Manexia
Journal of Business, Management, and Creative Economy

e-ISSN: 3124-6532
Vol. 2 | Issue 1 | January 2026
Pages: 82-98
DOI
https://doi.org/10.66203/manexia.02107

The AI Productivity Paradox Revisited: A Multi-Level Theory of Performance Divergence in SME-Dominated Digital Ecosystems

Ahmad Mundzir[1]*

***Corresponding Mail:**
mundzir@udex.or.id

Abstrak

Artificial intelligence (AI) has intensified debates surrounding the contemporary productivity paradox, where rapid technological advances coexist with uneven improvements in measured productivity. While growing evidence demonstrates that AI can significantly enhance task-level performance, these gains do not always translate into consistent firm-level productivity outcomes, particularly in small and medium-sized enterprises (SMEs) operating within platform-mediated digital markets. This article develops a conceptual framework that revisits the AI productivity paradox through a multi-level theoretical perspective. Integrating insights from productivity paradox research, general-purpose technology theory, task-based technological change, and platform ecosystem scholarship, the study proposes that AI-induced productivity gains propagate unevenly across four analytical layers: tasks, SMEs, platforms, and digital ecosystems. Three generative mechanisms—complement lag, measurement wedge, and compounding learning effects—are theorized to shape how productivity gains are translated, amplified, or redistributed across these levels. While SMEs may experience delayed or partially observable productivity improvements due to complement constraints and measurement limitations, platform infrastructures can accumulate accelerated productivity gains through data-enabled learning and cross-merchant aggregation. The framework introduces the concept of productivity divergence to explain how ecosystem-level efficiency may increase even when individual firms experience uneven productivity outcomes. This perspective offers new insights into the strategic and organizational implications of AI adoption in platform-dominated digital economies.

Keywords

artificial intelligence; productivity paradox; platform ecosystems; digital markets; productivity divergence

Article History:
Submitted: 11-08-2025
Approved: 08-11-2025
Published: 05-01-2026

[1] VISTA Research Center, UDEX Institute, Tasikmalaya, Indonesia

1. Introduction

Artificial intelligence (AI) has rapidly shifted from an experimental capability to an embedded infrastructure in digital markets (Agrawal, Gans, & Goldfarb, 2022). A growing body of micro-level evidence indicates that AI—especially generative and predictive systems—can raise task productivity by reducing completion time, improving output quality, and standardizing routine decisions. Experimental and field studies report meaningful gains in writing-intensive and customer-facing work, with particularly strong effects among less experienced workers (Noy & Zhang, 2023; Brynjolfsson *et al*., 2023). At the task level, the productivity potential of AI is therefore increasingly difficult to dispute.

Yet this micro-level optimism sits uneasily alongside a persistent macro-level puzzle. Despite accelerating diffusion, measured productivity growth remains uneven across firms, sectors, and regions. In many contexts, small and medium-sized enterprises (SMEs)—which constitute the backbone of most economies—report AI adoption without commensurate improvements in conventional performance metrics (OECD, 2021). At the same time, the digital platforms that orchestrate SME participation often exhibit accelerating efficiency, scale, and revenue growth. This divergence sharpens a central tension: if AI can improve the productivity of tasks, why do productivity gains fail to translate uniformly into organizational and ecosystem-level performance?

This tension revives the modern productivity paradox, which highlights the disconnect between rapid technological progress and stubborn productivity statistics (Brynjolfsson, Rock, & Syverson, 2017). Contemporary explanations emphasize implementation lags, mismeasurement of digital value, redistribution of gains, and excessive expectations. However, most existing accounts remain either macro-aggregative—treating firms as undifferentiated units within the economy—or firm-centric—treating technology adoption as largely internal to organizational boundaries. Both perspectives are increasingly incomplete for AI, because AI is now deployed through layered infrastructures that blur the causal pathway from task improvement to realized performance. In particular, platform-mediated markets embed AI directly into the coordination architecture that connects firms to consumers (Parker, Van Alstyne, & Choudary, 2016), logistics, advertising, and payment systems. Under such conditions, the locus of productivity gains may shift across levels of analysis rather than accumulating within the adopting firm.

In SME-dominated digital ecosystems, this architecture is especially consequential. SMEs frequently access AI not through proprietary development, but through platform-provided modules embedded in advertising dashboards, recommendation systems, customer-service interfaces, logistics tools, and content-generation utilities. As a result, productivity effects emerge within a nested structure: tasks are transformed within SMEs; SMEs operate inside platform coordination regimes; platforms aggregate learning across merchants and consumers; and ecosystem outcomes reflect both firm-level translation and platform-level amplification. Importantly, these layers can move out of alignment. Even when task productivity improves, organizational productivity can remain flat if complementary investments are underdeveloped, coordination demands rise, or measurement fails to capture quality improvements. Simultaneously, platform-level learning can compound rapidly due to cross-merchant data aggregation, producing ecosystem growth that may not be mirrored by SMEs' measured performance.

Prior scholarship offers important but fragmented explanations for parts of this puzzle. General-purpose technology perspectives emphasize that productivity gains often require intangible complements—organizational capital, skills, and workflow redesign—and may therefore follow a J-curve pattern in which performance initially stagnates before rising once complements mature (Brynjolfsson *et al*., 2019). Organizational theory further highlights the automation–augmentation paradox, suggesting that AI can increase efficiency while simultaneously raising coordination burdens and altering work design in non-linear ways (Raisch & Krakowski, 2021). Digital economics research shows that digital technologies reduce transaction costs and enable data-enabled learning, generating compounding performance advantages at scale (Goldfarb & Tucker, 2019; Hagiu & Wright, 2023). Yet these streams rarely converge into an integrated explanation of how AI's productivity effects propagate across nested levels of analysis in platform-embedded SME markets. As a consequence, observed divergence is often misread as technological failure rather than structural decoupling.

This study addresses that gap by advancing a multi-level theory of AI productivity divergence in SME-dominated digital ecosystems. The guiding question is: How does AI integration generate divergent productivity outcomes across task, SME, platform, and ecosystem levels within the same technological environment? Rather than asking whether AI increases productivity, the analysis focuses on where productivity gains materialize, through what mechanisms they translate across levels, and under what conditions they become amplified or attenuated.

The central theoretical move is to reconceptualize the AI productivity paradox as a problem of multi-level divergence rather than a simple absence of gains. Productivity divergence refers to the structural decoupling of productivity outcomes across analytical levels—task, firm, platform, and ecosystem—within the same technological environment. Unlike productivity redistribution, which refers to the transfer of gains across economic actors, productivity divergence captures the vertical misalignment of productivity outcomes across organizational layers.

Building on this definition, three mechanisms are proposed through which AI-induced task gains may fail to accumulate within SMEs while simultaneously contributing to platform- and ecosystem-level performance. First, a complement lag mechanism suggests that SMEs require intangible complements—such as absorptive capacity, workflow modularity, and managerial routines—to translate task improvements into measured productivity. Second, a measurement wedge mechanism suggests that AI often improves quality, responsiveness, and consistency in ways that are imperfectly captured by conventional productivity indicators, producing a gap between quality-adjusted and measured performance. Third, a compounding redistribution mechanism suggests that platform-level learning effects—enabled by cross-merchant data aggregation and coordination scope—compound more rapidly than SME-level learning, creating performance divergence across ecosystem layers without presuming intentional extraction.

This study makes four contributions. First, it extends the modern productivity paradox into platform-embedded ecosystems by specifying how lags, mismeasurement, and redistribution operate across nested organizational layers rather than only across the macroeconomy. Second, it integrates task-level AI productivity evidence with complement-based organizational accounts and platform learning economics, linking literatures that are typically treated separately. Third, it introduces productivity divergence as a theoretically distinct construct that explains how ecosystem-level efficiency can increase even when SME-level measured productivity remains uneven or stagnant. Fourth, it clarifies boundary conditions that intensify divergence in SME-dominated markets, including limited complement maturity and high platform dependence. The framework also contributes to strategic management research by explaining how AI adoption can simultaneously increase ecosystem efficiency while generating uneven firm-level productivity, thereby shifting the locus of competitive advantage in platform-mediated markets.

By shifting the analytical focus from aggregate productivity averages to cross-level propagation mechanisms, the article provides a structured explanation for why AI can simultaneously enhance task performance, accelerate platform efficiency, and yet yield uneven firm-level outcomes. In doing so, it offers a theoretically grounded basis for evaluating AI's strategic consequences in the dominant organizational form of contemporary digital economies: SME participation within platform-mediated ecosystems.

2. Theoretical Foundations

Artificial intelligence (AI) has revived longstanding debates about technology and productivity, yet the contemporary digital economy presents conditions that differ significantly from earlier technological transformations. Unlike earlier information technologies that primarily automated discrete organizational routines, contemporary AI systems are increasingly embedded within digital infrastructures that shape decision-making, workflow coordination, and market interactions simultaneously. In platform-mediated environments, AI operates not only as a firm-level tool but also as an ecosystem-level coordination mechanism. Consequently, understanding the productivity implications of AI requires theoretical integration across multiple levels of analysis.

To develop such an explanation, this study draws on four foundational theoretical traditions: the modern productivity paradox literature, general-purpose technology theory and the role of intangible complements, task-based perspectives on technological change and the automation–augmentation paradox, and research on platform ecosystems and data-enabled learning. Each of these literatures offers important insights into how technological advances shape productivity outcomes, yet they typically examine these dynamics at different analytical levels. When considered together, they provide the conceptual building blocks for explaining how productivity gains generated by AI may propagate unevenly across task, firm, platform, and ecosystem layers in SME-dominated digital markets.

2.1 The Modern Productivity Paradox and Aggregate Explanations

The productivity paradox literature originated from the observation that rapid advances in information technology were not always accompanied by corresponding improvements in measured productivity. Contemporary formulations refine this debate by identifying several mechanisms through which technological progress may fail to translate into observable performance outcomes (Brynjolfsson, Rock, & Syverson, 2017). These mechanisms include implementation lags, measurement limitations, redistribution of gains, and unrealistic expectations surrounding emerging technologies.

Implementation lags arise because organizations require time to adapt structures, routines, and skill bases in response to technological change. New technologies are often adopted before complementary organizational adjustments are completed, creating a temporal gap between technological capability and realized productivity. Mismeasurement further complicates this relationship. Digital technologies frequently improve product variety, service quality, convenience, and speed—dimensions of value that are difficult to capture through traditional productivity indicators. As a result, improvements in real economic value may remain only partially visible in standard productivity statistics.

Another explanation emphasizes the redistribution of gains. Technological innovation can generate productivity improvements that accrue disproportionately to certain actors—such as technology providers, platform coordinators, or highly complementary firms—rather than being evenly distributed across all adopting organizations. Finally, expectations surrounding transformative technologies may temporarily exceed realized benefits, creating periods in which investment outpaces measurable productivity gains.

Although these mechanisms provide a compelling macro-level explanation for productivity stagnation, they remain limited in their ability to explain how productivity gains move across nested organizational layers. In digital ecosystems characterized by strong interdependencies among firms, platforms, and users, technological adoption rarely occurs in isolation. AI tools are frequently embedded within shared infrastructures that mediate interactions across multiple actors. As a result, the processes described by productivity paradox theory—lags, mismeasurement, and redistribution—may unfold not only across sectors but across levels within the same ecosystem. Understanding AI's productivity effects therefore requires a framework capable of tracing how productivity gains propagate across interconnected organizational layers.

2.2 Intangible Complements and the J-Curve Logic

General-purpose technology (GPT) theory provides an important lens for understanding why technological adoption does not immediately produce productivity gains. GPTs—such as electricity, computing, or digital technologies—generate widespread economic impact only when combined with complementary investments in organizational capital, human skills, and process redesign. Empirical studies of digital transformation demonstrate that productivity often follows a J-curve pattern: performance may initially stagnate or decline during the early stages of adoption before rising once complementary assets mature (Brynjolfsson *et al*., 2019).

AI amplifies this dynamic because it influences not only operational tasks but also decision processes and knowledge flows within organizations. Effective use of AI requires data governance routines, employee capabilities, workflow modularity, and managerial oversight structures that allow algorithmic outputs to be integrated into everyday operations. Organizations that lack these complementary assets may adopt AI tools without achieving meaningful productivity improvements.

For SMEs, the accumulation of such complements can be particularly challenging. Limited managerial capacity, constrained investment resources, and reliance on standardized digital infrastructures may restrict the depth of organizational redesign required to fully exploit AI capabilities. Under these conditions, improvements observed at the task level may fail to translate into sustained firm-level productivity gains. GPT theory therefore helps explain temporal and structural variation in AI productivity outcomes.

However, GPT theory remains primarily firm-centric. It focuses on how internal complements enable organizations to realize technological benefits but pays less attention to how productivity dynamics unfold when firms operate within platform-mediated ecosystems. In such environments, productivity gains are shaped not only by internal capabilities but also by external coordination structures and learning dynamics. Integrating GPT theory with ecosystem-level perspectives is therefore essential for understanding how AI productivity effects propagate across interconnected actors.

2.3 Task Recomposition and the Automation–Augmentation Paradox

Task-based theories of technological change emphasize that productivity effects depend on how technology reshapes the composition of tasks within organizations. Rather than simply replacing human labor, new technologies often reorganize the distribution of activities between humans and machines (Acemoglu & Restrepo, 2019). Automation may eliminate certain routine tasks while generating new complementary activities that require oversight, interpretation, and coordination.

Organizational research conceptualizes this tension as the automation–augmentation paradox (Raisch & Krakowski, 2021). AI simultaneously automates standardized activities and augments human judgment through predictive insights, recommendations, or generative outputs. While augmentation can improve decision speed and quality, it may also increase coordination requirements and create new dependencies between algorithmic systems and human actors.

Empirical evidence on generative AI illustrates this duality. Studies show that AI assistance can substantially increase productivity in tasks such as writing, coding, and customer communication, particularly for workers with lower prior expertise (Noy & Zhang, 2023; Brynjolfsson *et al*., 2023). At the same time, AI adoption may generate new verification tasks, oversight responsibilities, and workflow adjustments that alter organizational coordination demands.

For SMEs, where roles are often multifunctional and workflows less formally structured, these coordination effects can be particularly pronounced. AI-driven task recomposition may increase interdependence among activities that were previously loosely coupled, requiring new routines for monitoring, validation, and integration. Consequently, task-level productivity gains may not automatically translate into firm-level productivity gains. Task-based theory thus provides the microfoundations necessary to understand why AI productivity benefits can remain localized within individual tasks.

Yet task recomposition alone does not explain why productivity divergence becomes especially visible in digital ecosystems dominated by platforms. To account for these dynamics, it is necessary to examine how learning processes operate across organizational boundaries.

2.4 Platform Ecosystems, Data-Enabled Learning, and Compounding Effects

Platform ecosystems organize economic activity through digital infrastructures that coordinate interactions among firms, consumers, and complementary service providers. Rather than functioning as traditional market intermediaries, platforms operate as meta-organizations that structure interdependence among heterogeneous actors while enabling scalable coordination (Kretschmer, Leiponen, & Schilling, 2022).

A defining feature of platform ecosystems is the aggregation of data generated through large volumes of transactions and interactions. AI systems embedded within these infrastructures benefit from data-enabled learning: as more participants engage with the platform, algorithms continuously refine predictions, recommendations, and operational decisions (Hagiu & Wright, 2023). This learning process creates compounding productivity gains that scale with ecosystem participation.

Because platforms aggregate data across many firms and consumers, their learning capacity often exceeds that of individual SMEs. While SMEs primarily learn from their own limited operational data, platforms learn from ecosystem-wide patterns. As a result, algorithmic improvements may occur more rapidly at the platform level than at the firm level.

This asymmetry has important implications for productivity translation. Even when SMEs experience moderate task-level improvements, platforms may capture disproportionately large productivity gains through transaction optimization, demand forecasting, logistics coordination, and advertising allocation. Ecosystem-level productivity growth may therefore reflect platform-level learning acceleration rather than uniform improvements across participating firms.

Importantly, this dynamic does not necessarily depend on strategic intent or exploitative governance structures. Instead, it arises from structural differences in data access and learning scale inherent in centralized digital infrastructures. Productivity divergence thus emerges as a systemic outcome of asymmetric learning dynamics rather than solely as a consequence of market power.

2.5 Toward a Multi-Level Theory of AI Productivity Divergence

Taken individually, the preceding theoretical perspectives illuminate distinct aspects of the productivity puzzle. Productivity paradox theory explains why technological advances may not immediately appear in aggregate statistics. General-purpose technology theory highlights the importance of complementary investments within firms. Task-based perspectives clarify how technological change reorganizes work at the micro level. Platform ecosystem research demonstrates how learning dynamics and coordination architectures shape performance at the system level.

The following table clarifies the analytical architecture of the framework by specifying how productivity dynamics differ across the four nested levels examined in the study. By mapping actors, AI functions, and productivity mechanisms, the table helps readers understand how productivity gains propagate through the digital ecosystem.

Table 1. Multi-Level Architecture of AI Productivity Propagation in Digital Ecosystems

Analytical Level	Primary Actor	Role of AI	Productivity Dynamic

Task	Individual worker or operational task	Automation and augmentation of routine and semi-structured activities	Increased task efficiency and output quality
SME (Firm)	Small and medium-sized enterprise	Integration of AI into workflows and decision processes	Productivity depends on organizational complements and coordination
Platform	Digital platform operator	Algorithmic coordination across transactions, advertising, logistics, and recommendations	Data-enabled learning and optimization at scale
Ecosystem	Network of SMEs, users, and platform infrastructure	System-level coordination of interactions and market matching	Productivity divergence across organizational layers

Source: Author's conceptualization

By structuring the framework around distinct analytical layers, Table 1 clarifies how productivity gains generated by AI move through different organizational contexts. The overview provided in Table 1 prepares the reader for the subsequent sections that examine task-level productivity effects, SME-level translation mechanisms, and platform-level learning amplification within the broader ecosystem.

Yet these literatures rarely intersect in a single analytical framework. When integrated, they reveal a critical structural insight: productivity gains generated by AI originate at the task level, are filtered through firm-level complements and coordination structures, are amplified by platform-level learning dynamics, and ultimately shape ecosystem-level performance patterns that may diverge from individual firm outcomes.

This multi-level perspective provides the theoretical foundation for the conceptual model developed in the next section. Building on these insights, the following analysis formalizes three generative mechanisms—complement lags, measurement wedges, and compounding redistribution—that explain how AI integration produces productivity divergence across task, SME, platform, and ecosystem levels in digital markets dominated by SMEs.

3. A Multi-Level Theory of AI Productivity Divergence

AI-induced productivity cannot be adequately explained at a single level of analysis. Productivity effects originate at the task level, are filtered through firm-level complements and coordination structures, are amplified by platform-level learning dynamics, and ultimately shape ecosystem-level performance patterns. Explaining these dynamics requires tracing how productivity gains propagate across nested organizational layers rather than assuming that technological improvements translate linearly from tasks to firms and markets. From this perspective, AI integration generates productivity improvements at the task level, yet the translation of these gains depends on three mechanisms operating across higher levels of analysis: complement lag, measurement wedge, and compounding learning effects, which together explain why productivity gains may accumulate unevenly across SMEs, platforms, and digital ecosystems.

The table below summarizes the core mechanisms that explain how AI-driven productivity gains propagate unevenly across organizational layers. Presenting the mechanisms in a concise structure clarifies the theoretical logic that guides the conceptual development of the model.

Table 2. Generative Mechanisms of AI Productivity Divergence

Mechanism	Level of Operation	Core Logic	Expected Productivity Outcome

Complement lag	SME	Organizational complements (skills, routines, workflow redesign) are required to translate AI task gains into firm-level performance	Firm productivity improvements may be delayed or uneven
Measurement wedge	SME	AI improves quality, responsiveness, and decision consistency not fully captured by conventional productivity metrics	Quality-adjusted productivity rises while measured productivity may remain stagnant
Compounding learning	Platform	Platforms learn from aggregated cross-merchant data, enabling faster algorithmic improvement	Platform productivity grows faster than SME productivity

Source: Author's conceptualization

As summarized in Table 2, the mechanisms operate at different analytical layers but jointly explain how productivity gains generated by AI can propagate unevenly across tasks, firms, and platforms. The structure provided by Table 2 clarifies the mechanisms that underpin the multi-level framework developed in the subsequent conceptual sections.

3.1 Task-Level Productivity Effects

AI integration reshapes task execution primarily through automation and augmentation. Automation reduces the time and cognitive effort required to perform structured activities, while augmentation enhances human decision-making by providing predictive insights, structured suggestions, or generative outputs. In many operational contexts, AI systems therefore increase the efficiency with which individuals complete tasks and improve the consistency and quality of outputs.

Empirical evidence indicates that AI-assisted task performance can significantly increase productivity, particularly in activities that are moderately complex yet sufficiently structured to be partially codified (Noy & Zhang, 2023; Brynjolfsson *et al*., 2023). Under these conditions, AI tools can reduce search costs, streamline information processing, and standardize routine decisions. Consequently, the integration of AI into task workflows is expected to increase productivity at the level of individual activities.

Proposition 1. AI integration intensity positively influences task-level productivity through automation and augmentation effects.

However, productivity gains are unlikely to be uniform across tasks or individuals. AI systems tend to perform best when tasks exhibit predictable structures and when workers possess sufficient contextual knowledge to interpr*et al*gorithmic outputs. Workers with lower prior expertise may therefore experience larger relative productivity gains, while highly specialized tasks may benefit less from AI assistance.

Proposition 2. The productivity effects of AI integration vary across task complexity and worker capability.

Although task-level productivity gains are increasingly well documented, their organizational implications depend on how AI reshapes coordination among tasks. Automation and augmentation frequently introduce new dependencies between human actors and algorithmic systems. Tasks that were previously independent may require monitoring, validation, or integration with AI-generated outputs. As AI becomes more deeply embedded within workflows, these interdependencies can increase coordination demands within the organization.

Proposition 3. AI-driven task recomposition increases coordination requirements within firms as integration intensity rises.

Task-level productivity gains therefore represent only the initial stage in a broader process of organizational translation.

This figure isolates the organizational translation problem that sits between AI-enabled task improvements and observable firm-level productivity. It specifies the internal frictions and enabling complements that determine whether task gains accumulate into measured performance in SMEs.

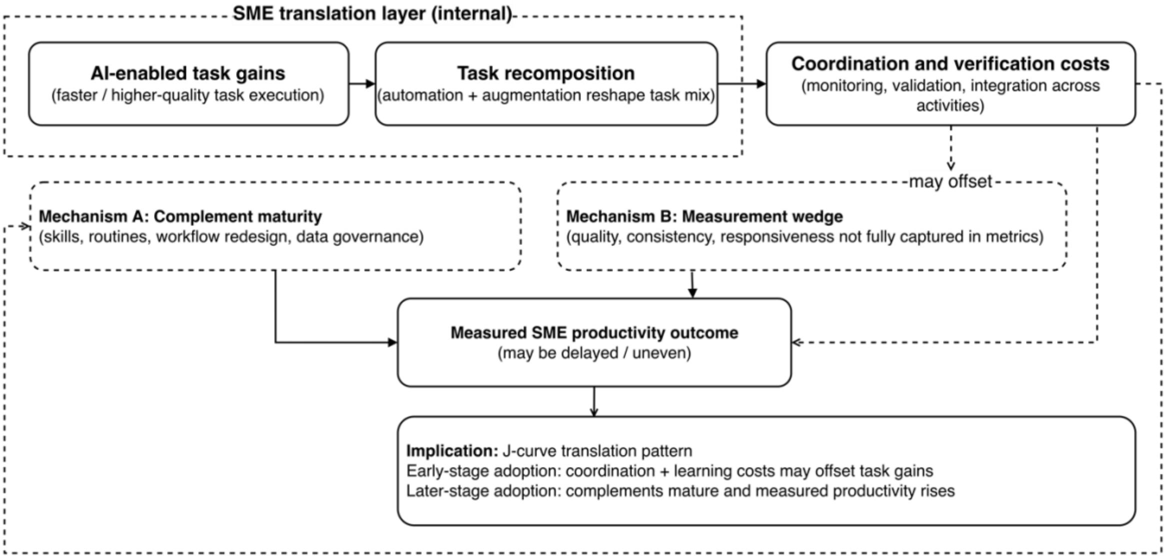

Figure 1. SME Translation Mechanisms Linking AI Task Gains to Measured Firm Productivity
Source: Author's conceptualization

By specifying task recomposition and the coordination/verification burdens it introduces, Figure 1 explains why task-level improvements can fail to aggregate into measured SME productivity unless organizational complements mature and measurement limitations are addressed. The logic in Figure 1 directly supports the paper's argument that the paradox is not an absence of AI gains, but a translation problem that can generate delayed, uneven, or partially observed firm-level outcomes.

3.2 SME-Level Translation Mechanisms

The translation of task-level productivity into firm-level outcomes is shaped primarily by two mechanisms: complement lag and measurement wedge. For productivity gains to emerge at the firm level, task-level improvements must be integrated into organizational processes. General-purpose technology theory suggests that this translation depends heavily on complementary assets such as managerial capabilities, digital skills, workflow modularity, and data governance routines (Brynjolfsson *et al.*, 2019). Without these complements, technological adoption may generate experimentation costs and coordination frictions that delay or attenuate productivity gains.

In SMEs, complement constraints can be particularly pronounced. Limited managerial bandwidth and constrained investment resources often restrict the extent to which firms can redesign processes to fully exploit new technologies. As a result, the relationship between AI integration and measured firm-level productivity may follow a non-linear trajectory. In early stages of adoption, coordination costs and learning requirements may offset task-level gains, producing a temporary decline or stagnation in measured productivity before improvements eventually materialize.

Proposition 4. The relationship between AI integration and SME-level measured productivity follows a J-curve pattern moderated by the availability of intangible complements.

Complement constraints may also intensify coordination challenges created by task recomposition. When AI tools are introduced across different functions—such as marketing analytics, customer service automation, and operational forecasting—firms may experience fragmented optimization across activities rather than integrated efficiency improvements.

Without coordinated redesign of workflows, productivity gains realized in individual tasks may fail to aggregate at the firm level.

Proposition 5. The presence of organizational complements positively moderates the translation of task-level productivity gains into firm-level productivity outcomes.

Another factor influencing firm-level productivity measurement is the nature of the value generated by AI systems. AI frequently improves responsiveness, service consistency, personalization quality, and error reduction—dimensions of performance that enhance customer experience but may not be fully reflected in conventional productivity metrics such as revenue per employee or output per labor hour.

This discrepancy creates a measurement wedge, in which quality-adjusted productivity improves while measured productivity remains stagnant. In digital service contexts, improvements in customer interaction quality or decision speed may increase long-term value creation without immediately appearing in short-term productivity statistics.

Proposition 6. AI integration increases quality-adjusted productivity even when measured SME productivity remains unchanged.

Together, complement constraints and measurement wedges explain why task-level productivity gains may not translate directly into observable firm-level productivity gains.

3.3 Platform-Level Learning Amplification

The translation of task-level productivity into firm-level outcomes is shaped primarily by two mechanisms: complement lag and measurement wedge. While SMEs translate AI productivity gains through internal complements, platforms benefit from a different mechanism: ecosystem-wide learning. Platforms aggregate large volumes of data generated through interactions among merchants, consumers, and service providers. This aggregation allows AI systems embedded in platform infrastructures—such as recommendation engines, advertising algorithms, and logistics optimization tools—to learn from cross-merchant patterns rather than from a single firm's operations.

Data-enabled learning enables platforms to continuously refine predictions and optimize coordination across the ecosystem (Hagiu & Wright, 2023). As participation increases, the volume and diversity of data available for training algorithms expands, accelerating the pace of model improvement. These learning dynamics generate compounding productivity gains that may exceed those achievable by individual SMEs operating with limited data resources.

Proposition 7. Platform-level productivity increases as AI systems learn from aggregated cross-merchant data.

Importantly, the rate of learning differs across organizational levels. SMEs typically rely on internal operational data and therefore accumulate experience gradually. Platforms, by contrast, observe interactions across the entire ecosystem. As a result, algorithmic improvements at the platform level may accelerate more rapidly than learning within individual firms.

Platform-mediated AI productivity should be understood through asymmetric learning scope rather than simple adoption effects. The diagram below contrasts how SMEs and platforms learn from data at different scales, clarifying why platform productivity can compound faster even when individual SMEs experience modest or uneven gains.

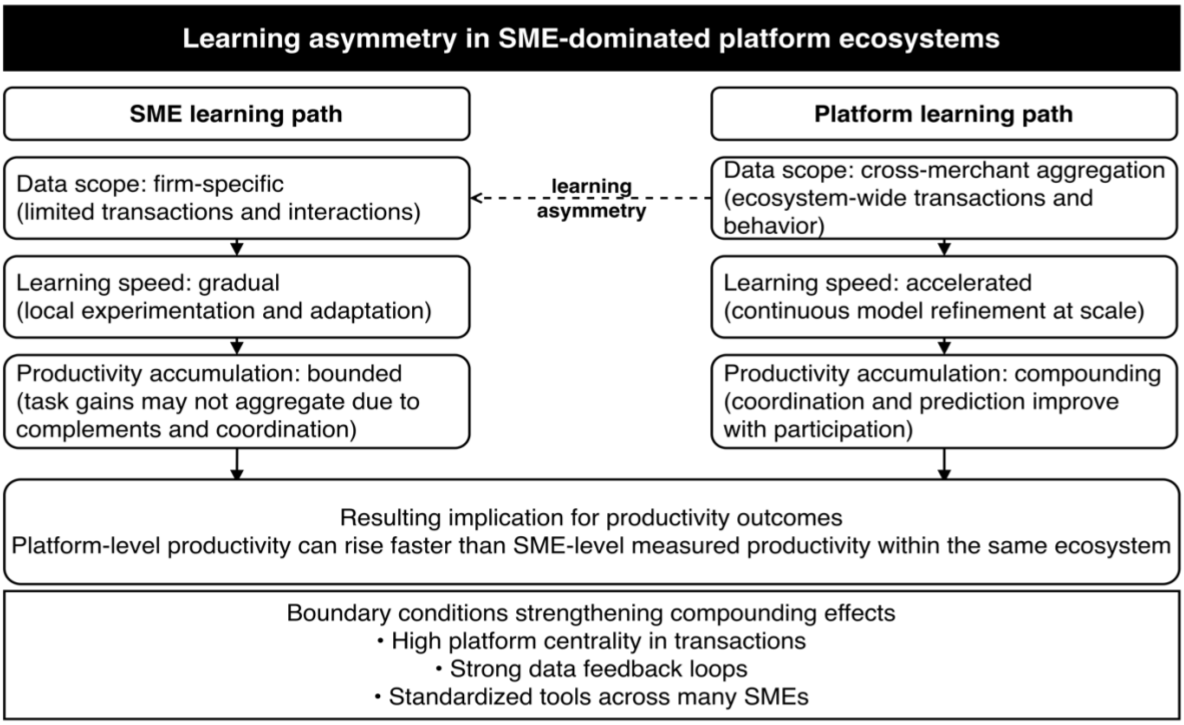

Figure 2. SME Translation Mechanisms Linking AI Task Gains to Measured Firm Productivity
Source: Author's conceptualization

By contrasting the scope of data, the speed of learning, and the nature of productivity accumulation across SMEs versus platform coordinators, Figure 2 reorients the explanation toward compounding learning effects as a structural mechanism. In doing so, Figure 2 supports the article's claim that ecosystem-level efficiency gains can emerge from platform-level algorithmic refinement even when individual SMEs face bounded learning and translation constraints.

Proposition 8. Platform-level learning effects compound more rapidly than SME-level learning under conditions of asymmetric data access.

This learning asymmetry creates the potential for productivity gains to accumulate disproportionately within platform coordination infrastructures.

3.4 Ecosystem-Level Productivity Divergence

When the mechanisms described above interact, productivity outcomes may diverge across levels of the digital ecosystem. Task-level gains improve operational efficiency within firms, yet complement constraints and measurement wedges may limit observable improvements at the SME level. At the same time, platform-level learning can generate accelerating productivity gains that improve coordination, matching, and transaction flows across the ecosystem.

Under such conditions, overall ecosystem productivity—reflected in faster transactions, improved matching efficiency, or higher total output—may increase even if individual SMEs experience uneven productivity improvements. Productivity growth therefore becomes distributed across the ecosystem rather than concentrated within participating firms.

Proposition 9. Ecosystem-level productivity growth may coexist with uneven or stagnant productivity among individual SMEs.

Over time, these dynamics can produce persistent divergence in performance outcomes. Platform-level learning continues to compound as data accumulation accelerates algorithmic refinement, while SMEs lacking sufficient complements struggle to translate task-level gains into firm-level productivity improvements. Divergence becomes particularly pronounced in ecosystems dominated by SMEs with limited absorptive capacity and high dependence on platform infrastructures.

Proposition 10. Productivity divergence intensifies in SME-dominated digital ecosystems characterized by complement constraints and high platform dependence.

3.5 Integrative Model

Taken together, these propositions articulate a multi-level theory of AI productivity divergence. AI integration initiates productivity gains at the task level through automation and augmentation effects. These gains are subsequently filtered through firm-level translation mechanisms, including complement availability, coordination demands, and measurement wedges. Simultaneously, platform-level learning dynamics amplify productivity through cross-merchant data aggregation and algorithmic refinement. The interaction of these processes ultimately shapes ecosystem-level productivity patterns.

AI-enabled productivity should be read as a cross-level propagation problem rather than a single firm-level outcome. The framework below organizes the model into four nested analytical layers and shows where translation frictions and learning amplification intervene along the pathway from task improvements to ecosystem-level performance patterns.

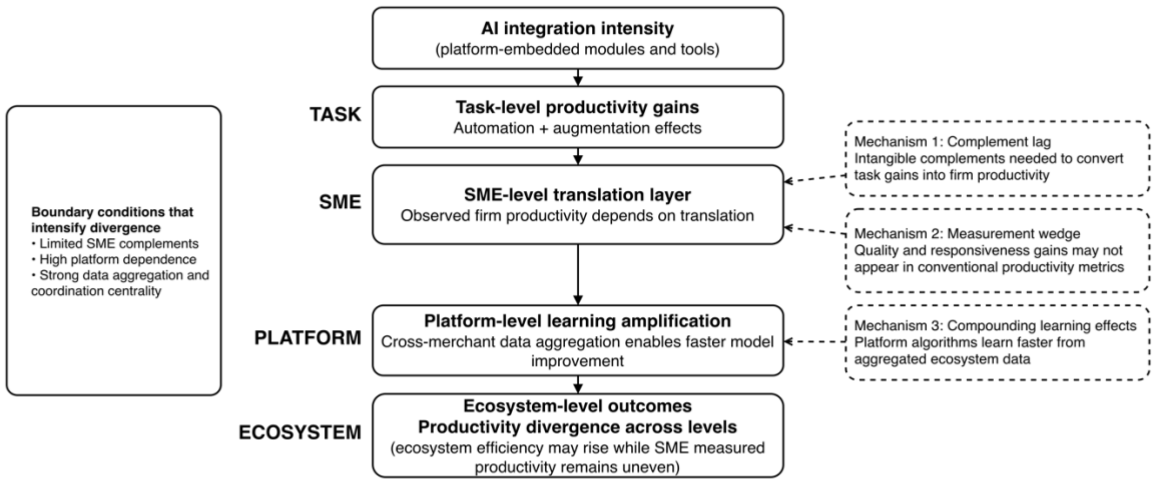

Figure 3. Multi-Level Propagation Mechanisms Driving AI Productivity Divergence in SME-Dominated Digital Ecosystems
Source: Author's conceptualization

The framework articulated in Figure 3 clarifies how AI-generated productivity improvements originate at the task level but are filtered by SME translation frictions (complement lag and measurement wedge) while being amplified by platform-level compounding learning effects. By making the cross-level pathway explicit, Figure 1 supports the article's central claim that the contemporary AI productivity paradox is better understood as a structured misalignment of productivity outcomes across nested layers rather than as an absence of productivity gains.

4. Discussion

The framework presented in this study reframes the contemporary AI productivity paradox by demonstrating how productivity gains propagate unevenly across nested organizational layers in SME-dominated digital ecosystems. Rather than treating productivity as a single outcome at the firm or macroeconomic level, the analysis highlights how AI-induced improvements originate at the task level but are subsequently shaped by organizational complements, measurement dynamics, and ecosystem learning processes. This perspective suggests that uneven productivity outcomes do not necessarily indicate technological underperformance. Instead, they reflect structural translation mechanisms that redistribute gains across tasks, firms, platforms, and ecosystems.

Situating these mechanisms within the broader literature on technological change and digital markets allows a deeper interpretation of AI's productivity effects. The discussion below revisits the productivity paradox through this multi-level lens, clarifies the theoretical implications for strategic management and digital ecosystem research, and outlines boundary conditions that shape the emergence of productivity divergence.

4.1 Reinterpreting the AI Productivity Paradox

The productivity paradox has long captured the tension between rapid technological advancement and relatively modest gains in aggregate productivity statistics. Early discussions of this paradox centered on information technologies, while more recent analyses highlight artificial intelligence as a new source of similar tensions (Brynjolfsson, Rock, & Syverson, 2017). Traditional explanations emphasize implementation lags, mismeasurement of digital value, redistribution of gains, and inflated expectations surrounding emerging technologies.

The present framework complements these explanations by showing that the paradox increasingly reflects cross-level performance dynamics within digitally coordinated ecosystems. Empirical studies of generative AI indicate substantial improvements in individual task performance, including faster completion times and higher output quality (Noy & Zhang, 2023; Brynjolfsson *et al*., 2023). However, improvements observed at the micro level do not necessarily translate into firm-level productivity growth. Organizational translation processes, particularly the development of intangible complements and coordination routines, determine whether task-level efficiency becomes visible in firm-level outcomes (Brynjolfsson *et al*., 2019).

This perspective aligns with general-purpose technology theory, which emphasizes that technological innovations generate economic impact only when accompanied by complementary organizational changes. The framework proposed here extends that insight by showing that complement constraints may interact with ecosystem coordination structures. In SME-dominated markets, firms often access AI through platform-provided infrastructures rather than proprietary development. Consequently, productivity gains generated at the task level may be partially absorbed by platform coordination systems before they appear in SME-level performance indicators.

From this perspective, the productivity paradox should not be interpreted as evidence that AI fails to improve productivity. Instead, it reflects a structural decoupling between levels of analysis. Productivity gains may exist simultaneously at the task and ecosystem levels while remaining unevenly distributed across participating firms.

4.2 Theoretical Contributions to Strategy and Digital Ecosystem Research

Understanding these dynamics offers several contributions to the literature on technological change, strategic management, and platform ecosystems. At a theoretical level, the analysis extends the productivity paradox literature by embedding it within platform-mediated market structures. Traditional accounts typically treat productivity as either a macroeconomic indicator or a firm-level outcome. The multi-level perspective developed here suggests that productivity should instead be examined as a distributed phenomenon shaped by interactions among multiple organizational layers.

This insight also contributes to research on general-purpose technologies. Prior work demonstrates that complementary investments in organizational capital, skills, and workflow redesign determine whether firms capture the benefits of new technologies (Brynjolfsson *et al*., 2019). The present framework shows that complement dynamics may interact with external coordination architectures. Even when firms develop internal capabilities, ecosystem-level learning processes may shift productivity gains toward centralized infrastructures that aggregate data and interactions across participants.

The analysis further extends research on task-based technological change. Studies of automation and AI highlight how technological systems reorganize work by replacing some tasks while augmenting others (Acemoglu & Restrepo, 2019). Organizational theory similarly emphasizes the automation–augmentation paradox, in which AI simultaneously enhances and complicates decision processes (Raisch & Krakowski, 2021). Integrating these insights with ecosystem perspectives reveals that task-level improvements are only the first stage of productivity translation. Whether these improvements scale into firm-level performance depends on how organizations redesign workflows and coordination routines in response to AI integration.

Finally, the framework contributes to the growing literature on digital platforms and data-enabled learning. Platform ecosystems function as meta-organizations that coordinate interactions among diverse participants (Kretschmer, Leiponen, & Schilling, 2022). Because platforms aggregate large volumes of transactional and behavioral data, AI systems embedded within them benefit from accelerated learning dynamics. Data-enabled learning allows algorithms to refine predictions and operational decisions as ecosystem participation expands (Hagiu & Wright, 2023). The resulting compounding effects can amplify productivity at the platform level even when firm-level learning remains constrained.

Taken together, these theoretical perspectives suggest that the productivity effects of AI are shaped by structural asymmetries in complement development, learning scope, and coordination architecture. Productivity divergence therefore emerges as a systemic feature of platform-mediated digital ecosystems rather than as an anomaly in technological performance.

4.3 Strategic Implications for SMEs in AI-Embedded Markets

The multi-level interpretation of AI productivity also carries important implications for strategic management in SME-dominated markets. Firms increasingly encounter AI not as a standalone technology but as a component of digital infrastructures that coordinate marketing, logistics, payments, and customer interactions. Under these conditions, productivity gains depend less on access to AI tools and more on the ability to integrate those tools into coherent organizational routines.

Complement development therefore becomes a critical strategic capability. SMEs that invest in digital literacy, workflow modularity, and data governance are better positioned to translate AI-enabled task improvements into measurable firm-level performance. This observation reinforces findings from research on digital transformation, which emphasizes the importance of intangible organizational assets in realizing technological value.

At the same time, participation in platform ecosystems introduces new strategic tensions. Platforms provide scalable AI infrastructures that enable SMEs to access advanced capabilities at relatively low cost. However, the same infrastructures also accelerate ecosystem-level learning dynamics that may outpace individual firm learning. When platforms aggregate data across thousands of firms, algorithmic improvements may benefit the ecosystem as a whole while limiting the extent to which any single firm captures the resulting productivity gains.

Strategic differentiation thus becomes increasingly important. SMEs may need to develop capabilities that complement rather than replicate platform-level learning, such as specialized domain knowledge, localized market insights, or unique customer relationships. These capabilities allow firms to capture value from AI-enabled coordination without relying solely on standardized platform tools.

Importantly, productivity divergence does not necessarily imply exploitative governance or intentional value extraction by platforms. Structural learning asymmetries alone may generate uneven productivity outcomes. Recognizing this distinction is essential for understanding how digital ecosystems evolve and how firms position themselves within them.

4.4 Boundary Conditions and Future Research

The extent to which productivity divergence emerges depends on several contextual conditions. First, organizational absorptive capacity influences how effectively SMEs translate AI-generated task improvements into firm-level productivity. Firms with stronger digital capabilities and learning routines are more likely to convert algorithmic insights into operational improvements.

Second, workflow modularity affects the coordination burden associated with AI integration. Modular processes enable organizations to incorporate AI tools without generating excessive interdependencies among tasks. In contrast, tightly coupled workflows may experience coordination bottlenecks that offset task-level efficiency gains.

Third, platform centrality shapes ecosystem learning dynamics. As platforms become increasingly embedded in transaction flows and decision processes, the scale advantage of data aggregation intensifies. Under these conditions, platform-level productivity gains may compound more rapidly than firm-level gains, amplifying divergence across the ecosystem.

Future research could examine these dynamics empirically by tracking productivity trajectories across multiple levels of analysis. Longitudinal studies may help distinguish between short-term complement lags and persistent structural divergence. Quantitative analyses could combine firm-level performance data with platform-level indicators of algorithmic learning and ecosystem activity. Qualitative research may further illuminate how SMEs redesign organizational routines to adapt to AI-enabled coordination architectures.

Improving the measurement of productivity in digital environments also remains an important research agenda. Traditional productivity indicators often fail to capture improvements in service quality, responsiveness, and user experience that arise from AI integration. Developing metrics that incorporate these dimensions may provide a more accurate understanding of technological value creation in digital ecosystems.

Taken together, these conditions suggest that the productivity consequences of AI adoption cannot be evaluated solely at the firm level. Instead, productivity outcomes emerge from the interaction between organizational capabilities and ecosystem coordination structures. This perspective highlights how digital infrastructures reshape the distribution of productivity gains across actors participating in platform-mediated markets.

5. Conclusion

This study revisits the contemporary AI productivity paradox by proposing a multi-level explanation of performance divergence in SME-dominated digital ecosystems. Rather than interpreting uneven productivity outcomes as evidence of technological underperformance, the analysis demonstrates that AI-generated gains originate at the task level but propagate unevenly across organizational and ecosystem layers. Complement constraints, coordination frictions, measurement limitations, and asymmetric learning dynamics jointly shape how productivity improvements are translated and distributed across tasks, firms, platforms, and ecosystems.

Integrating insights from productivity paradox theory, general-purpose technology research, task-based technological change, and platform ecosystem scholarship provides a structured explanation for these dynamics. AI improves the efficiency of individual tasks through automation and augmentation mechanisms, yet the realization of firm-level productivity depends on the availability of organizational complements and the ability to redesign workflows around algorithmic systems. At the same time, platform infrastructures that aggregate interactions and data across participants enable accelerated learning processes that may amplify productivity gains at the ecosystem level.

The resulting outcome is not the absence of productivity improvement but the emergence of productivity divergence. Ecosystem efficiency may increase even when SMEs experience uneven or delayed productivity gains, reflecting structural asymmetries in complement development and data-enabled learning. Recognizing this divergence shifts the analytical focus from whether AI increases productivity to where and how productivity gains materialize within digitally coordinated markets.

This perspective contributes to strategic management and digital ecosystem research by clarifying the conditions under which technological innovation generates uneven performance outcomes across interconnected actors. Evaluating the economic consequences of AI adoption therefore requires attention not only to technological capabilities but also to the organizational and ecosystem structures that shape how productivity gains are translated, amplified, and distributed.

References

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives, 33*(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Agrawal, A., Gans, J., & Goldfarb, A. (2022). *Power and prediction: The disruptive economics of artificial intelligence*. Harvard Business Review Press.

Brynjolfsson, E., Li, D., & Raymond, L. R. (2023). Generative AI at work. *National Bureau of Economic Research Working Paper No. 31161*. https://doi.org/10.3386/w31161

Brynjolfsson, E., Rock, D., & Syverson, C. (2017). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (pp. 23–57). University of Chicago Press.

Brynjolfsson, E., Rock, D., & Syverson, C. (2019). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. *American Economic Journal: Macroeconomics, 11*(1), 3–42. https://doi.org/10.1257/mac.20180386

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128–152. https://doi.org/10.2307/2393553

Goldfarb, A., & Tucker, C. (2019). Digital economics. *Journal of Economic Literature, 57*(1), 3–43. https://doi.org/10.1257/jel.20171452

Hagiu, A., & Wright, J. (2023). Data-enabled learning, network effects, and competitive advantage. *The RAND Journal of Economics, 54*(4), 638–667. https://doi.org/10.1111/1756-2171.12470

Kretschmer, T., Leiponen, A., & Schilling, M. A. (2022). Platform ecosystems as meta-organizations: Implications for platform strategies. *Strategic Management Journal, 43*(3), 405–424. https://doi.org/10.1002/smj.3250

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science, 381*(6654), 187–192. https://doi.org/10.1126/science.adh2586

OECD. (2021). *OECD SME and entrepreneurship outlook 2021*. OECD Publishing. https://doi.org/10.1787/97a5bbfe-en

Parker, G. G., Van Alstyne, M. W., & Choudary, S. P. (2016). *Platform revolution: How networked markets are transforming the economy and how to make them work for you*. W. W. Norton & Company.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research, 122*, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022