



Artificial Intelligence for Strategic Adaptation in International Business: Navigating Deglobalization Challenges

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Abstract

International businesses increasingly face deglobalization pressures that challenge their ability to coordinate activities, interpret uncertainty, and adapt strategic decisions across markets. At the same time, artificial intelligence is becoming a relevant support for managerial decision-making, although its effects remain ambiguous. This study investigates how AI integration can enhance or hinder the dynamic capabilities required by multinational firms under deglobalization pressures. We adopt a qualitative multi-case study design focused on three customer-facing multinational firms: Unilever, Amazon, and Starbucks. The unit of analysis is the AI integration, resulting in six embedded cases across supply-chain forecasting, logistics coordination, recruitment, personalization, and inventory management. Data collection combines semi-structured interviews with secondary sources, including company reports, public declarations, media documentation, and indirect executive interviews. Data analysis follows an inductive three-stage coding approach. Findings show that AI can improve strategic decision-making when it supports cross-border detection, uncertainty processing, and operational responsiveness. However, AI can also create problems when automated judgment becomes opaque, biased, inaccurate, or disconnected from contextual interpretation. The study identifies enhancing, hindering, and mixed effects of AI integration. It contributes by connecting AI-enabled decision support with dynamic capabilities, value co-creation, and value co-destruction in international business. For managers, the study suggests that firms should evaluate AI through decision quality, contextual fit, and governance rather than efficiency alone.

Keywords: Strategic decision-making, International businesses, Deglobalization, Multi-case study

1. Introduction

International business increasingly unfolds in environments where firms must coordinate activities across borders while facing unstable institutional conditions (Buckley & Casson, 2009). These conditions have become more demanding as globalization has entered a phase

marked by political contestation and fragmented openness (Witt, 2019). Deglobalization does not only reduce international interdependence but also changes how multinational enterprises organize value creation across markets (Petricevic & Teece, 2019). In this context, firms need dynamic capabilities to interpret change, act strategically, and reconfigure resources over time (Teece, 2007). These capabilities are especially relevant when firms must adapt business models to preserve value under uncertainty (Teece, 2018). At the same time, artificial intelligence increasingly supports strategic decision-making by expanding what managers can process in complex contexts (Duan et al., 2019). AI may therefore help firms respond to international uncertainty, but it may also create problems when automation replaces contextual judgment (Raisch & Krakowski, 2021). From a service-dominant logic perspective, AI can support value co-creation when it improves interaction and resource integration (Vargo & Lusch, 2008). However, AI can also contribute to value co-destruction when automated decisions reduce well-being or amplify problematic assumptions (Lumivalo et al., 2024). Despite these insights, limited research explains how AI-enabled decision support affects dynamic capabilities in international businesses facing deglobalization pressures (Berente et al., 2021).

To address this gap, this study adopts a qualitative multi-case study design set within international business (Yin, 2018). The research focuses on customer-facing multinational firms with digitally enabled services and decision-making operations. This setting is appropriate because these firms operate across markets, rely on data-intensive coordination, and face globalization pressures within their supply chains. The study examines three companies: Unilever, Amazon, and Starbucks. These companies were selected because each provides evidence of AI integrations connected to strategic decision-making. The unit of analysis is the AI integration rather than the company as a whole. Accordingly, the study investigates six embedded cases, with two AI integrations for each company. Data collection combines primary and secondary evidence to support triangulation (Yin, 2018). Primary evidence consists of 18 semi-structured interviews connected to the six AI integrations. The interviews were conducted according to qualitative interviewing principles concerning informed consent, confidentiality, recording, transcription, and anonymization (Kvale, 2007). Secondary evidence includes company declarations, reports, public documentation, media articles, and indirect executive interviews. Data analysis follows an inductive three-stage approach inspired by the Gioia methodology (Gioia et al., 2013). This approach supports movement from empirical material to first-order concepts, second-order themes, and aggregate dimensions.

The findings show that AI integration can affect strategic decision-making in three different ways. First, AI can improve adaptation when it helps firms detect cross-border change and process uncertainty. This pattern appeared in supply-chain forecasting, logistics coordination, inventory positioning, and store-level adaptation. In these cases, AI helped transform dispersed information into more timely operational decisions. Second, AI can create problems when automated judgment becomes difficult to interpret or control. This was visible in recruitment and inventory automation, where algorithmic systems raised concerns about opacity, bias, inaccuracy, and contextual misinterpretation. Third, AI can generate uneven results when the same technology accelerates adaptation while disrupting routines. These mixed effects show that AI is not inherently beneficial or harmful. Its consequences depend on how the system is embedded in organizational processes, how managers interpret its outputs, and whether human oversight remains active.

The study contributes by linking AI-enabled decision support to dynamic capabilities and value outcomes under deglobalization pressures (Teece, 2007). It also shows that AI can become a double-edged mechanism, supporting value co-creation (Vargo & Lusch, 2008) or

generating value co-destruction (Lumivalo et al., 2024) depending on implementation conditions and international fragmentation pressures (Witt, 2019). Managerially, the study suggests that firms should evaluate AI not only through efficiency, but through decision quality, contextual fit, and governance.

2. Literature review

2.1 Strategic Challenges for International Businesses Facing Deglobalization

International business concerns firms whose activities extend across national borders and depend on the coordination of international operations (Buckley & Casson, 2009). These actors operate in environments where strategic choices are shaped by distance, institutional diversity, and cross-border interdependence (Nambisan et al., 2019). As a result, international competitiveness cannot rely only on existing resources, since firms must continuously adapt to external change (Teece et al., 1997). The dynamic capabilities perspective is useful here because it explains how firms recognize change, act upon it, and transform their resource base over time (Teece, 2007). This perspective is especially relevant when international firms need to redesign business models in response to unstable market conditions (Teece, 2018). Strategic adaptation also depends on managerial cognition, because managers must interpret ambiguous signals before making consequential decisions (Helfat & Peteraf, 2015).

Dynamic capabilities should therefore be understood as adaptive processes that help firms renew their strategies across changing contexts (Eisenhardt & Martin, 2017). These challenges have become more demanding as globalization has entered a phase marked by stronger political contestation and weaker international openness (Witt, 2019). Deglobalization does not simply mean less globalization, but a broader transformation in the conditions under which international firms operate (Petricevic & Teece, 2019). In this context, multinational enterprises face greater pressure to rethink how they organize cross-border activities and manage exposure to uncertainty (Cuervo-Cazurra et al., 2020).

Some scholars argue that globalization remains economically necessary, although firms must still adjust to higher levels of international risk (Contractor, 2022). Other scholars suggest that growing political and institutional contestation is creating deglobalization pressures that reshape the conditions under which international firms operate (Witt, 2019). Digitalization can partly mitigate these pressures by helping firms coordinate across distance and maintain resilience during disruption (Autio et al., 2021). Overall, deglobalization creates a strategic setting in which international firms need stronger capabilities for adaptation, coordination, and resource reconfiguration (Teece, 2007).

2.2 The Role of AI in Decision Support Systems

Artificial intelligence can be understood as a family of computational technologies that support organizational decisions through advanced analytical capabilities (Duan et al., 2019). In organizations, AI is increasingly important because it expands what managers can process when decision environments become complex (Berente et al., 2021). Decision support is central to this role, since AI can complement human cognition when information exceeds ordinary managerial capacity (Jarrahi, 2018). AI also changes how decisions are organized, because algorithmic systems may influence where judgment and authority are located (Shrestha et al., 2019). These shifts require governance arrangements that translate ethical principles into accountable organizational practices, rather than relying on abstract AI guidelines alone (Jobin et al., 2019; Mittelstadt, 2019). This creates a tension between

automation and augmentation, since AI can both replace parts of decision-making and support human expertise (Raisch & Krakowski, 2021). The strategic value of AI therefore depends on whether managers use algorithmic outputs as substitutes for judgment or as inputs for interpretation (Jarrahi, 2018). In marketing and service contexts, AI can create value by improving how firms understand customers and adapt their strategic actions (Huang & Rust, 2021). AI also reshapes service work because machine capabilities increasingly support tasks that previously depended on human employees (Huang & Rust, 2018). From a service-dominant logic perspective, however, value is not produced by technology alone but emerges through interaction (Vargo & Lusch, 2008). AI can therefore support value co-creation when it enables actors to combine knowledge more effectively in decision processes (Davenport et al., 2020). At the same time, AI can undermine value when its use generates negative experiences for the people affected by it (Puntoni et al., 2021).

Resistance to AI may emerge when automated decisions are perceived as insensitive to personal circumstances and contextual uniqueness (Longoni et al., 2019). Fairness concerns are especially relevant because algorithmic systems can reproduce biased patterns in data, making internal auditing important before deployment (Mehrabi et al., 2021; Raji et al., 2020). These problems connect with value co-destruction, which occurs when interaction leads to a decline in well-being for involved actors (Plé & Chumpitaz Cáceres, 2010). Recent research shows that value co-destruction can unfold across different moments of service interaction, rather than only at the outcome stage (Lumivalo et al., 2024). AI decision support is especially risky when apparently objective data conceal uncertain expert judgment and missing practical know-how (Lebovitz et al., 2021). In international business, these risks are further complicated by cross-border regulatory competition and the uneven development of risk-based AI rules across jurisdictions (Smuha, 2021; Veale & Zuiderveen Borgesius, 2021).

2.3 Theoretical speculations

AI-enabled decision support may strengthen international businesses by helping firms interpret uncertainty in deglobalizing environments (Teece, 2007). By processing weak signals across the international environment, AI can help firms recognize cross-border changes earlier (Duan et al., 2019). This may create value when algorithmic insight becomes a resource integrated into managerial strategic interpretation (Vargo & Lusch, 2008). Such value co-creation depends on managers using AI outputs to improve judgment, not to avoid judgment (Jarrahi, 2018). AI can also support strategic action by helping firms compare alternatives and respond more coherently across dispersed operations (Teece, 2018). This is important because deglobalization often requires timely decisions about how international activities should be reorganized (Petricevic & Teece, 2019). These decisions are further complicated by regulatory competition and risk-based AI rules, thus making governance of these emerging technologies a cross-border strategic issue rather than only a technical concern (Smuha, 2021; Veale & Zuiderveen Borgesius, 2021). Therefore, AI may further assist strategic renewal by revealing how resources can be redeployed across the firm's international network (Nambisan et al., 2019).

In this sense, AI can become a microfoundation of dynamic capabilities when embedded in managerial decision processes (Helfat & Peteraf, 2015). However, the same technology can generate value co-destruction when managers over-rely on algorithmic outputs without contextual interpretation (Lumivalo et al., 2024). Overreliance is problematic because AI systems may encode incomplete knowledge while still appearing highly reliable to decision-makers (Lebovitz et al., 2021). The automation–augmentation paradox suggests that firms must manage AI as a tension rather than a simple efficiency tool (Raisch & Krakowski,

2021). If AI narrows managerial attention, firms may respond faster but misread the complexity of international environments (Witt, 2019). If AI instead supports dialogue across the organization, it may improve strategic adaptation and value co-creation (Vargo & Lusch, 2008). The key theoretical issue is therefore not whether AI improves decisions, but under which conditions it improves them (Berente et al., 2021). This paper speculates that AI creates strategic value when it augments the dynamic capabilities required under deglobalization pressures (Teece, 2007). At the same time, AI may co-destroy value when automation weakens the human interpretation required for international strategic decisions (Lumivalo et al., 2024).

3. Methods

This study adopts a qualitative multi-case study design set within international business (Yin, 2018). This design is appropriate because the research examines how AI integration shapes strategic decision-making in complex organizational contexts. A qualitative approach allows the study to capture context-specific mechanisms that would be difficult to observe through standardized measures alone. Furthermore, the multi-case design improves analytical variety, since it enables comparison across firms that differ in industry position, organizational structure, and AI implementation outcomes. The study is not designed to produce statistical generalization, but to develop theoretical insight into how AI may enhance or weaken dynamic capabilities under globalization and deglobalization pressures. More specifically, the research setting includes customer-facing multinational firms with digitally enabled services and decision-making operations. This setting is relevant because these firms operate internationally, interact with large consumer bases, and depend heavily on data-intensive coordination. To ensure comparability across cases, we selected three companies according to the following criteria: they operate internationally; they interact directly with large consumer bases; they rely on data-intensive decision-making; they use AI, or may use AI, to adapt operations across markets; and they face globalization pressures within their supply chains.

We identified three companies: Unilever, Amazon, and Starbucks. These companies were chosen according to four criteria. First, they operate across multiple national markets and therefore face international strategic complexity. Second, they interact directly with large consumer groups, making value creation and value co-destruction visible in practice. Third, they rely on digitally enabled decision-making systems to coordinate activities across dispersed operations. Fourth, each company offers public evidence of both promising and problematic AI applications. The unit of analysis is not the company as a whole, but the specific AI integration used to support strategic decision-making. Accordingly, the study includes six embedded cases, with two AI integrations for each company.

In Unilever, the first case concerns AI-enabled customer connectivity and supply-chain forecasting, which supports demand interpretation and operational planning. The second case concerns AI-enabled recruitment and talent screening, which supports workforce selection but raises concerns about fairness and opacity. In Amazon, the first case concerns AI-enabled logistics and inventory positioning, which supports delivery speed, forecasting, and resource allocation. The second case concerns the abandoned AI recruiting tool, which illustrates how algorithmic decision-making can reproduce organizational bias. In Starbucks, the first case concerns Deep Brew, an AI platform connected to personalization, store operations, and customer experience. The second case concerns the automated inventory-counting tool, which was introduced to improve stock visibility but later abandoned because of operational inaccuracies.

Data collection combined primary and secondary sources to ensure triangulation and strengthen construct validity (Yin, 2018). Secondary data were collected first to contextualize the three companies and reconstruct the six embedded AI integrations. These sources included company declarations, official reports, press releases, public documentation, media articles, technology-related materials, and indirect executive interviews. The collection process followed a purposive search strategy based on company names, AI-related keywords, and decision-making domains. Secondary sources were retained when they met three criteria: they referred directly to one selected company or AI integration; they provided information connected to strategic decision-making, dynamic capabilities, or value outcomes; and they were traceable to an identifiable organizational, sectoral, or media source.

For Unilever, secondary evidence clarified how AI-supported customer connectivity and supply-chain forecasting contributed to demand interpretation, while evidence on recruitment and talent screening helped identify fairness and opacity concerns. For Amazon, secondary evidence reconstructed how AI logistics and inventory positioning supported operational responsiveness, while evidence on the abandoned recruiting tool illustrated bias risks in automated selection. For Starbucks, secondary evidence contextualized Deep Brew as a personalization and store-support system, while evidence on the automated inventory-counting tool clarified implementation problems linked to operational inaccuracies.

Primary data consisted of 18 semi-structured interviews, with six interviews conducted for each company and three assigned to each embedded case. These three interviewees comprised one managerial informant, one operational informant, and one external or user-side informant. Interviewees were selected through purposive sampling because the study required participants with direct or informed knowledge of AI-supported decision-making. Within each embedded case, managerial interviews clarified the strategic rationale and expected contribution of the AI integration, while operational interviews explained how AI-supported decisions affected organizational routines, resource allocation, and service interactions.

External or user-side interviews, involving customers, applicants, or sectoral experts, captured perceived benefits and risks from outside the organization. Together, these perspectives supported the triangulation of each case. The interview protocol was organized around four themes: the purpose of the AI integration, its role in decision-making, its perceived benefits, and its unintended consequences. The semi-structured format allowed comparable themes to emerge while preserving flexibility for case-specific insights. Interviews were conducted according to qualitative interviewing principles, with attention to informed consent, confidentiality, and respectful treatment of participants (Kvale, 2007). All interviews were recorded with permission, transcribed verbatim, and anonymized before analysis.

Data analysis followed an inductive three-stage approach inspired by the Gioia methodology (Gioia et al., 2013). This approach was useful because it allowed the analysis to move from empirical evidence toward theoretically informed interpretation. In the first stage, interview transcripts and secondary materials were coded to identify first-order concepts close to the language of participants and documents. These concepts captured how AI was described in relation to uncertainty, decision support, adaptation, operational improvement, bias, error, or implementation difficulty. In the second stage, related first-order concepts were grouped into second-order themes reflecting broader mechanisms. These themes included AI-enabled sensing, faster strategic response, resource reconfiguration, algorithmic overreliance, contextual misinterpretation, and operational disruption. In the third stage, second-order themes were aggregated into broader theoretical dimensions. These aggregate dimensions

were value co-creation, value co-destruction, and ambivalent value outcomes. A value co-creation outcome was assigned when both primary and secondary evidence indicated that the AI integration improved strategic decision-making and supported organizational adaptation. A value co-destruction outcome was assigned when both evidence streams indicated that the AI integration created harmful consequences, such as bias, inaccuracy, or poorer decision quality. An ambivalent outcome was assigned when the evidence showed both beneficial and problematic effects within the same AI integration.

The analysis then moved from within-case interpretation to cross-case comparison. Within-case analysis reconstructed how each AI integration affected decision-making in its specific organizational context. Cross-case analysis compared whether similar mechanisms appeared across different companies and decision domains. This procedure helped identify whether AI supported dynamic capabilities by improving interpretation, response, and adaptation. It also helped identify conditions under which AI weakened decision-making by encouraging overreliance, reducing contextual understanding, or amplifying errors. Through this analytical process, the study developed a theoretical explanation of AI as a double-edged mechanism in international strategic decision-making.

4. Results

4.1 Improvements in Adaptation and Operational Responsiveness

Results show that AI can improve the ability of international firms to interpret change and respond across dispersed operations. Unilever's AI-enabled customer connectivity and supply-chain forecasting supported a closer connection between customer demand and operational planning. The integration allowed the company to combine sales information with production and replenishment decisions more quickly. This was particularly relevant because consumer goods firms must continuously adjust supply decisions across markets with different demand patterns. In this case, AI appeared useful because it helped translate fragmented demand information into more timely operational responses. Unilever's public explanation of its AI-enabled ice-cream supply chain captured this logic by stating that AI helps the firm understand "where to sell" and "how much we are going to sell," while also freeing employees from "repetitive tasks like number crunching." Therefore, technology did not replace strategic decision-making, but strengthened the informational basis on which planning decisions were made.

A similar pattern emerged from Amazon's logistics and inventory-positioning systems. These AI integrations supported the company's ability to anticipate demand and organize delivery operations. They helped identify where products should be located before customers placed orders. This improved the connection between demand prediction and resource allocation across the logistics network. Amazon CEO Andy Jassy similarly described AI as a way to "improve inventory placement, demand forecasting, and the efficiency of our robots," showing how algorithmic systems supported operational responsiveness across the fulfillment network. The strategic relevance of the case lies in the way AI supported coordination across a highly international and operationally complex system. The technology enabled faster decisions about inventory, delivery routes, and local availability. In this case, AI was useful because it reduced the distance between market information and operational execution.

Starbucks provides another example of AI being used to support responsiveness rather than replace human judgment. Deep Brew connected customer data, store operations, and personalization. The system helped the company adapt offerings and store-level activities to changing customer behavior. This was important because Starbucks operates through

thousands of customer-facing stores across different markets. AI therefore supported a more responsive connection between customer interaction and operational adjustment. A Starbucks customer said “The recommendations were often useful, but the experience worked best when employees could still adapt them to what I actually wanted”. This account suggests that AI supported the customer experience most effectively when its recommendations remained open to human interpretation and adjustment. Across the three companies, AI was most useful when it improved interpretation, accelerated operational response, and preserved space for managerial judgment.

4.2 Problems Emerging from Automated Judgment

Further investigation revealed that AI integration can also create problems when automated judgment becomes difficult to interpret or control. Unilever’s AI-enabled recruitment and talent screening promised efficiency in processing large numbers of applications. The system allowed the company to reduce the time and resources needed for early-stage candidate evaluation. However, recruitment decisions are socially sensitive because they affect access to employment and organizational opportunity. In this setting, AI raised concerns about opacity, fairness, and the criteria used to evaluate candidates. A Unilever spokeswoman quoted by *The Guardian* presented the recruitment system as “just one of many tools” used in graduate recruitment, yet the same report noted concerns around automated assessment of video interviews. Even when such systems improve speed, they may also make it harder for applicants to understand how decisions are made. The case therefore suggests that efficiency gains can be accompanied by reputational and ethical risks.

The abandoned recruiting tool at Amazon offers a clearer example of problematic automated judgment. The system was designed to support hiring decisions by ranking applicants through historical data. However, the tool reportedly learned patterns from past recruitment outcomes and reproduced biased preferences. This case shows the risk of treating historical organizational data as a neutral basis for future decisions. Reuters’ account of Amazon’s abandoned recruiting tool stated that the system was “not rating candidates” for technical posts in a gender-neutral way, illustrating how historical hiring patterns could be reproduced through automated judgment. When past decisions contain structural distortions, AI can reproduce them at scale. The problem was not only technical, but strategic, because hiring affects the capabilities a firm develops over time. Amazon’s decision to abandon the tool illustrates how AI can fail when its outputs conflict with organizational fairness and decision quality.

Operational problems appeared differently in the Starbucks inventory-counting case. The system was introduced to improve product availability and reduce manual counting in stores. However, reported inaccuracies meant that the tool sometimes failed to identify products correctly. This weakened its usefulness as a basis for operational decisions. Instead of simplifying store routines, the tool risked adding confusion to everyday work. The case shows that AI can become problematic when implementation conditions differ from the assumptions embedded in the system. Across the three companies, the main issue was not AI adoption itself, but the gap between algorithmic output and situated organizational judgment.

4.3 Uneven Results Across Implementation Features

Finally, findings show that AI integrations rarely produce only beneficial or harmful consequences. The Unilever recruitment case illustrates this ambiguity clearly. On one side, AI screening allowed the company to process applications faster and reduce the burden of repetitive evaluation. On the other side, the same integration raised questions about how

candidates were assessed and whether automated evaluation could capture human potential. The outcome therefore depended on how the tool was embedded in the broader recruitment process. When AI supported human recruiters, it could improve efficiency. When it became too central to judgment, it risked weakening transparency and trust. This ambiguity is reflected in Unilever's public framing of automated assessment as "just one of many tools," suggesting that AI could be positioned as support while still raising concerns over influence and transparency.

Amazon's cases show that outcomes also varied across decision domains. In inventory positioning and delivery planning, AI strengthened operational coordination by linking demand prediction with resource deployment. However, the recruitment case showed that similar analytical logic could produce problematic results in a different decision domain. Reuters reported that Amazon recruiters "looked at the recommendations generated by the tool" but did not rely solely on its rankings, showing that assistance and influence can become difficult to separate in practice. The comparison indicates that AI is not universally beneficial or harmful across the organization. Its effects depend on the quality of data, the sensitivity of the decision, and the availability of human oversight. AI worked more convincingly when the decision task involved operational prediction. It became more problematic when the task required social interpretation and fairness-sensitive evaluation.

A comparable contrast appeared across Starbucks' two AI integrations. Deep Brew supported broader decision-making by connecting customer interaction with store-level adaptation. The inventory-counting tool, by contrast, struggled when product recognition had to work reliably in everyday store conditions. Both cases involved AI in operational decision-making, but their consequences differed because their practical requirements differed. The findings suggest that AI performs better when it informs decisions rather than mechanically closing them. They also suggest that managers must evaluate AI systems through actual use, not only through promised efficiency. Across the six cases, AI integration produced stronger results when it remained connected to human interpretation, organizational learning, and contextual adjustment. Results are synthesized in Table 1, which compares the six embedded AI integrations across companies and value outcomes.

Table 1. Cross-case synthesis of AI integration effects

Company	Embedded AI integration	Value outcome
Unilever	AI-enabled customer connectivity and supply-chain forecasting	Enhancing
	AI-enabled recruitment and talent screening	Mixed
Amazon	AI-enabled logistics and inventory positioning	Enhancing
	Abandoned AI recruiting tool	Hindering
Starbucks	Deep Brew	Mixed
	Automated inventory-counting tool	Hindering

Source: Authors' Research

5. Discussion

Based on the findings, this study shows that AI integration can enhance decision-making and support value co-creation, or hinder decision-making and generate value co-destruction. These effects influence how firms respond to deglobalization pressures, either improving

strategic adaptation or intensifying existing international challenges. Overall, AI produces enhancing, hindering, or mixed effects depending on how it is implemented.

The enhancing effect occurs when AI supports both cross-border detection and uncertainty processing. Cross-border detection refers to the ability to recognize relevant changes across markets before they become strategic problems. Uncertainty processing refers to the ability to interpret these signals and connect them with managerial action. In the cases examined, AI supported this process when it helped firms transform dispersed information into more timely operational decisions. This was visible in supply-chain forecasting, logistics coordination, and store-level adaptation.

From a dynamic capabilities perspective, these mechanisms strengthen the firm's ability to recognize change, act upon it, and reorganize resources. Under deglobalization pressures, this matters because firms must respond to fragmented demand, institutional uncertainty, and supply-chain disruptions. AI therefore contributes to value co-creation when it improves the interaction between data, managerial interpretation, and organizational response. This finding extends service-dominant logic by showing that AI can become a resource integrated into strategic decision-making processes. However, the enhancing outcome depends on AI remaining connected to human judgment rather than replacing it. In this sense, AI supports dynamic capabilities when it augments managerial interpretation under international uncertainty.

The hindering effect emerges when automation overreliance and sensitivity reduction occur together. Automation overreliance happens when managers treat algorithmic outputs as more reliable than contextual judgment. Sensitivity reduction occurs when AI systems simplify complex decisions and ignore social, institutional, or operational nuances. The recruitment cases illustrate this risk because automated screening may accelerate selection while weakening fairness and interpretability. Similarly, inventory automation may promise efficiency but create operational confusion when the system misreads practical store conditions. These findings connect with value co-destruction because AI can reduce well-being when interaction becomes opaque, inappropriate, or harmful. The risk is especially high when historical data are treated as neutral, although they may contain biased or incomplete assumptions. This problem reflects the danger of relying on artificial "ground truth" in knowledge-intensive work. Under deglobalization pressures, such failures can worsen strategic vulnerability because firms already face unstable and politically sensitive environments. If AI narrows managerial attention, firms may respond quickly but incorrectly to international complexity. Therefore, AI hinders dynamic capabilities when automation weakens interpretation, reduces flexibility, and amplifies problematic decisions at scale.

The mixed effect appears when AI accelerates adaptation but also produces routine disruption. This means that the same integration can improve some decision processes while weakening others. For example, AI may help firms coordinate operations faster, but it may also create dependence on systems that employees do not fully understand. These effects are mixed because AI does not operate independently from organizational routines, data quality, or managerial oversight. A tool that supports operational prediction can work well in logistics but fail in hiring because the decision context differs. This suggests that AI's strategic effect depends less on the technology itself than on the relationship between the technology and its use context. The mixed outcome is theoretically important because it shows that value co-creation and value co-destruction can coexist within the same AI integration. This supports the idea that AI should be understood as a double-edged mechanism in strategic decision-making. Under deglobalization, this ambiguity becomes even more important because firms must adapt quickly without losing contextual awareness. AI can help firms manage

international fragmentation, but it can also intensify fragmentation when decisions become automated without sufficient interpretation. Thus, mixed effects arise when AI accelerates adaptation while simultaneously disrupting routines that sustain strategic judgment.

6. Implications

This study contributes theoretically by connecting AI-enabled decision support with dynamic capabilities under deglobalization pressures. It shows that AI can become part of the microfoundations through which firms interpret change, act strategically, and reorganize resources (Teece, 2007; Teece, 2018). It also extends service-dominant logic by showing that AI can support value co-creation when it improves interaction between data, managers, and organizational routines (Vargo & Lusch, 2008). At the same time, the study clarifies how AI can generate value co-destruction when automation reduces contextual interpretation or amplifies problematic assumptions (Lebovitz et al., 2021; Lumivalo et al., 2024). These findings also support the view that AI creates a persistent automation–augmentation tension in management (Berente et al., 2021; Raisch & Krakowski, 2021).

Managerially, the study suggests that firms should not evaluate AI only through efficiency or speed. Under deglobalization pressures, managers should apply a brief evaluative checklist before adopting or scaling AI-supported decisions. First, decision quality: does AI improve the detection of cross-border change and the interpretation of uncertainty? Second, contextual fit: is the system appropriate for the specific market, institutional setting, and decision domain in which it is used? Third, governance: are data assumptions, fairness risks, and accountability responsibilities clearly defined? Fourth, oversight: can human actors question, correct, or stop algorithmic outputs when they conflict with local knowledge or stakeholder well-being? These checks help firms use AI as a disciplined support for strategic adaptation within the deglobalization landscape.

7. Conclusion

This study presents limitations that need to be addressed in future research. First, it relies on a small number of cases within customer-facing contexts. Second, the findings are analytically useful but not statistically generalizable. Finally, some AI integrations were reconstructed through secondary evidence, which may limit access to internal decision-making processes.

Future research should extend this study through larger comparative designs across industries, countries, and types of AI integration. Longitudinal studies could examine how AI-supported decision-making evolves over time, especially as firms learn from failure and redesign governance routines. Further research could also compare managerial, employee, and customer perspectives to understand how AI affects value outcomes across different actors. Finally, quantitative studies could test whether specific AI governance practices improve dynamic capabilities under deglobalization pressures.

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