into growth depends on the complementary capabilities the firm can mobilize rather than on access itself [34]. These findings are consistent with the framework's claim that commoditized access equalizes the model layer while leaving advantage to be determined by the unequally distributed complements and absorptive capacity that surround it. Where the framework advances beyond this evidence is in unifying these dispersed observations, on capability substitution, on the adoption divide, and on micro-firm constraints, within a single mechanism, the relocation of advantage under capability commoditization, from which each can be derived rather than observed in isolation.

### 5.3. Implications for Practice

For founders, the central implication is that competitive strategy in the age of generative AI is not an AI-adoption strategy but a complement-building strategy. Because adopting a foundation model confers parity rather than advantage, the strategic priority is to build and protect the assets the model cannot supply: proprietary data captured through customer interaction, domain expertise embedded in the product, relationships that create switching costs, and the orchestration capability to combine these with AI into a distinctive offering. For investors, the framework offers a due-diligence lens: the relevant question is not whether a venture uses AI, which conveys little, but whether it possesses or is building the complements that convert commoditized AI into defensible advantage, and whether its advantage is of a faster-eroding or more durable kind. For ecosystem and policy actors, particularly in resource-constrained settings, the implication is that broadening access to AI tools, while necessary, is insufficient; the higher-leverage interventions build complementary capabilities, data infrastructure, skills, and absorptive capacity, which determine whether access translates into advantage.

### 5.4. Limitations and Future Research

As a conceptual contribution, the paper develops propositions rather than testing them, and its synthesis draws in part on a fast-moving literature in which some sources, particularly on the most recent developments, remain working papers rather than peer-reviewed articles; these are used to characterize the emerging phenomenon, while the framework's theoretical weight rests on established, peer-reviewed foundations and the propositions are anchored throughout in peer-reviewed evidence. The framework invites empirical examination. The relocation of advantage to complements (Propositions 1 and 2) could be tested by relating ventures' complementary-asset endowments, rather than their AI adoption, to performance among AI-using startups. The orchestration proposition (Proposition 3) calls for measures of the capacity to exploit a common model, distinguishing it from mere access; candidate proxies include the standardization of prompt-engineering practice, the extent of workflow and API integration of the model into core processes, and the speed of feature deployment relative to competitors. The erosion proposition (Proposition 4) could be operationalized through the time elapsed between a frontier-model release and the convergence of feature parity among competing applications, a directly observable measure of how quickly model-derived advantage dissipates. The erosion proposition (Proposition 4) requires longitudinal designs tracking the durability of AI-derived advantage. The boundary condition (Proposition 5) could be examined comparatively across settings differing in complement availability. These tests acquire force when situated in concrete settings rather than left abstract. Propositions 1 and 2 could be examined within a single accelerator or incubator cohort, where member ventures hold broadly comparable access to the same foundation models, by relating each venture's complementary-asset endowment, proprietary data, domain expertise, customer relationships to subsequent performance; the framework predicts that advantage tracks these endowments and not model access or choice. Proposition 3 could be tested in firms deploying an identical commercial model (for example, a widely used API), comparing those with formalized orchestration routines against those without, while holding asset stocks constant. Proposition 5, the boundary condition, is most cleanly examined through a comparative design across ecosystems that differ sharply in complement availability for instance, contrasting startups in a high-infrastructure hub such as a North American or Western European technology cluster with those in lower-infrastructure emerging-economy ecosystems such as those of East or sub-Saharan Africa, where reliable connectivity, digital skills, and ecosystem support are less evenly distributed. Such a design would test the framework's central prediction directly: that commoditized access narrows differences at the model layer while advantage continues to track the unequally held complements, so that the same technology yields convergence in access but divergence in outcomes. Recent evidence of a stratified generative-AI divide across user populations [5], [34] suggests such comparative variation is both real and measurable. Because the phenomenon is recent and evolving rapidly, such work will need to be both timely and attentive to the moving frontier of model capability. Table 2 summarizes candidate operational proxies for the framework's central constructs, offered to guide empirical work.

**Table 2:** Candidate operationalization's of the framework's constructs for empirical research.

| Construct | Proposition | Candidate proxy measure(s) | Indicative data source |
|---|---|---|---|
| **Complementary-asset endowment** | P1, P2 | Proprietary data holdings; share of revenue from proprietary vs. general capability; depth of customer switching costs | Firm surveys; product/IP audits; customer-retention records |
| **Static vs. dynamic data advantage** | P2 | Presence of a founder/firm proprietary dataset at inception; growth rate of interaction-generated data over time | Founding documents; data-asset inventories; longitudinal usage logs |
| **Orchestration capability** | P3 | Standardization of prompt-engineering practice; extent of model API/workflow integration into core processes; speed of feature deployment vs. competitors | Process audits; engineering records; release-cadence data |
| **Absorptive capacity (baseline)** | P3 | Prior related technical knowledge; share of staff with relevant AI/digital expertise | HR records; skills inventories |

| Construct | Proposition | Candidate proxy measure(s) | Indicative data source |
|---|---|---|---|
| **Erosion rate of AI-derived advantage** | P4 | Time elapsed between frontier-model release and competitor feature-parity convergence | Product-release timelines; competitive feature tracking |
| **Complement availability (context)** | P5 | Local digital-infrastructure reliability; digital-skills supply; ecosystem-support density | National/ecosystem indicators; infrastructure and skills surveys |

***Source:*** *Author's own work.*

## 6. Conclusion

When every startup can access the same generative AI, the AI itself can no longer be the answer to where a venture's advantage lies. This paper has argued that the answer has not disappeared but moved: from the model, which commoditization has made common, to the complements, proprietary data, domain judgment, customer relationships, and orchestration capability, which the model cannot replicate and that remain scarce. The resource-based view, properly applied, does not break under commoditization but predicts exactly this relocation, and the information-technology debate of two decades ago anticipated its shape while differing in a way that makes the generative AI case more radical. For founders, investors, and the ecosystems that support them, the strategic task is correspondingly clear: to compete in the age of generative AI is to build what the AI cannot supply. The tools have been levelled; the advantage has not.

## 7. 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] D. Audretsch, M. Belitski, and N. Rejeb, 'Unlocking AI robotics adoption in innovative firms: Make, buy or ally?', *Technological Forecasting and Social Change*, vol. 231, p. 124793, Oct. 2026, doi: 10.1016/j.techfore.2026.124793.

[5] A. Nakagomi, N. Abe, and T. Tabuchi, 'Emerging generative AI divide: Personal, positional, and resource-based factors associated with use and reasons for non-use', *Telematics and Informatics*, vol. 104, p. 102360, Jan. 2026, doi: 10.1016/j.tele.2025.102360.

[6] H. Ali, A. U. Mustafa, and A. F. Aysan, 'Global adoption of generative AI: What matters most?', *Journal of Economy and Technology*, vol. 3, pp. 166–176, Nov. 2025, doi: 10.1016/j.ject.2024.10.002.

[7] A. Islam, M. A. Islam, F. Dal Mas, J. Fijałkowska, M. Rahman, and M. Massaro, 'Configuring AI-guided sustainable competitive advantage for SMEs through business model innovation: A systematic literature review approach', *Journal of Engineering and Technology Management*, vol. 78, p. 101921, Oct. 2025, doi: 10.1016/j.jengtecman.2025.101921.

[8] A. Sarkar, 'From AI Hype to Workflow Reality: A Strategic Framework for Integrating Generative AI Across Organizational Functions', *Organizational Dynamics*, vol. 55, no. 1, p. 101202, Mar. 2026, doi: 10.1016/j.orgdyn.2025.101202.

[9] A. Gupta, F. Qian, E. Simintzi, and Y. Sun, 'Generative AI and Entrepreneurship', 2025, *SSRN*. doi: 10.2139/ssrn.5971474.

[10] 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.

[11] 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.

[12] E. Brynjolfsson and L. M. Hitt, 'Beyond Computation: Information Technology, Organizational Transformation and Business Performance', *Journal of Economic Perspectives*, vol. 14, no. 4, pp. 23–48, Nov. 2000, doi: 10.1257/jep.14.4.23.

[13] 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.

[14] D. J. Teece, G. Pisano, and A. Shuen, 'Dynamic Capabilities and Strategic Management', *Strategic Management Journal*, vol. 18, no. 7, pp. 509–533, 1997.

[15] 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.

[16] K. M. Eisenhardt and J. A. Martin, 'Dynamic capabilities: what are they?', *Strategic Management Journal*, vol. 21, no. 10-11, pp. 1105–1121, 2000.

[17] G. Lanfranchi, A. Cioli, A. Amanti, and L. Marinelli, 'Reconfiguring competitive advantage: a resource dynamic framework for generative AI adoption in digital content marketing', *European Journal of Innovation Management*, vol. 29, no. 3, pp. 770–798, Apr. 2026, doi: 10.1108/EJIM-03-2024-0317.

[18] C. Zabel and D. O'Brien, 'Understanding dynamic capabilities in emerging technology markets: antecedents, sequential nature, and impact on innovation performance in the extended reality industry', *EJIM*, vol. 27, no. 9, pp. 305–336, Dec. 2024, doi: 10.1108/EJIM-07-2023-0574.

[19] A. Cataldo and R. McQueen, 'Strategic Driver or Unimportant Commodity? A Decade After "IT Doesn't Matter," SMEs Prove That It Really Does', *Industrial Engineer*, vol. 46, no. 2, pp. 36–41, 2014.

[20] S. Mitropoulos and C. Douligeris, 'Why and how informatics and applied computing can still create structural changes and competitive advantage', *Applied Computing and Informatics*, vol. 21, no. 3–4, pp. 198–208, Oct. 2025, doi: 10.1108/ACI-06-2021-0149.

[21] A. R. Doshi, J. J. Bell, E. Mirzayev, and B. S. Vanneste, 'Generative artificial intelligence and evaluating strategic decisions', *Strategic Management Journal*, vol. 46, no. 3, pp. 583–610, Mar. 2025, doi: 10.1002/smj.3677.

[22] F. Marty and T. Warin, 'Data and Computing Power: The New Frontiers of Competition in Generative AI', Groupe de REcherche en Droit, Economie, Gestion (GREDEG CNRS), Université Côte d'Azur, Nice, France, GREDEG Working Papers 2025–38, Sep. 2025. [Online]. Available: https://ideas.repec.org/p/gre/wpaper/2025-38.html

[23] A. Abbott and S. Marar, 'Is Data Really a Barrier to Entry? Rethinking Competition Regulation in Generative AI', *Albany Law Journal of Science and Technology*, vol. 36, no. 1, 2026, [Online]. Available: https://www.albanylawscitech.org/article/159591-is-data-really-a-barrier-to-entry-rethinking-competition-regulation-in-generative-ai

[24] H. Inciarte, 'Tacit expertise as competitive differentiation: Why generic AI implementations fail in domain-specific business contexts', Social Science Research Network (SSRN), 2026. [Online]. Available: https://dx.doi.org/10.2139/ssrn.6704758.

[25] J. Vipra and A. Korinek, 'Market Concentration Implications of Foundation Models', Nov. 02, 2023, *arXiv*: arXiv:2311.01550. https://doi.org/10.48550/arXiv.2311.01550.

[26] P. Azoulay, J. Krieger, and A. Nagaraj, 'Old Moats for New Models: Openness, Control, and Competition in Generative AI', National Bureau of Economic Research, Cambridge, MA, w32474, May 2024. doi: 10.3386/w32474.

[27] A. Eisfeldt, G. Schubert, and M. B. Zhang, 'Generative AI and Firm Values', National Bureau of Economic Research, Cambridge, MA, w31222, May 2023. doi: 10.3386/w31222.

[28] 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.

[29] N. G. Carr, 'IT Doesn't Matter', *Harvard Business Review*, vol. 81, no. 5, pp. 41–49, 2003, doi: 10.1109/emr.2004.25006.

[30] R. Raghavan, 'Moat Half-Life: Modeling Competitive Advantage in Technology Companies', 2026, *SSRN*. http://dx.doi.org/10.2139/ssrn.6814958.

[31] K. F. Nzembayie and D. Urbano, 'Generative AI platforms as institutional catalysts of digital entrepreneurship: Enablement, dependence & power dynamics', *Technology in Society*, vol. 84, p. 103074, Mar. 2026, doi: 10.1016/j.techsoc.2025.103074.

[32] N. Shidende and A. Mwogosi, 'Exploring the impact of generative AI tools on healthcare delivery in Tanzania', *Journal of Health Organization and Management*, vol. 39, no. 8, pp. 1580–1599, Nov. 2025, doi: 10.1108/JHOM-01-2025-0007.

[33] Y. Liu, J. Huang, and H. Wang, *Who on Earth Is Using Generative AI? Global Trends and Shifts in 2025*. Washington, DC: World Bank, 2025. doi: 10.1596/1813-9450-11231.

[34] F. Shahzad, M. T. Hoque, I. S. Khan, and A. Arslan, 'AI for the underdogs: Navigating risk and growth in high-tech micro-firms through generative artificial intelligence', *Journal of Strategy & Innovation*, vol. 37, no. 1, p. 200566, May 2026, doi: 10.1016/j.jsinno.2026.200566.