

RESEARCH NOTE

The AI Efficiency Trap: Why Local Automation Gains Fail to Become Organizational Value

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Email: 75431035@qq.com**Abstract**

Purpose: Artificial intelligence (AI) can generate substantial improvements in task-level productivity, yet faster and cheaper individual tasks do not necessarily produce superior customer, organizational, or risk outcomes. This Research Note conceptualizes this disconnect as the *AI efficiency trap*: a condition in which observable local AI-enabled efficiency gains fail to translate into corresponding end-to-end organizational value.

Design/methodology/approach: Drawing on research on IT business value, effective technology use, digital transformation, organizational AI capability, omnichannel customer journeys, and human-AI collaboration, the article develops a conceptual value-conversion framework. It introduces *conversion loss* as the mechanism through which local AI-generated efficiency gains may be dissipated as they move through organizational value flows.

Findings: The framework distinguishes four forms of conversion loss: coordination loss, continuity loss, verification loss, and governance loss. Organizational complementarity provides the overarching conversion architecture, while task-appropriate omnichannel integration and human-AI task fit determine whether local efficiency gains survive their transmission across organizational boundaries. Outcome-based feedback further determines whether conversion losses are corrected or become self-reinforcing.

Originality/value: The article shifts attention from AI adoption and automation rates toward the organizational mechanisms through which technical gains are preserved, dissipated, or transformed. It develops four propositions explaining when local AI efficiency is most likely to become end-to-end organizational value.

KEYWORDS

artificial intelligence; organizational value; organizational complementarity; omnichannel integration; human-AI collaboration; digital transformation; business process management

1 | INTRODUCTION

Organizations increasingly deploy artificial intelligence to accelerate decisions, automate routine activities, personalize customer interactions, and augment professional judgment. Evidence that AI can improve individual worker or task productivity is growing. Generative AI, for example, has produced measurable productivity improvements in

customer-support work, particularly for less experienced employees (Brynjolfsson et al. 2025). At the organizational level, AI capabilities have also been associated with creativity and firm performance (Mikalef and Gupta 2021). Yet these findings raise a second and less understood question. *What happens after AI makes an individual task more efficient?*

A claims-intake system may register losses more rapidly while downstream assessment, repair coordination, and payment remain unchanged. An online assistant may accelerate reactivity but create little customer value if customers must repeat their information when transferred to an adviser (Lissillour and Sahut 2026). A generative AI system may produce a professional recommendation in seconds, yet the apparent time saving disappears if specialists cannot verify its reasoning

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and consequently reconstruct the analysis manually. Recent evidence from banking similarly suggests that AI chatbots can perform routine customer-service activities effectively while continuing to encounter limitations when interactions require flexibility, contextual interpretation, or richer human responses (Lissillour and Sahut 2026). These examples illustrate an important distinction: AI can increase the efficiency of a task without increasing the performance of the value flow in which that task is embedded.

This distinction extends a longstanding problem in information systems and management research. IT business-value research has shown that technology does not generate performance independently of complementary organizational resources (Melville et al. 2004). Research on effective use similarly distinguishes having or using technology from employing it in ways that actually advance organizational goals (Burton-Jones and Grange 2013). Affordance-actualization research shows that technological potential only becomes organizational change through multilevel processes involving actors, goals, and interconnected organizational arrangements (Strong et al. 2014). Digital transformation research reinforces the same general principle: technology contributes to value creation through changes in organizational structures, processes, capabilities, and strategic arrangements rather than through implementation alone (Vial 2019).

AI makes this problem particularly salient. AI readiness involves strategy, resources, knowledge, data, and organizational culture rather than purely technological capability (Jöhnk et al. 2021), while AI business-value research increasingly emphasizes complementary organizational resources and process change (Enholm et al. 2022). Empirical evidence further indicates that AI generates organizational performance partly through business-process capabilities, automation, organizational learning, and process innovation rather than by adoption alone.

Nevertheless, these perspectives primarily explain *whether* organizations possess the conditions to generate value from technology. Less attention has been paid to what happens between an observable AI-generated improvement at one point in a process and the eventual customer or organizational outcome. We address this gap by conceptualizing the *AI efficiency trap*. We define the AI efficiency trap as a condition in which:

1. AI generates an observable improvement in at least one local task-level efficiency indicator;
2. relevant end-to-end customer, organizational, or risk outcomes do not improve proportionately, or the local benefit is materially offset elsewhere; and
3. an identifiable breakdown exists in the organizational mechanisms through which the local efficiency gain should have been transmitted into broader value.

We introduce the concept of *conversion loss* to explain this phenomenon. Conversion loss is the portion of a local AI-generated efficiency gain that is dissipated as the task output travels through subsequent organizational activities before reaching a meaningful end

outcome. This formulation distinguishes the AI efficiency trap from a simple implementation failure. The AI itself may work. The task may actually become faster. The problem lies in the conversion of that local gain into organizational value.

We develop four arguments. First, *organizational complementarity* constitutes the overarching architecture through which local AI efficiency becomes organizational value. Second, *task-appropriate omnichannel integration* determines whether customer-facing gains survive movement across touchpoints and organizational units. Third, *human-AI task fit* determines whether automation eliminates work or merely relocates it into downstream verification, exception handling, and professional reconstruction. Fourth, *outcome-based feedback* determines whether conversion losses are corrected or instead become persistent because highly visible local efficiency metrics obscure dispersed downstream costs. The paper contributes by shifting the central question from: “Does AI improve performance?” to: “Under what conditions does an observable AI efficiency gain survive its journey through the organization and become end-to-end value?”

2 | THEORETICAL POSITIONING: FROM AI CAPABILITY TO AI VALUE CONVERSION

2.1 | Existing explanations of the AI value gap

Several established theoretical perspectives help explain why technological potential and organizational performance may diverge. The *IT business-value perspective* argues that information technologies generate value conditionally upon complementary organizational resources and environmental conditions (Melville et al. 2004). The *productivity J-curve* focuses on temporal delay. General-purpose technologies may initially produce disappointing productivity outcomes because complementary intangible investments—including organizational redesign and human capital—take time to develop (Brynjolfsson et al. 2021). The *digital transformation perspective* moves beyond technology adoption toward organizational change in value-creation processes (Vial 2019). The *AI capability and readiness literatures* identify bundles of technological, human, strategic, and organizational resources that enable firms to exploit AI successfully (Jöhnk et al. 2021, Mikalef and Gupta 2021, Enholm et al. 2022). The *effective-use perspective* distinguishes technology usage from the extent to which usage advances organizational objectives (Burton-Jones and Grange 2013). Finally, the *automation-augmentation perspective* examines how AI and human capabilities should be allocated across tasks rather than assuming that automation is always preferable (Raisch and Krakowski 2021). These perspectives are complementary, but none directly conceptualizes the dissipation of an already observable task-level AI gain as that gain moves through an organizational value flow.

TABLE 1 Positioning the AI efficiency trap

Perspective	Central question	Primary explanatory mechanism	What the AI efficiency trap adds
IT business value	When does IT affect firm performance?	Complementary resources	Locates where an observable task gain is lost
Productivity J-curve	Why are technology returns delayed?	Time and intangible investment	Separates transmission failure from temporal delay
Digital transformation	How does digital technology reshape value creation?	Organizational transformation	Focuses specifically on task-to-outcome conversion
AI readiness/capability	What enables organizations to exploit AI?	Resource and capability configurations	Examines what occurs after AI capability produces a local gain
Effective use	When does technology use advance goals?	Quality of system use	Extends effective use across interconnected activities and units
Automation-augmentation	How should work be divided between humans and AI?	Human-AI task allocation	Links task allocation to downstream conversion loss
AI efficiency trap	Why does demonstrated local AI efficiency sometimes fail to become end-to-end value?	Conversion loss across the value flow	Connects local efficiency to customer, organizational, and risk outcomes

2.2 | Conversion loss: the mechanism inside the trap

Consider a local AI intervention that saves ten minutes in one activity. The theoretical question is not simply whether ten minutes have been saved. It is whether some, all, or more than those ten minutes subsequently reappear as waiting, coordination, correction, verification, exception handling, customer repetition, or risk-management work elsewhere. We define *conversion loss* as: the dissipation of potential value between an observable local AI-enabled efficiency improvement and the realization of the corresponding end-to-end customer, organizational, or risk outcome. Four conceptually distinct forms are particularly relevant.

Coordination loss. A local improvement creates little system-level value when downstream units, responsibilities, or workflows remain misaligned. Bottlenecks migrate rather than disappear.

Continuity loss. Information, identity, authorization, customer history, or task status fails to travel appropriately across channels or organizational boundaries. Customers or employees repeat work that the AI apparently eliminated upstream.

Verification loss. Humans cannot adequately understand, trust, review, or reuse AI output and consequently repeat substantial portions of the automated task. Learning algorithms can reshape expertise, occupational boundaries, coordination, and control precisely because their operation may be opaque or difficult to evaluate (Faraj et al. 2018).

Governance loss. Efficiency improvements generate offsetting costs or risks through inappropriate delegation, reduced customer autonomy, weak accountability, bias, privacy exposure, or inadequate escalation. AI implementation is not organizationally neutral: transparency and control may themselves be embedded in power relationships (Lissillour and Monod 2024), and scholarship similarly emphasizes that responsibility for AI must be actively designed into implementation and use rather than assumed to emerge automatically (Chapuis and Guégan 2024).

These four forms need not occur independently. A poorly integrated AI recommendation can generate continuity loss, force human reconstruction, and ultimately create governance concerns simultaneously. The efficiency trap therefore describes the state, whereas conversion loss explains the mechanism producing that state.

3 | A VALUE-CONVERSION FRAMEWORK

3.1 | Organizational complementarity as the conversion architecture

AI is increasingly conceptualized as an organizational capability rather than simply an information technology. Mikalef and Gupta (2021), for example, conceptualize AI capability as a combination of organizational resources associated with creativity and performance. Jöhnk et al. (2021) similarly identify strategic alignment, resources, knowledge, culture, and data as prerequisites for organizational AI readiness. Yet possessing resources does not necessarily mean they are aligned around a specific value flow. We therefore use *organizational complementarity* more narrowly to describe alignment among four sets of organizational arrangements required to preserve an AI-generated gain:

Process and responsibility complementarity specifies how work and accountability move across units.

Data and knowledge complementarity ensures that employees and systems can access sufficiently coherent information, rules, and knowledge.

Human capability complementarity ensures that employees possess the expertise necessary to interpret, challenge, and extend AI output.

Incentive complementarity ensures that organizational units are rewarded for improving end-to-end outcomes rather than optimizing isolated activity metrics.

The importance of complementarity increases as task interdependence rises. When an AI-enabled activity is highly modular, local improvement can generate value relatively independently. When its output becomes the input of several subsequent activities, however, surrounding organizational arrangements increasingly determine whether the gain survives. This suggests:

Proposition 1. *For a given level of local AI-enabled efficiency, higher alignment among process responsibilities, data and knowledge, human capabilities, and incentives will reduce conversion loss and strengthen the relationship between local AI efficiency and end-to-end organizational value. This effect will be stronger as interdependence among activities in the value flow increases.*

This proposition makes complementarity the conversion architecture, rather than one variable among several.

3.2 | Task-appropriate omnichannel integration and continuity loss

In customer-facing environments, value conversion frequently occurs across channels. Omnichannel research has progressively shifted from channel proliferation toward coordination across touchpoints and the continuity of customer journeys (Verhoef et al. 2015, Lemon and Verhoef 2016, Neslin 2022). Insurance research shows that customers' interaction choices vary according to task, stage of the journey, and the value sought from each interaction (Barwitz and Maas 2018). The implication is important: AI efficiency at one touchpoint has limited value if the customer journey cannot preserve it. Suppose an AI tool reduces quotation time by 80 percent. If switching to an adviser requires customers to re-enter the same information, some of the efficiency gain disappears through continuity loss. But the opposite extreme is also problematic.

Full technical integration of every channel, dataset, professional unit, and service provider may involve substantial coordination expense, privacy exposure, information-governance requirements, and organizational rigidity. Customer autonomy may also decline if integrated systems limit meaningful alternatives or make algorithmic recommendations difficult to challenge. The relationship between integration and value conversion is therefore better understood through fit than maximization. For standardized, frequent tasks, extensive information continuity may produce substantial value. For low-frequency, highly specialized tasks, a relatively independent professional channel combined with a reliable handoff may be superior to full channel homogenization. We therefore propose:

Proposition 2. *The conversion of customer-facing AI efficiency into end-to-end value will increase as omnichannel integration approaches the level required by the customer task, but will decrease when integration falls materially below or exceeds those task requirements. Under-integration generates continuity loss, whereas over-integration generates coordination and governance costs.*

This proposition differs from a conventional “more integration is better” argument. The theoretical construct is task-integration fit.

3.3 | Human-AI task fit and verification loss

A second conversion boundary exists between AI outputs and human work. The automation-augmentation paradox shows that automation and augmentation are interdependent rather than mutually exclusive (Raisch and Krakowski 2021). Shrestha et al. (2019) similarly identify several structures through which human and AI decision-making can be combined depending on decision characteristics. Professional work makes this particularly clear. Recent research on legal practice argues that AI is especially suited to automating routine activities while professional judgment remains central to ethical and strategic decisions (Nguyen 2026). In organizational supervision, Monod (2025) likewise

shows that AI acceptance and effectiveness cannot be detached from power, justice, trust, and organizational context. We identify four dimensions that determine appropriate AI delegation: task complexity; standardizability of inputs, rules, and evidence; reviewability and interpretability of the output; and consequences for customer rights and organizational risk.

As standardizability and reviewability increase, automation becomes more attractive. As ambiguity, complexity, and consequences increase, augmentation becomes more attractive because accountable professional judgment has greater value. This logic is visible in customer-facing financial services. AI chatbots perform comparatively well when customers request standardized information or routine transactions, whereas complex or emotionally sensitive interactions expose limitations in contextual responsiveness and flexibility (Lissillour and Sahut 2026). Human participation, however, is not automatically valuable. Requiring professionals to review every automated decision can simply recreate the original workload. Effective augmentation requires selective review supported by traceable evidence, uncertainty indicators, and meaningful escalation rules. Hence:

Proposition 3. *Fit between the degree of AI delegation and the complexity, standardizability, reviewability, and consequence of a task will reduce verification and governance losses. Automation will produce greater end-to-end value for standardized and readily reviewable tasks, whereas accountable human-AI augmentation will produce greater value as ambiguity and decision consequences increase.*

The proposition therefore concerns fit, not the inherent superiority of automation or augmentation.

3.4 | Why the efficiency trap persists: metric visibility and organizational feedback

A remaining question is important: Why call this a trap rather than simply poor implementation? The answer lies in an asymmetry of visibility. Local AI benefits are often highly measurable. Organizations can observe response times, model accuracy, processing speed, automation rates, number of customer interactions, or cost per transaction.

Conversion losses are typically less visible. Waiting occurs in another department. Customers repeat information in another channel. Professional reconstruction appears as employee workload rather than AI cost. Complaints occur weeks later. Risk consequences may emerge months later. No single organizational unit necessarily sees the complete loss.

Consequently, organizations can receive a strong local signal that an AI project is successful while receiving only weak and dispersed signals that the corresponding value flow has not improved. Performance systems organized around functional rather than end-to-end metrics can reinforce the problem. This creates a self-reinforcing mechanism: visible local efficiency → perceived AI success → further automation or scaling → persistence of unchanged organizational interfaces → additional conversion loss.

The trap is broken when organizations observe and learn from end-to-end outcomes. Affordance-actualization research stresses that organizational effects arise through ongoing processes rather than automatically from technological properties (Strong et al. 2014). Recent work on AI business value similarly indicates that process management, organizational learning, and process innovation contribute to converting AI adoption into organizational performance.

This adaptive perspective is also consistent with recent work connecting digital transformation with human-capital development and organizational capabilities rather than treating transformation as purely technological (Boateng and Etroo 2026). We therefore propose:

Proposition 4. *Organizations that evaluate AI primarily through local task and adoption metrics will experience more persistent conversion loss than organizations that combine local indicators with end-to-end customer, process, business, and risk outcomes. Cross-functional outcome feedback will weaken the AI efficiency trap by triggering reconfiguration of organizational complementarities, channel integration, and human–AI task allocation.*

Proposition 4 makes the model dynamic. Organizations do not simply possess the right or wrong architecture. They continually learn whether their architecture is allowing AI-generated efficiency to travel.

Taken together, the four propositions form a dynamic value-conversion framework. Local AI efficiency creates potential rather than realized organizational value. Organizational complementarities provide the architecture through which this potential travels, while task-appropriate omnichannel integration and human–AI task fit determine the extent of conversion loss during transmission. End-to-end outcome feedback subsequently reveals these losses and enables organizations to reconfigure the underlying conversion mechanisms. Figure 1 summarizes these relationships.

The framework implies that organizations should measure AI at several levels simultaneously.

The key diagnostic is therefore not whether an AI application performs well in isolation. It is whether: Local efficiency gain – conversion loss = observable end-to-end value. This expression is conceptual rather than an accounting identity, but it captures the central logic of the framework.

4 | DISCUSSION AND CONCLUSION

The growing evidence that AI can increase task productivity should not be confused with evidence that AI necessarily generates equivalent organizational value. This paper conceptualizes the gap between the two as the AI efficiency trap. The theoretical argument has two levels. At the first level, an efficiency trap exists when AI demonstrably improves local task performance but end-to-end outcomes fail to improve proportionately because the gain is dissipated before reaching the relevant organizational outcome. At the second level, conversion loss explains where that dissipation occurs. Coordination loss arises when surrounding activities remain misaligned. Continuity loss arises when customers,

information, or responsibilities cannot move effectively across touchpoints. Verification loss arises when employees must reconstruct AI-generated work. Governance loss arises when efficiency is offset by accountability, autonomy, privacy, bias, or risk consequences.

Four mechanisms determine whether organizations escape the trap. Organizational complementarity provides the conversion architecture. Task-appropriate omnichannel integration preserves customer-facing gains across touchpoints. Human–AI task fit determines whether automation eliminates work or relocates it. End-to-end feedback determines whether conversion losses trigger organizational adaptation or remain hidden behind attractive local performance indicators. The final mechanism is especially important because it explains why the efficiency trap can persist.

A company may legitimately report that its chatbot responds faster, its claims system automates more cases, or its generative AI assistant prepares documents more quickly. Every statement may be correct. The organization may nevertheless create little additional value if customers repeat information, employees reconstruct automated outputs, bottlenecks migrate downstream, or new governance work absorbs the apparent savings.

The managerial implication is therefore not that firms should automate less. It is that they should manage AI around value flows rather than around applications. The appropriate question is not merely: “Did AI make this task faster?” It is: “How much of that gain survived the journey to the outcome that ultimately matters?” That shift—from AI efficiency to AI value conversion—offers a more demanding basis for understanding when artificial intelligence becomes an organizational capability rather than an isolated technical achievement.

The AI efficiency trap generates several opportunities for empirical research. First, researchers should distinguish *temporary conversion delay* from *persistent conversion loss*. Longitudinal designs can determine whether initially disappointing results disappear as complementary investments mature, as predicted by the productivity J-curve, or remain because identifiable organizational transmission failures persist. Second, researchers could examine complete value flows rather than isolated AI applications. A useful design would follow claims, customer inquiries, underwriting decisions, or service cases from initiation to completion and compare AI-enabled and non-AI processes. Third, organizational complementarity could be operationalized through process ownership, cross-functional responsibility, information coherence, AI-related employee capability, and alignment of performance incentives. Fourth, Proposition 2 suggests testing *integration misfit* rather than simply integration intensity. Both insufficient and excessive integration should be examined relative to task characteristics. Fifth, Proposition 3 encourages configurational research on human–AI work. Rather than asking whether automation or augmentation is superior, research should examine combinations of task complexity, standardizability, interpretability, decision consequence, and escalation design. Sixth, Proposition 4 raises questions about organizational attention and measurement. Researchers could investigate whether firms emphasizing automation rates and usage metrics experience greater discrepancies between local

Figure 1. The AI Efficiency Trap: A Value-Conversion Framework

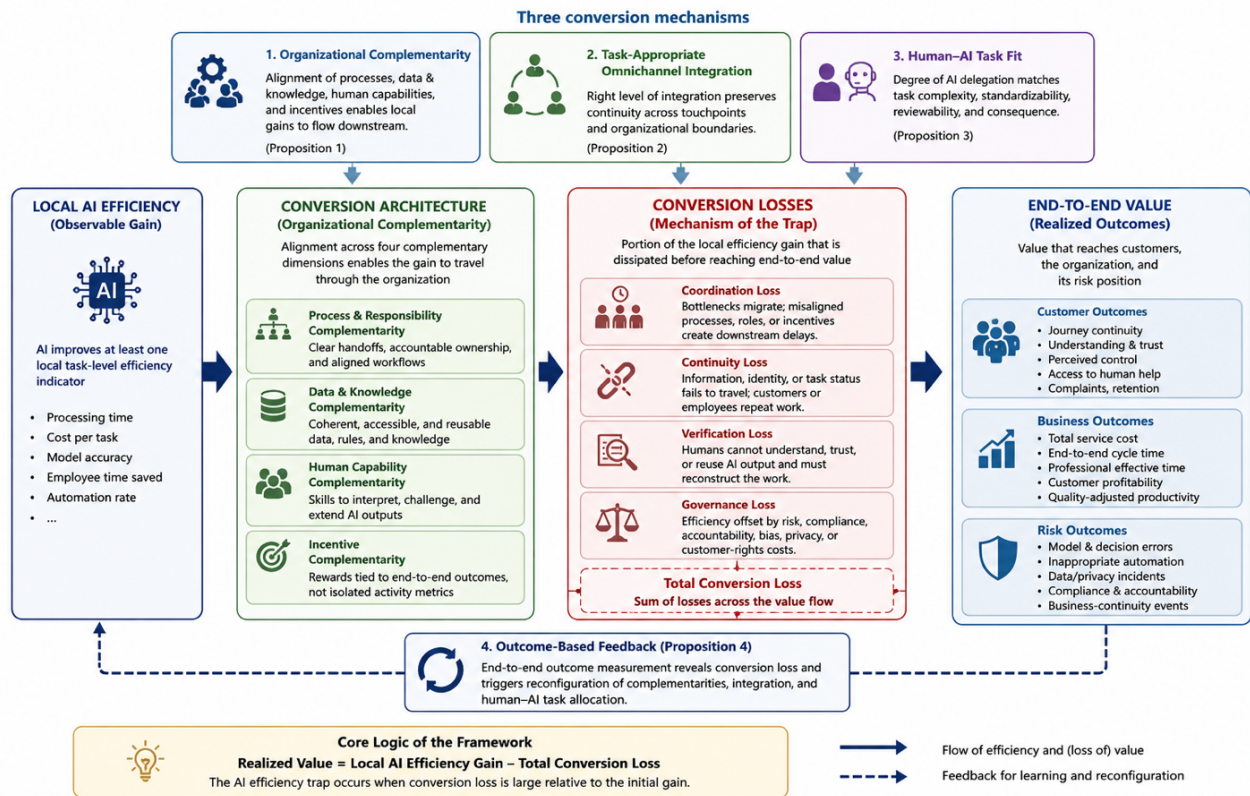


FIGURE 1 The AI Efficiency Trap: A Value-Conversion Framework

TABLE 2 Multi-level indicators for diagnosing the AI efficiency trap

Level	Indicators
Local efficiency.	- processing time; - cost per task; - model accuracy; - employee time saved; - automation rate.
Conversion loss.	- waiting between process stages; - repeated customer data entry; - cross-channel information loss; - rework; - human overrides; - complete reconstruction of AI-generated work; - unsuccessful handoffs; - exception escalation; - downstream bottlenecks.
Customer outcomes	- journey continuity; - understanding; - perceived control; - trust; - access to human assistance; - complaints; - renewal and retention.
Business outcomes	- total service cost; - professional effective time; - end-to-end processing duration; - customer profitability; - expense and claims outcomes; - quality-adjusted productivity.
Risk outcomes	- model errors; - inappropriate automation; - disputed decisions; - human intervention; - data and privacy incidents; - business-continuity events; - customer-rights violations.

and end-to-end outcomes than organizations using value-flow score-cards.

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CONFLICT OF INTEREST

The author declares no conflict of interest.

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