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FROM PILOT TO SCALE: DETERMINANTS OF SUCCESSFUL ARTIFICIAL INTELLIGENCE, ROBOTICS, AND AUTOMATION ADOPTION IN SUPPLY CHAIN AND FULFILLMENT OPERATIONS

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ABSTRACT

Artificial intelligence, robotics, and automation offer substantial promise for supply chain and fulfillment operations, yet a large share of adoption initiatives stall after promising pilots and never reach enterprise scale, a pattern often described as pilot purgatory. This paper develops a conceptual framework that explains the determinants separating firms that successfully scale these technologies from those whose initiatives remain trapped at the pilot stage. Integrating the technology-organization-environment framework, the diffusion of innovations, the technology acceptance and unified acceptance traditions, absorptive capacity and dynamic capabilities, and sociotechnical systems theory, the framework organizes adoption determinants into three established contexts, technological, organizational, and environmental, and specifies four cross-cutting enabling conditions that are especially decisive for scaling in operational settings: data readiness and integration, workforce and change capability, systems and process integration, and adoption governance. The framework distinguishes the pilot stage from the scaling stage and argues that the determinants of a successful pilot differ from the determinants of successful scaling, which explains why pilots frequently succeed while scaling fails. It further links successful scaling to operational and resilience outcomes, including cost, service, flexibility, and robustness to disruption, thereby connecting technology adoption to supply chain competitiveness. The framework is expressed as a set of testable propositions, illustrated through hypothetical adoption scenarios in fulfillment and logistics, and translated into implications for managers, technology providers, and policymakers concerned with industrial competitiveness and supply chain resilience. A research agenda for empirical validation is outlined. The contribution is a transferable, theory-grounded account of why operational technology adoption so often stalls and what operational capabilities enable it to scale.

Keywords: Artificial intelligence; Robotics; Automation; Technology Adoption; Supply Chain; Fulfillment; Pilot Purgatory; Supply chain resilience; TOE framework; Absorptive capacity

1. INTRODUCTION

Artificial intelligence, robotics, and automation have become central to the modernization of supply chain and fulfillment operations. Warehouse robotics, autonomous material handling, machine-learning demand forecasting, computer-vision quality inspection, and analytics-driven planning collectively promise gains in cost, speed, accuracy, and resilience (Brynjolfsson & McAfee, 2014; Frank *et al.*, 2019; Toorajipour *et al.*, 2021). The rise of electronic commerce, with its demands for rapid, accurate, high-volume fulfillment, has intensified the pressure to adopt these technologies (Boysen *et al.*, 2019). Yet a persistent and widely observed problem tempers this promise: a large proportion of adoption initiatives that succeed as pilots fail to scale into durable, enterprise-wide operational capability. This phenomenon, often termed pilot purgatory or the proof-of-concept trap, is a defining challenge of contemporary operational technology adoption (Fountaine *et al.*, 2019; Ransbotham *et al.*, 2017).

The gap between successful pilots and successful scaling is consequential. When firms cannot scale operational technologies, they forgo the productivity and resilience benefits those technologies could provide, and the aggregate effect is a drag on industrial competitiveness and supply chain robustness. Understanding why scaling fails, and what distinguishes firms that scale successfully, is therefore a question of both managerial and economic importance. The premise of this paper is that the determinants of a successful pilot differ systematically from the determinants of successful scaling, and that the latter are predominantly operational and organizational rather than narrowly technological. A pilot can succeed on the strength of an enthusiastic team, a favorable use case, and vendor support, yet scaling requires data infrastructure, integration with existing systems and processes, workforce capability, and governance that pilots do not test.

This paper develops a conceptual framework that identifies and organizes the determinants of successful adoption at scale for artificial intelligence, robotics, and automation in supply chain and fulfillment operations. The framework integrates several established theoretical traditions in technology adoption and operations management and specifies the enabling conditions that are especially decisive when moving from pilot to scale. It is developed as a conceptual contribution, articulating constructs and their relationships and expressing them as testable propositions, in the tradition of theory-building conceptual research (Meredith, 1993; Whetten, 1989).

The paper makes three contributions. First, it synthesizes fragmented adoption theory into a coherent, operations-focused framework distinguishing pilot determinants from scaling determinants. Second, it identifies four cross-cutting enabling conditions, data readiness and integration, workforce and change capability, systems and process integration, and adoption governance, that operate across the standard adoption contexts and are particularly binding at the scaling stage. Third, it links successful scaling to operational and resilience outcomes, connecting technology adoption to supply chain competitiveness and thereby to industrial resilience. The remainder of the paper reviews the pilot-to-scale problem, presents the theoretical background, delimits the technologies in scope, develops the framework and its determinants, advances the propositions, links scaling to outcomes, illustrates application, and discusses implications before concluding.

2. BACKGROUND AND THEORETICAL FOUNDATIONS

2.1 The Pilot-to-Scale Problem in Operational Technology

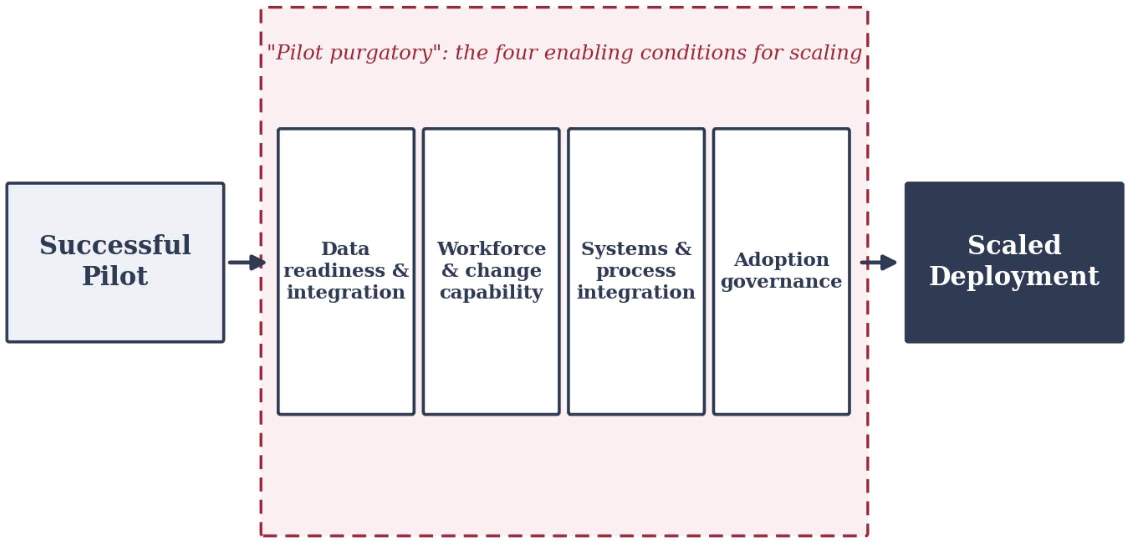

Figure 1: The pilot-to-scale problem. A successful pilot reaches scaled deployment only by crossing the four enabling conditions; firms that fail to build them remain in "pilot purgatory."

The observation that operational technology initiatives frequently stall after pilots is well established in both practitioner and scholarly accounts. Surveys of artificial intelligence adoption consistently report that many firms experiment while comparatively few achieve production-scale deployment that materially affects operations (Benbya *et al.*, 2020; Fountaine *et al.*, 2019; Ransbotham *et al.*, 2017). The pattern is not confined to artificial intelligence; the broader Industry 4.0 literature documents difficulty in moving from isolated demonstrations to integrated, scaled implementation across manufacturing and logistics (Frank *et al.*, 2019; Xu *et al.*, 2018). The recurring theme is that scaling is qualitatively different from piloting, and that the capabilities required for one differ from those required for the other.

Several structural reasons explain why pilots understate the difficulty of scaling. Pilots are typically conducted in favorable, bounded conditions, on a single site, with a curated dataset, a supportive team, and vendor attention, none of which generalizes automatically to enterprise-wide operation. Scaling exposes the initiative to heterogeneous data, legacy systems, diverse workforces, and the full complexity of live operations. It also shifts the binding constraints from technical feasibility, which the pilot demonstrates, to organizational and operational integration, which the pilot does not test. Consequently, a framework that explains scaling must attend to determinants that pilots systematically fail to surface.

This reasoning reframes the adoption question. The relevant managerial question is not merely whether a technology works, which pilots answer, but whether the firm possesses the operational and organizational conditions to integrate the technology into standard operations at full scale and to sustain it. The framework developed below is organized around that question, and it treats the pilot-to-scale transition as the phenomenon to be explained rather than adoption in the abstract.

2.2 Theoretical Background

The framework integrates several complementary traditions in technology adoption and operations management. The technology-organization-environment framework provides the organizing structure, positing that the adoption and implementation of technological innovations by firms are shaped by three contexts: the characteristics of the technology, the characteristics of the organization, and the characteristics of the external environment (Baker, 2012; Tornatzky & Fleischer, 1990). The framework has been applied extensively to firm-level information-technology adoption and is well suited to operational technologies because it accommodates organizational and environmental determinants that individual-level acceptance models omit (Oliveira & Martins, 2011; Zhu *et al.*, 2006).

The diffusion of innovations tradition complements the technology-organization-environment framework by specifying attributes of innovations, including relative advantage, compatibility, complexity, trialability, and observability, that influence their rate of adoption (Rogers, 2003). These attributes are directly relevant to operational technologies: complexity and compatibility, in particular, shape how difficult a technology is to integrate at scale. Organizational-level diffusion research further distinguishes the stages of adoption and assimilation, emphasizing that assimilation into routine use is a distinct and more demanding achievement than initial adoption (Fichman, 2004; Fichman & Kemerer, 1997; Swanson, 1994).

Individual-level acceptance theory explains the behavioral response of the workers who must use new technologies. The technology acceptance model links perceived usefulness and perceived ease of use to acceptance (Davis, 1989; Davis *et al.*, 1989), and the unified theory of acceptance and use of technology consolidates competing models into performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh *et al.*, 2003; Venkatesh & Bala, 2008). These constructs matter for scaling because enterprise-wide deployment depends on acceptance by a large, heterogeneous workforce rather than by a self-selected pilot team.

Absorptive capacity and dynamic capabilities explain why firms differ in their capacity to adopt and operationalize new technologies. Absorptive capacity, the ability to recognize, assimilate, and apply new external knowledge, depends on prior related knowledge and internal integration mechanisms (Cohen & Levinthal, 1990; Zahra & George, 2002). Dynamic capabilities, the capacity to integrate, build, and reconfigure competences, govern the organizational reconfiguration that scaling requires (Teece, 2007; Teece *et al.*, 1997). Firms with stronger absorptive capacity and dynamic capabilities can move from pilot to scale more rapidly and with less disruption.

Finally, sociotechnical systems theory frames technology adoption as the joint optimization of a social system and a technical system rather than the insertion of technology into a passive organization (Bostrom & Heinen, 1977; Trist & Bamforth, 1951). This perspective is essential for operational automation and robotics, where technology reshapes work, roles, and coordination on the operations floor. It warns that scaling which optimizes the technical system while neglecting the social system will encounter resistance, workarounds, and degraded performance (Leonardi, 2011; Orlikowski, 1992). Together, these traditions supply the constructs from which the framework is composed.

2.3 Technologies in Scope

The framework addresses three overlapping categories of operational technology whose adoption in supply chain and fulfillment shares the pilot-to-scale challenge. The first is robotics and physical automation, including autonomous mobile robots, automated storage and retrieval systems, robotic picking and palletizing, and conveyor and sortation automation. Warehouse robotics has advanced rapidly under electronic-commerce demand, and the coordination of large fleets of autonomous vehicles in fulfillment centers is a recognized technical and operational achievement (Bogue, 2016; Boysen *et al.*, 2019; Wurman *et al.*, 2008). Physical automation is capital-intensive and tightly coupled to facility design and process flow, which makes its scaling especially dependent on integration with existing operations (de Koster *et al.*, 2007).

The second category is artificial intelligence and machine learning applied to operational decisions, including demand forecasting, inventory and replenishment optimization, network and routing optimization, computer-vision inspection, and predictive maintenance. Machine learning offers substantial gains where data are abundant and decisions are repetitive, but its operational value depends on data quality and on integration into decision processes (Baryannis *et al.*, 2019; Choi *et al.*, 2018; Toorajipour *et al.*, 2021). The third category is advanced analytics and data-driven decision systems, encompassing the descriptive and predictive analytics that increasingly underpin planning and control (Gunasekaran *et al.*, 2017; Waller & Fawcett, 2013; Wamba *et al.*, 2017). These categories are treated together because, despite their technical differences, they present a common scaling problem: each succeeds in bounded pilots and each requires data, integration, workforce, and governance conditions to scale, which is the focus of the framework. Applied operations studies demonstrate this pattern, applying machine learning and predictive analytics to demand forecasting, IoT-enabled predictive management, and AI-based operational decision support (Adelanwa *et al.*, 2024; Akin-Oluyomi *et al.*, 2023; Kumuyi *et al.*, 2024). Related applied work applies machine-learning demand forecasting and algorithmic route optimization to the forecasting, replenishment, and logistics decisions that operations increasingly delegate to these systems (Tonoyan *et al.*, 2021; Tonoyan *et al.*, 2025).

Table 1: The three categories of operational technology in scope.

Category	Representative technologies	Scaling characteristic
Robotics and physical automation	Autonomous mobile robots; automated storage and retrieval; robotic picking and palletizing; conveyor and sortation.	Capital-intensive and tightly coupled to facility design and process flow.
Artificial intelligence and machine learning	Demand forecasting; inventory and replenishment optimization; network and routing optimization; computer-vision inspection; predictive maintenance.	Value depends on data quality and on integration into decision processes.
Advanced analytics and data-driven decision systems	Descriptive and predictive analytics that underpin planning and control.	Succeed in bounded pilots; scaling requires data, integration, and governance.

3. THE ADOPTION FRAMEWORK

3.1 A Framework of Adoption Determinants

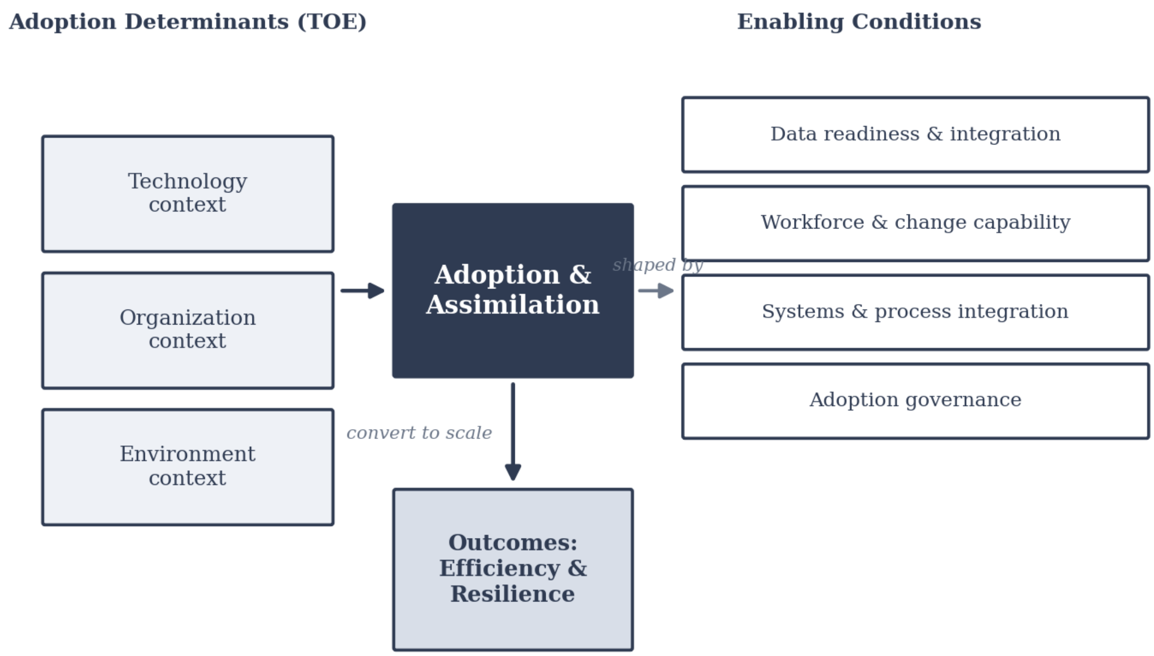

Figure 2: The adoption framework. Technology, organization, and environment determinants drive adoption; four cross-cutting enabling conditions convert adoption into scaled deployment and operational and resilience outcomes.

The framework organizes the determinants of successful adoption using the three contexts of the technology-organization-environment framework, and it specifies four cross-cutting enabling conditions that operate across these contexts and are especially decisive at the scaling stage. The three contexts identify the broad categories of determinant; the four enabling conditions identify the operational capabilities that, in the setting of supply chain and fulfillment, most strongly differentiate firms that scale from those that stall.

Technological context. The characteristics of the technology influence its adoption and scaling, consistent with the diffusion attributes of relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003). For operational technologies, compatibility with existing processes and complexity of integration are particularly consequential at scale, because a technology that is straightforward to demonstrate in isolation may be difficult to integrate across heterogeneous sites and legacy systems. Relative advantage that is clear in a pilot may also attenuate at scale if the technology performs unevenly across the full range of operating conditions.

Organizational context. The characteristics of the organization, including its resources, structure, leadership, absorptive capacity, and change capability, shape its ability to scale. Top-management support, slack resources, and a supportive structure are consistently associated with successful assimilation of technological innovations (Fichman, 2004; Zhu *et al.*, 2006). Absorptive capacity determines how effectively the firm assimilates the knowledge that scaling requires

(Cohen & Levinthal, 1990), and dynamic capabilities govern the reconfiguration of processes and structures that enterprise-wide deployment entails (Teece, 2007). The organizational context is where the four enabling conditions predominantly reside.

Environmental context. The external environment, including competitive pressure, customer requirements, the maturity of the technology and vendor ecosystem, and the regulatory and labor context, conditions adoption and scaling. Competitive and customer pressure, notably the demands of electronic commerce, can accelerate adoption (Boysen *et al.*, 2019), while the maturity of the vendor and integration ecosystem affects the feasibility and cost of scaling. Labor-market conditions and the availability of relevant skills also belong to this context and interact with the workforce enabling conditions (Acemoglu & Restrepo, 2020; Autor, 2015).

3.2 The Four Cross-Cutting Enabling Conditions for Scaling

Within the organizational context, and interacting with the technological and environmental contexts, four enabling conditions are especially decisive in moving operational technologies from pilot to scale. These conditions are the operational capabilities that pilots do not test and that most frequently constitute the binding constraint on scaling.

Data readiness and integration. Artificial intelligence and analytics depend on data that are available, accurate, consistent, integrated, and accessible across the operation. Data quality is a well-documented determinant of the value realized from analytics, and poor data quality is a primary reason initiative fail at scale (Hazen *et al.*, 2014; Redman, 1998; Wang & Strong, 1996). A pilot can be run on a curated dataset from a single site; scaling requires data integration across sites, systems, and partners, and the absence of this integration is a frequent binding constraint. Data readiness also conditions physical automation, which increasingly depends on data for coordination and control. Firms that have invested in data governance, integration, and quality can scale data-dependent technologies that firms with fragmented data cannot. Applied research reinforces the point, tying data-driven supply-chain optimization and enterprise business-intelligence capability to the integrated data foundations that scaling depends on (Akinleye *et al.*, 2023; Efobi *et al.*, 2022). Applied frameworks for asset-lifecycle and inventory visibility and for risk-based business-intelligence architecture underscore that integrated, trustworthy data across the operation is the substrate on which scaled analytics depend (Mbonu *et al.*, 2021; Okonkwo *et al.*, 2023).

Workforce and change capability. Scaling operational technology reshapes work and requires acceptance and new competencies across a large workforce, not merely a pilot team. Acceptance theory indicates that use depends on perceived usefulness, ease of use, and facilitating conditions (Davis, 1989; Venkatesh *et al.*, 2003), and sociotechnical theory indicates that neglecting the social system produces resistance and degraded performance (Bostrom & Heinen, 1977; Trist & Bamforth, 1951). Automation also changes skill requirements and can displace or reconfigure tasks, making workforce reskilling and change management central to scaling (Acemoglu & Restrepo, 2020; Autor, 2015). Firms with strong change capability and workforce development scale with less disruption than firms that treat adoption as a purely technical exercise. Applied studies of digital transformation and human-in-the-loop deployment similarly stress structured change management and the deliberate retention of human oversight as automation and machine learning are introduced (Ladapo *et al.*, 2022, 2024). Structured user-acceptance-testing and validation practices in operational technology deployment similarly formalize the acceptance and facilitating conditions that scaled use depends on (Eyetsemitan *et al.*, 2023).

Systems and process integration. Operational technologies deliver value only when integrated into the systems and processes of the operation. Physical automation must integrate with facility design, material flow, and warehouse-management and control systems; analytics and machine learning must integrate into planning and control processes so that their outputs drive decisions (de Koster *et al.*, 2007; Frank *et al.*, 2019). Integration is precisely what pilots avoid and scaling requires, and the maturity of the firm existing systems and the complexity of legacy integration are therefore decisive. Poorly integrated deployments produce islands of automation that do not improve end-to-end performance. Applied work on enterprise platform integration and large-scale cloud migration documents both the integration discipline this requires and the performance cost when it is absent (Ladapo *et al.*, 2025; Okoruwa *et al.*, 2024). Applied frameworks that integrate SOP design, automation, and compliance for scaling operations, and that connect IT and procurement systems at national scale, illustrate the integration discipline that converts isolated capability into end-to-end performance (Eyetsemitan *et al.*, 2025; Okonkwo *et al.*, 2025).

Adoption governance. Scaling requires governance that pilots rarely establish: a portfolio and prioritization mechanism, defined ownership and accountability, funding and resourcing for the transition from pilot to production, performance measurement, and management of the risks that operational technologies introduce. Research on the assimilation of innovations emphasizes that sustained, coordinated management is necessary to convert adoption into routine use (Fichman & Kemerer, 1997; Markus, 2004; Swanson, 1994). Without governance, promising pilots proliferate without a path to production, funding lapses at the pilot-to-scale boundary, and accountability for enterprise outcomes is diffuse. Governance also encompasses the management of model risk, safety, and reliability that operational artificial intelligence and robotics require. Applied governance research develops these mechanisms for AI-enabled operations, specifying deployment governance, risk management, and organizational-readiness structures alongside KPI-driven prioritization and adoption oversight (Badmus *et al.*, 2025; Edivri & Oteri, 2024). Applied governance frameworks for digital supply chains and for agile transformation with embedded risk and compliance controls specify the ownership, risk, and compliance structures that sustained, scaled adoption requires (Mbonu *et al.*, 2020; Okonkwo *et al.*, 2024).

Table 2: The four cross-cutting enabling conditions for scaling.

Enabling condition	Description
Data readiness and integration	Sufficient, high-quality, integrated data across the operation to support scaled analytics and automation.
Workforce and change capability	Capacity to reskill, redeploy, and lead the workforce through the role changes that automation introduces.
Systems and process integration	Embedding new technologies into enterprise systems and end-to-end processes rather than isolated deployments.
Adoption governance	Ownership, prioritization, risk and model governance, and oversight that carry pilots into sustained production use.

4. PROPOSITIONS AND OUTCOMES

4.1 Propositions

The framework yields propositions that specify the expected relationships among the determinants, the pilot-to-scale transition, and outcomes. The propositions are stated to be testable in the empirical program described later.

Proposition 1. The determinants of successful piloting differ from the determinants of successful scaling, such that pilot success is a weak predictor of scaling success, and firms that achieve scale are distinguished primarily by the four enabling conditions rather than by pilot performance.

Proposition 2. Data readiness and integration is a necessary condition for scaling data-dependent artificial intelligence and analytics, such that low data readiness constrains scaling regardless of the strength of other determinants.

Proposition 3. Workforce and change capability is positively associated with the speed and completeness of scaling and negatively associated with implementation disruption, and this relationship is stronger for technologies that substantially reshape work.

Proposition 4. Systems and process integration mediates the relationship between technology adoption and operational performance improvement, such that deployments that are not integrated into end-to-end processes yield limited performance gains even when technically successful.

Proposition 5. Adoption governance moderates the conversion of pilots into scaled deployments, such that firms with stronger governance convert a higher proportion of pilots into production and sustain them more reliably.

Proposition 6. Absorptive capacity and dynamic capabilities are positively associated with scaling success and operate in part through their effect on the four enabling conditions.

Proposition 7. Successful scaling of these technologies improves not only operational performance, in cost, service, and flexibility, but also supply chain resilience, in robustness and recoverability, and the resilience benefit is contingent on the design of the deployment.

Table 3: Summary of the seven propositions.

	Proposition (summary)
P1	The determinants of successful piloting differ from those of successful scaling; pilot success is a weak predictor of scaling success.
P2	Data readiness and integration is a necessary condition for scaling data-dependent artificial intelligence and analytics.
P3	Workforce and change capability raises the speed and completeness of scaling and lowers implementation disruption.
P4	Systems and process integration mediates the link between technology adoption and operational performance improvement.
P5	Adoption governance moderates the conversion of pilots into scaled production deployments.
P6	Absorptive capacity and dynamic capabilities support scaling success, partly through the four enabling conditions.
P7	Successful scaling improves both operational performance (cost, service, flexibility) and supply chain resilience.

4.2 From Scaling to Operational and Resilience Outcomes

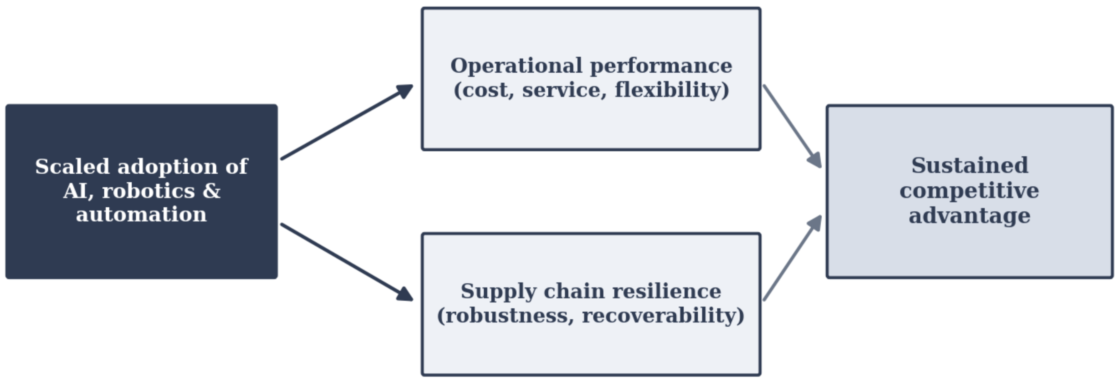

Figure 3. Outcome pathway. Scaled adoption improves operational performance and supply chain resilience, which together support sustained competitive advantage.

The value of scaling operational technologies lies in the outcomes it produces, and the framework links successful scaling to two families of outcome. The first is operational performance, encompassing cost, quality, speed, and flexibility. Robotics and automation can reduce unit costs and increase throughput and accuracy in fulfillment; analytics and machine learning can improve forecast accuracy, inventory efficiency, and routing (Choi *et al.*, 2018; Gunasekaran *et al.*, 2017; Waller & Fawcett, 2013). These gains, however, are realized only when the technology is integrated into processes and used consistently, which is why the framework treats integration and workforce acceptance as conditions for outcome realization rather than automatic consequences of adoption. Applied studies link digital operational transformation and engineered service-assurance systems to efficiency and to sustained reliability as transaction volumes grow (Okoruwa *et al.*, 2025; Oteri & Edivri, 2026). Applied studies link algorithmic process optimization and scalable workflow automation directly to cost reduction and process efficiency at scale (Eyetsemitan *et al.*, 2024; Tonoyan *et al.*, 2022).

The second family is supply chain resilience, the capacity of the operation to resist, absorb, and recover from disruption. Resilience has become a central concern following widespread disruption to global supply chains, and it is analytically distinct from efficiency (Christopher & Peck, 2004; Pettit *et al.*, 2010; Ponomarov & Holcomb, 2009; Sheffi & Rice, 2005). Operational technologies can enhance resilience by improving visibility, enabling rapid replanning, and providing flexible capacity, and analytics and artificial intelligence specifically support the sensing and response that resilience requires (Baryannis *et al.*, 2019; Ivanov *et al.*, 2017). Applied logistics research illustrates this through predictive, technology-enabled resilience design and formal resilience indexing for supply networks under disruption (Anene & Clement, 2022; Efobi *et al.*, 2023). Applied supply-chain research develops predictive vendor-risk and resilience frameworks that link technology-enabled monitoring to networks that withstand disruption (Ogunwole *et al.*, 2021; Tonoyan *et al.*, 2024). The resilience benefit is contingent, however: automation that is highly efficient but rigid can reduce flexibility and increase fragility, so the design of a scaled deployment determines whether it strengthens or weakens resilience (Brandon-Jones *et al.*, 2014; Wieland & Wallenburg, 2013). By linking scaling to both efficiency and resilience outcomes, the framework connects firm-level technology adoption to the competitiveness and robustness of supply chains, and thereby to the broader concern with industrial resilience.

5. APPLICATION AND IMPLICATIONS

5.1 Illustrative Adoption Scenarios

Three hypothetical scenarios illustrate the framework as a diagnostic lens on the pilot-to-scale transition. They are constructed to demonstrate the framework logic and do not report empirical cases.

Scenario A: Warehouse robotics stalled at one site. A fulfillment operator pilots autonomous mobile robots successfully at a single site but fails to replicate the result across its network. Applying the framework, the binding constraint is systems and process integration: the pilot site was configured around the robots, but the other sites differ in layout and warehouse-management systems, and the firm lacks a standardized integration approach. The framework directs attention to establishing an integration and facility-design standard and to the governance needed to fund and manage multi-site rollout, rather than to the robotics technology itself, which the pilot has already validated.

Scenario B: A forecasting model that never reaches production. A retailer develops a machine-learning demand-forecasting model that outperforms its incumbent method in a pilot but cannot deploy it into planning. The framework identifies two binding constraints: data readiness, because production data across the full assortment are fragmented and inconsistent unlike the curated pilot dataset, and process integration, because the planning process is not designed to consume model outputs. The prescriptive implication is to invest in data integration and to redesign the planning process to act on the forecasts, addressing the enabling conditions that the pilot did not test.

Scenario C: Automation that erodes resilience. A logistics firm scales a highly automated sortation system that reduces cost but proves brittle when volumes spike or inputs vary, reducing service during disruptions. The framework interprets this through the resilience contingency in Proposition 7: the deployment optimized efficiency at the expense of flexibility. The implication is that scaling decisions should weigh resilience alongside efficiency and that deployment design should preserve flexible capacity, illustrating that successful scaling is not solely a matter of cost reduction.

5.2 Implications for Practice and Policy

For operations and technology leaders, the framework reframes the adoption challenge around the pilot-to-scale transition and directs attention to the four enabling conditions that pilots do not test. It implies that firms should assess data readiness, workforce and change capability, systems and process integration, and adoption governance before committing to scaling, and should treat a successful pilot as necessary but far from sufficient. The framework also implies that investment should be sequenced to relieve the binding enabling condition rather than distributed evenly, since scaling is constrained by the weakest condition. Recognizing that pilot success predicts scaling success only weakly can help firms avoid the common error of scaling on the strength of pilot results alone. Applied research on managing high-demand technology programs and system rollouts underscores that disciplined rollout and performance-optimization practices govern whether validated pilots translate into dependable enterprise-scale operation (Oteri & Edivri, 2024).

For technology providers and integrators, the framework indicates that the value proposition for operational technologies must address the enabling conditions, not only the technology. Providers that support data integration, workforce transition, systems integration, and governance help customers cross the pilot-to-scale boundary and thereby realize the value on which sustained adoption depends. This reframes the provider role from selling capability to enabling operational integration.

For policymakers concerned with industrial competitiveness and supply chain resilience, the framework implies that programs to accelerate operational technology adoption should build the enabling conditions, particularly data readiness, workforce capability, and integration know-how, rather than subsidize technology acquisition alone. Because the enabling conditions are firm capabilities that are costly to build and unevenly distributed, public support for capability building, workforce reskilling, and the diffusion of integration methodologies may yield more durable competitiveness and resilience gains than support for acquisition. Applied work on localized supply-chain capacity reinforces the link between regional operational infrastructure and economic resilience (Anene & Clement, 2024). The framework also connects firm-level adoption to supply chain resilience, a matter of national economic importance, and suggests that resilience should be an explicit criterion in the evaluation of automation investments rather than an afterthought to efficiency.

6. EXTENDED THEORETICAL DISCUSSION

6.1 Foundations of Technology Adoption and Assimilation

The framework builds on a deep literature on individual and organizational technology adoption. Acceptance research beyond the original acceptance model specifies the perceptions that drive use, including relative advantage, compatibility, and the facilitating conditions that support sustained adoption (Moore & Benbasat, 1991; Venkatesh & Bala, 2008; Venkatesh *et al.*, 2012). The behavioral foundations of these models, including the roles of attitude, intention, and perceived behavioral control, clarify why worker acceptance is decisive when automation reshapes a large number of roles rather than a single pilot team (Ajzen, 1991; Davis *et al.*, 1989).

At the organizational level, the diffusion and assimilation literatures explain how the attributes of an innovation and the readiness of the adopting organization jointly govern uptake (Iacovou *et al.*, 1995; Tornatzky & Klein, 1982; Zhu *et al.*, 2006). This work distinguishes initial adoption from the deeper assimilation through which a technology becomes embedded in routine use, a distinction that maps directly onto the pilot-to-scale problem at the center of the framework.

Implementation research further shows that assimilation proceeds through stages and depends on organizational learning, top-management engagement, and the resolution of the tensions that new systems create with established practice (Cooper & Zmud, 1990; Gallivan, 2001; Liang *et al.*, 2007; Robey *et al.*, 2002). Applied studies of technology deployment and regulatory-compliance workflow design in operating environments illustrate the same requirement to translate a validated capability into governed, routine practice (Eyetsemitan *et al.*, 2021).

6.2 Industry 4.0, Big Data, and Artificial Intelligence in Operations

The technologies in scope are situated within the broader Industry 4.0 transformation, whose adoption research links digital manufacturing and logistics technologies to operational performance while documenting uneven implementation and persistent barriers to scaling (Buchi *et al.*, 2020; Dalenogare *et al.*, 2018; Ivanov *et al.*, 2019; Kamble *et al.*, 2018). This body of work reinforces the central claim of the framework that technological availability is necessary but far from sufficient for operational value.

The value of analytics and machine learning depends on a firm ability to build a distinctive data-analytics capability rather than merely to acquire tools, a finding consistent across the big-data-capability literature (Brynjolfsson & McAfee, 2014; Dubey *et al.*, 2019; Grover *et al.*, 2018; Mikalef *et al.*, 2019). This capability view parallels the data-readiness enabling condition and explains why firms with comparable technologies realize very different returns.

Research on artificial intelligence in business and operations similarly emphasizes that value is realized through integration into decisions and processes, appropriate governance of model risk, and realistic expectations about capability (Brock & von Wangenheim, 2019; Davenport & Ronanki, 2018; Enholm *et al.*, 2022; Makridakis, 2017; Min, 2010). These themes recur across the enabling conditions and motivate the treatment of governance as a distinct condition for scaling.

6.3 Robotics and Automation in Warehousing and Fulfillment

The physical-automation category draws on operations research into warehousing and intralogistics, which reviews the design, control, and performance of automated and robotized systems and the conditions under which they deliver advantage (Azadeh *et al.*, 2019; Baker & Halim, 2007; Boysen *et al.*, 2019; Fragapane *et al.*, 2021). A consistent theme is that the benefit of automation depends on its integration with facility design, material flow, and control systems, echoing the systems-and-process-integration enabling condition.

Automation also reconfigures the division of labor between people and machines, and sociotechnical research shows that scaled deployments require deliberate attention to human roles, collaboration, and acceptance rather than treating automation as a purely technical substitution (Klumpp, 2018). Applied process-redesign work demonstrates how restructuring workflows around new capability, rather than overlaying it on existing processes, is what converts automation into throughput and quality gains at scale (Oyeleye *et al.*, 2022).

6.4 Data, Governance, and Integration Foundations

The integration enabling condition is grounded in supply-chain-management scholarship that defines cross-boundary integration and connects it to performance and collaborative advantage (Cao & Zhang, 2011; Chen & Paulraj, 2004; Mentzer *et al.*, 2001). Scaling operational technologies typically deepens interdependence across systems and partners, so the maturity of integration mechanisms is decisive for whether a scaled deployment improves end-to-end performance.

The governance enabling condition connects to applied work on data governance and on the coordination of processes across parties in regulated environments. Studies of enterprise data-sensitivity classification, data-lakehouse governance, and multi-stakeholder governance alignment specify the ownership, classification, and control mechanisms that scaled, data-intensive operation requires (Aliliele *et al.*, 2024; Aliliele *et al.*, 2025; Eyetsemitan *et al.*, 2020). These mechanisms are precisely the structures that pilots omit and that scaling makes indispensable.

6.5 Resilience, Workforce, and Methodological Considerations

The resilience outcome connects to a large literature that defines supply chain resilience, distinguishes it from efficiency, and reviews the methods used to analyze it (Ali *et al.*, 2017;

Hosseini *et al.*, 2019; Tukamuhabwa *et al.*, 2015). Recent work specifically examines how analytics and artificial intelligence can strengthen resilience through improved sensing, prediction, and response (Belhadi *et al.*, 2022; Riahi *et al.*, 2021). Applied supply-chain research in high-risk, capital-intensive operations extends these ideas to network risk management and to the maintenance of operational uptime under stress (Agbabiaka *et al.*, 2019; Okonkwo *et al.*, 2018).

The workforce and regional dimensions of adoption connect the framework to broader questions of economic development. Because automation reshapes work and its benefits and costs are unevenly distributed, scaling decisions have consequences for regional economic resilience and for the diffusion of standardized operational capability across firms (Komi, 2025; Ogbete *et al.*, 2026). Positioning the framework within the analytics-capability and artificial-intelligence-value literatures also clarifies its validation agenda, which calls for capability measures with demonstrated reliability and for tests of whether the enabling conditions predict scaling outcomes across firms and technologies (Enholm *et al.*, 2022; Mikalef *et al.*, 2019).

6.6 Big Data Analytics Capability in Supply Chain and Logistics

Within operations specifically, a stream of research examines how big-data analytics create value in supply chain and logistics, distinguishing the possession of data from the capability to convert it into decisions (Nguyen *et al.*, 2018; Sanders, 2016; Wang *et al.*, 2016). These studies consistently find that analytics deliver value when they are embedded in decision processes and supported by organizational capabilities, reinforcing the data-readiness and integration conditions at the center of the framework.

Complementary work on analytics-enabled decision making in the era of large-scale data emphasizes the interplay between human judgment and algorithmic recommendation, and the organizational arrangements required to act on analytical output at scale (Duan *et al.*, 2019; Grover *et al.*, 2018). This literature helps explain why analytical capability, rather than analytical tooling, discriminates between firms that scale successfully and those that stall.

6.7 Artificial Intelligence, Augmentation, and Operational Work

A growing management literature reframes artificial intelligence in operations as a matter of augmentation as much as automation, arguing that scaled value depends on designing the division of labor between people and machines rather than pursuing substitution alone (Raisch & Krakowski, 2021; von Krogh, 2018; Davenport & Kirby, 2016). This augmentation view aligns with the workforce enabling condition and with the sociotechnical premise that human and technical subsystems must be jointly optimized.

Empirical and integrative studies of the business value of artificial intelligence show that returns accrue to firms that build complementary organizational capabilities and redesign processes, and that the effects of automation on work and organizations are mediated by managerial choices (Acemoglu & Restrepo, 2019; Cascio & Montealegre, 2016; Dwivedi *et al.*, 2021; Wamba-Taguimdje *et al.*, 2020). These findings underscore that the enabling conditions, not the technology alone, determine whether scaling delivers value. Broader scholarship on the economics and strategy of artificial intelligence reinforces this augmentation view, arguing that value depends on complementary organizational change and on treating prediction as an input to redesigned decisions (Agrawal *et al.*, 2018; Brynjolfsson *et al.*, 2021; Choi *et al.*, 2022; Iansiti & Lakhani, 2020; Kohli & Melville, 2019).

6.8 Post-Adoption Assimilation and Sustained Use

The pilot-to-scale problem is closely related to the post-adoption phase of technology use, which research shows is distinct from initial adoption and often more consequential for realized value (Purvis *et al.*, 2001; Zhu & Kraemer, 2005). Post-adoption studies find that deep, routinized use depends on assimilation mechanisms, knowledge integration, and management engagement, all of which are typically underdeveloped at the pilot stage.

This body of work complements the assimilation literature discussed earlier and clarifies why the framework treats scaling as the achievement of sustained, enterprise-wide use rather than as the completion of a deployment (Gallivan, 2001; Liang *et al.*, 2007). The enabling conditions can be read as the organizational supports that carry a technology from initial adoption through full assimilation.

6.9 Resilience under Disruption: Ripple Effects and Digital Capability

The resilience outcome is further illuminated by research on disruption propagation and recovery in supply chains, which analyzes how localized disruptions cascade through networks and how firms can design for containment and recovery (Dolgui *et al.*, 2018; Kamalahmadi & Parast, 2016). This literature specifies mechanisms through which the integration and data conditions translate into the capacity to withstand and recover from disruption.

Recent work shows how digital capabilities, including simulation-based analysis and digital-twin representations of the supply chain, can strengthen anticipation and response under severe disruption (Belhadi *et al.*, 2022; Ivanov, 2020; Ivanov & Dolgui, 2021). Scaling operational technologies therefore has a resilience dimension that pilots, conducted under normal conditions, are poorly designed to reveal.

6.10 Cross-Sector Applied Evidence on Operational Adoption

Applied research from professional operating environments provides cross-sector evidence for the enabling conditions. Studies of procurement and vendor governance, port and logistics efficiency, materials readiness and maintenance-driven supply-chain performance, and standardized operating procedures as strategic assets show how disciplined operating practice underpins the transition from isolated capability to scaled performance (Eyetsemitan *et al.*, 2022; Okonkwo *et al.*, 2019; Okonkwo *et al.*, 2020; Okonkwo *et al.*, 2021).

A second cluster concerns the data, governance, and automation foundations that scaled adoption requires. Frameworks for enterprise data-protection governance, automated log analytics and incident response, AI-enabled IT controls and audit automation, and predictive-analytics and valuation models illustrate how governed data and analytical capability support dependable operation at scale (Aliliele *et al.*, 2023; Mbonu *et al.*, 2018; Mbonu *et al.*, 2019; Mbonu *et al.*, 2022; Tonoyan *et al.*, 2023).

A third cluster provides field evidence on robotics, automation, and artificial intelligence in operational settings. Work on national-scale unmanned-aerial-vehicle deployment for infrastructure inspection, deep-learning classification for corridor management, and a maturity model for predicting audit outcomes in resource-constrained environments demonstrates both the operational value of these technologies and the assessment discipline that scaled deployment requires (Adeyelu & Dagodzo, 2024; Dagodzo *et al.*, 2022; Dagodzo & Ahiaeke Patrick, 2025).

A final cluster speaks to the workforce, assurance, resilience, and regional dimensions of adoption. Studies of workforce training models, internal assurance systems, near-miss data utilization for organizational learning, data-driven risk control in large-scale projects, healthcare-infrastructure performance metrics, standardized and scalable service-network design, edge intelligence for resilient control, and the link between community trust and infrastructure durability show that the enabling-condition logic generalizes across sectors and up to the regional scale (Aminu-Ibrahim *et al.*, 2025; Arumosoye & Obriki, 2019; Komi & Ganiu, 2023; Komi & Adeniji, 2024; Obogo *et al.*, 2020; Obriki & Arumosoye, 2018; Obriki *et al.*, 2022; Ogbete *et al.*, 2022).

Applied research in financial governance and control offers further cross-sector evidence for the governance enabling condition. Studies of strategic accounting systems, automated financial consolidation, data-driven tax compliance, financial governance and accountability in small and medium enterprises, and data-led cost governance and predictive budgeting show how the ownership, control, and reporting mechanisms that scaled, data-intensive operation requires are built in practice (Adesuyi *et al.*, 2022; Adesuyi *et al.*, 2023; Bola-Sadipe *et al.*, 2019; Bola-Sadipe *et al.*, 2022; Bola-Sadipe *et al.*, 2023; Eboh *et al.*, 2025; Filani *et al.*, 2023; Odihi *et al.*, 2026; Oluwo *et al.*, 2025). Related work on budget compliance and statutory reporting, reconciliation control and financial-workflow redesign, automated close controls in public-sector ERP systems, audit liaison and corrective-action governance, and donor-evidence and accountability standards further specifies the control and audit mechanisms that scaled, governed operation requires (Dogbatsey & Ebhojie, 2018; Dogbatsey *et al.*, 2019; Dogbatsey *et al.*, 2026; Ebhojie *et al.*, 2023; Oyeleye *et al.*, 2025).

A related cluster addresses treasury, forecasting, and strategic finance under uncertainty. Work on tiered treasury architecture and foreign-exchange risk control, entrepreneurial training, CFO-led strategic finance in cross-border partnerships, post-pandemic strategic collaboration for resilience and recovery, and machine-learning-based underwriting connects analytical and financial capability to the data-readiness and resilience themes of the framework (Dada *et al.*, 2021; Dada *et al.*, 2024; Isiekwu *et al.*, 2021; Isiekwu *et al.*, 2025; Oluwo *et al.*, 2022; Oluwo *et al.*, 2024).

Security governance and enterprise-systems research supplies evidence for the systems-integration and governance conditions. Conceptual models for insider-threat classification, risk-based cybersecurity assurance, identity-centric zero-trust architecture, privacy-centric security engineering, predictive maintenance for e-commerce systems, and enterprise directory and network management specify governance and integration mechanisms that scaled technology deployment requires (Akeju *et al.*, 2018; Fadayomi *et al.*, 2019; Ladapo *et al.*, 2018; Ladapo *et al.*, 2019; Mayo *et al.*, 2021; Ogbole *et al.*, 2021; Okoruwa *et al.*, 2020).

A final cluster addresses service operations, automation, workforce, and supply-chain performance. Work on KPI frameworks and revenue assurance, digital transformation of service delivery through automation and risk reduction, customer-centric innovation in utility and service operations, ESG-integrated sustainable procurement, human-resource development, the effect of artificial intelligence on the future of work, vendor management and supply-chain performance, and construction delivery through digital-twin monitoring and machine-learning cost forecasting demonstrates that the enabling-condition logic generalizes across sectors and delivery contexts (Ajirotutu *et al.*, 2019; Ajirotutu *et al.*, 2023; Essandoh *et al.*, 2025; Feboh *et al.*, 2018; Feboh *et al.*, 2023; Nnabueze *et al.*, 2023; Nnabueze *et al.*, 2024; Okafor *et al.*, 2025; Okojie *et al.*, 2020; Sakyi *et al.*, 2022; Sakyi *et al.*, 2023; Sakyi *et al.*, 2024; Wedraogo *et al.*, 2025).

7. LIMITATIONS AND FUTURE RESEARCH

As a conceptual contribution, the framework awaits empirical validation, which is its principal limitation. The propositions specify testable relationships, and a multi-method program is indicated. Comparative case studies of firms that scaled and firms that stalled would allow the pilot-versus-scaling determinant distinction in Proposition 1 to be examined in depth and would surface the mechanisms linking the enabling conditions to scaling outcomes. Survey research across a sample of adopting firms would permit tests of the associations in Propositions 2 through 6, provided the enabling conditions and scaling success are operationalized with validated measures. Longitudinal designs would be valuable because the pilot-to-scale transition unfolds over time and because resilience outcomes are observable primarily under disruption.

Several boundary conditions and extensions merit attention. The framework treats artificial intelligence, robotics, and automation together, and empirical work should examine whether the relative importance of the enabling conditions differs across these technology types, as the discussion of the technologies in scope suggests it may. The framework focuses on supply chain and fulfillment, and its transferability to other operational settings should be tested rather than assumed. The resilience contingency in Proposition 7 deserves dedicated study, since the conditions under which automation strengthens or weakens resilience are consequential and not fully understood. Finally, the interaction between the environmental labor context and the workforce enabling conditions, including the distributional consequences of automation, is an important direction that connects the framework to broader questions of workforce and regional economic development.

8. CONCLUSION

Artificial intelligence, robotics, and automation hold substantial promise for supply chain and fulfillment operations, but that promise is repeatedly frustrated by the failure of promising pilots to scale into durable operational capability. This paper has argued that the failure is not principally technological. The determinants of a successful pilot differ from the determinants of successful scaling, and the latter are predominantly operational and organizational: data readiness and integration, workforce and change capability, systems and process integration, and adoption governance. These enabling conditions are precisely what pilots do not test, which explains why pilots so often succeed while scaling fails.

The framework developed here organizes adoption determinants using the established technology-organization-environment structure, specifies the four cross-cutting enabling conditions that are decisive at the scaling stage, and links successful scaling to both operational performance and supply chain resilience. It integrates diffusion, acceptance, absorptive-capacity, dynamic-capability, and sociotechnical traditions into a coherent, operations-focused account, and it expresses that account as testable propositions and illustrates it through application scenarios. The framework reframes operational technology adoption as a problem of building the operational conditions for scaling rather than of demonstrating technical feasibility.

Because the framework is transferable across firms, sectors, and regions, it constitutes public knowledge that managers, technology providers, and policymakers can use to improve the odds that operational technology investments reach scale and deliver value. Its validation remains to be accomplished, and a multi-method research program has been specified to that end. If firms, and the ecosystems that support them, attend to the enabling conditions rather than to pilots alone, more operational technology initiatives will cross the pilot-to-scale boundary, with benefits for productivity, competitiveness, and the resilience of the supply chains on which the economy depends.

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