La compétence en IA rencontre la capacité d'absorption : leviers de résilience et de performance environnementale dans les chaînes d'approvisionnement

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Résumé :

Dans un environnement mondial marqué par l'incertitude, les bouleversements technologiques et les exigences croissantes en matière de durabilité, la performance de la supply chain dépend de plus en plus de deux dimensions stratégiques : la résilience et la performance environnementale. Si les technologies d'intelligence artificielle (IA) offrent un potentiel considérable pour relever ces défis, peu d'études ont analysé comment la compétence en IA, en tant que ressource organisationnelle essentielle, interagit avec la capacité d'absorption (ACAP) pour influencer la résilience et la performance environnementale de la supply chain. À l'aide de la théorie « resource-based view » et de la théorie des capacités dynamiques, cette recherche examine le rôle médiateur de l'ACAP dans la relation entre les compétences en IA et la performance des supply chains. Un modèle conceptuel est proposé et testé empiriquement auprès d'un échantillon de 351 personnes. Les résultats révèlent que les compétences en IA améliorent considérablement la résilience et la performance environnementale de la supply chain, et qu'une ACAP élevée renforce ces effets. L'étude met en évidence le rôle complémentaire des compétences en IA et des capacités organisationnelles (ACAP) dans la résilience et la performance environnementale de la supply chain.

Mots clés :

Compétences en IA, capacité d'absorption, résilience de la chaîne d'approvisionnement, performance environnementale de la chaîne d'approvisionnement.

AI Competency Meets Absorptive Capacity: Enablers of Resilience and Environmental Performance in Supply Chains

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Abstract

In a global environment marked by uncertainty, disruptive technological developments, and growing sustainability requirements, the performance of supply chains (SC) increasingly depends on two strategic dimensions: resilience and environmental performance. While artificial intelligence (AI) technologies offer great potential for addressing these challenges, few studies have analyzed how AI competency, as an essential organizational resource, interacts with absorptive capacity (ACAP) to influence SC resilience and environmental performance. Using the resource-based view theory and the dynamic capability theory, this research examines the mediating role of ACAP in the relationship between AI competency and SC performance. A conceptual model is proposed and empirically tested with a sample of 351 individuals. The results reveal that AI competency significantly improves the SC resilience and environmental performance, and that high ACAP reinforces these effects. The study highlights the complementary role of AI competency and organizational capabilities (ACAP) in SC resilience and environmental performance.

Keywords

AI competencies, Absorptive capacity, Supply chain resilience, Supply chain environmental performance.

1. Introduction

Over the past decade, Artificial Intelligence (AI) has become a major source of strategic and commercial value for firms, driving organizational innovation and improving performance (Fosso Wamba et al., 2023; Fosso Wamba, Queiroz, Pappas, et al., 2024; Richet et al., 2024). Whereas firms use AI both to automate tasks and to support innovation strategies, the supply chain function is central to this transformation (Fosso Wamba, Guthrie, et al., 2024; Jackson et al., 2024). While AI investments are expected to generate $22.3 trillion globally by 2030, representing approximately 3.7% of world GDP (IDC, 2025), 58% of supply chain managers report significant AI-driven improvements in planning, visibility, and sustainability (Alex et al., 2025). Indeed, the supply chain function benefits greatly from AI advances, as predictive analytics, real-time visibility, and risk management have undergone profound transformations (Jackson et al., 2024). For example, General Motors has successfully implemented predictive AI systems capable of anticipating disruptions and preventing more than 75 production stoppages, illustrating the transformative potential of these technologies (Ben & BusinessInsider, 2025). At Walmart, AI-based inventory management systems use algorithms to ensure stores in warmer states stock enough pool toys, while stores in colder states stock enough sweaters, according to a press release on the company's website (Shefali, 2025). At Target, using the Inventory Ledger, algorithms analyze data such as supply lead times, transportation costs, current inventory, and consumer demand to prevent stockouts and manage inventory (Shefali, 2025). These examples suggest that AI can enhance operational responsiveness and decision quality across supply chain activities.

However, despite these promises, a growing body of evidence highlights a paradox: supply chain resilience and environmental performance remain weak, even among firms that have invested heavily in AI (Dey et al., 2024; Leoni et al., 2022). Recent reports indicate that 80% of organizations still experience significant supply chain disruptions, suggesting that AI adoption has not yet translated into robust resilience capabilities (Sudarshan & Capgemini, 2025). Similarly, while AI is expected to reduce global greenhouse gas emissions by up to 4% by 2030, its deployment is also associated with substantial energy consumption and environmental costs (Volha & Mira, 2024). Several structural limitations help explain this gap. First, AI adoption remains largely experimental, with only a small proportion of firms achieving full-scale industrialization of AI solutions (Louise, 2026). Second, many AI projects fail to deliver tangible value, often due to poor data quality and fragmented information systems; some studies suggest that up to 95% of AI initiatives generate no operational impact (Trax, 2025). Third, organizations frequently lack the necessary internal capabilities, including data governance, technical expertise, and decision-making integration, leading to what some analysts describe as “AI theatre”, initiatives that signal innovation without producing real performance improvements (Insights, 2025). Moreover, the environmental impact of AI introduces additional complexity. While AI can optimize logistics and reduce emissions, its infrastructure, particularly data centers and computational processes, consumes significant energy, potentially offsetting sustainability gains (Marisa, 2026). Evidence also suggests that organizations are adopting AI faster than they are developing mechanisms to measure and manage its environmental impact (Marisa, 2026). These findings partly explain why supply chains remain weakly resilient and environmentally inefficient despite the rise of AI. Companies often remain mired in traditional operating methods (e.g., reliance on human labor and data silos) rather than adopting fully data-driven approaches. In short, the environmental performance of the supply chain will not improve simply by using AI; it also requires developing organizational capabilities aligned with these new technologies.

Yet, the current literature still primarily focuses on AI’s capabilities (Jackson et al., 2024), often overlooking the AI competencies required to leverage it fully (Mikalef et al., 2023). This oversight is especially problematic because the actual business value of AI depends more on understanding and applying its contributions than simply adopting the technology itself, which relates to AI competency (Mikalef et al., 2023). More specifically, in a context marked by frequent disruptions (e.g., healthcare crises, geopolitical tensions, climate emergencies), supply chain resilience (the ability to anticipate, withstand, and recover from unforeseen events) has become a strategic imperative for business continuity (Dey et al., 2024; Dubey et al., 2023; Jackson et al., 2024; Rojo et al., 2018; Singh & Goyal, 2023). Furthermore, the environmental performance of supply chains is emerging as a significant issue, impacting both resilience and sustainable competitiveness (Kumar et al., 2018; Shahzadi et al., 2024).

AI competencies play a crucial role in enhancing both factors. They enable companies to strengthen flow visibility, identify risks earlier, and reduce their environmental footprint through predictive models, intelligent planning systems, and real-time decision-making (Mikalef et al., 2023; Shahzadi et al., 2024;

Wang et al., 2019). However, these advantages can only be fully achieved if the organization has a strong capacity for absorption (Neirotti et al., 2021; Wang et al., 2019; Zhang et al., 2023; Zhang et al., 2025). This capacity enables translating AI technological contributions into organizational learning by rapidly integrating external knowledge into operational practices (Neirotti et al., 2021; Wang et al., 2019). By building this organizational strategic asset, AI competencies not only help companies respond to unexpected situations but also enable them to align their supply chain strategies with their sustainability goals (Kumar et al., 2018; Shahzadi et al., 2024).

Despite the growing integration of AI into key business functions, the existing research on the supply chain still focuses primarily on the technological capabilities of AI at the expense of AI-specific competencies (Riad et al., 2024; Shahzadi et al., 2024; Shawon et al., 2025; Tuo et al., 2024; Wong et al., 2024), i.e., the ability of firms to understand, learn, and leverage this technology strategically to boost their organizational capabilities and indirectly their organizational performance (Mikalef et al., 2023). Indeed, in supply chains, where resilience and environmental performance are increasingly critical issues, AI competencies can only generate value if they are absorbed, adapted, and internalized through organizational learning mechanisms (Shahzadi et al., 2024). This echoes the notion of absorptive capacity (Flatten et al., 2011; Zahra & George, 2002), which is a key lever for capturing the benefits of emerging technologies (Amabile et al., 2012; Zahra & George, 2002). However, the relationship between AI competency, absorptive capacity, supply chain resilience, and supply chain environmental performance remains largely unexplored in both strategic and technological literature. This gap raises a fundamental question: ***(RQ1)*** *To what extent does AI competency impact supply chain performance?* ***(RQ2)*** *To what extent does absorption capacity mediate the relationship between AI competency and supply chain performance?*

To address these research questions, we employ the resource-based view theory and dynamic capabilities theory to develop a conceptual research model. This research model is tested with a sample of 351 individuals using Covariance-based Structural Equation Modeling (CB-SEM). The results indicate that AI competency has a direct influence on absorptive capacity, supply chain resilience, and supply chain environmental performance, and an indirect influence on supply chain resilience and supply chain environmental performance through absorptive capacity as a mediator.

2. Theoretical background and hypotheses

In this section, we present the resource-based view theory (Barney, 1991; Wernerfelt, 1984) and dynamic capability theory (Teece, 2007; Teece et al., 1997) as the theoretical foundations of this study.

2.1. Artificial intelligence and absorption capacity: An examination based on resource-based view and dynamic capability theories

AI is now at the heart of the digital transformation of key business functions, offering advanced capabilities in data "*processing, prediction, reasoning, learning, perception, creativity, and optimization*" (Jackson et al., 2024). However, in an increasingly complex business environment, access to technology alone does not guarantee the creation of value (Mikalef et al., 2023). It is AI competencies, which refer to a company's ability to identify, develop, integrate, and leverage AI-based resources, that determine the effectiveness of its strategic adoption (Mikalef et al., 2023; Wang et al., 2019). According to the resource-based view (RBV) literature, AI competencies must be rare, specific, difficult to imitate, and integrated into organizational routines to generate a sustainable competitive advantage (Barney, 1991; Mikalef et al., 2023; Wang et al., 2019; Wernerfelt, 1984). In this context, AI competencies extend beyond simply possessing talent or technical infrastructure; they also encompass management skills for coordinating digital resources, adapting internal structures, and promoting organizational learning with AI tools (Mikalef et al., 2023; Wang et al., 2019). AI should be distinguished from traditional IT because it does more than store, transmit, or standardize information. AI systems generate probabilistic inferences from data, can autonomously recommend or execute actions, and can be recombined across tasks and workflows in ways that reshape organizational problem-solving (Jackson et al., 2024; Wamba-Taguimdje & Kala Kamdjoug, 2026). This gives AI a distinct organizational role by redistributing decision authority, altering managerial attention, and modifying coordination patterns between humans and systems (Pascal et al., 2026). We therefore conceptualize AI not as a deterministic support tool, but as an adaptive and partly autonomous sociotechnical mechanism whose value depends on how organizations govern and integrate algorithmic outputs into collective decision-making (Boussioux et al., 2024). Existing studies have shown that possessing AI competencies is essential for developing organizational capabilities and positively impacting organizational performance in terms of resilience, agility, financial, and environmental (Belhadi et al., 2022; Mikalef et al., 2023; Singh & Goyal, 2023; Wong et al., 2024). Similarly, according to the RBV, companies can improve their logistics performance by leveraging distinctive internal resources, such as AI competencies (Fosso Wamba, Guthrie, et al., 2024; Fosso Wamba et al., 2023; Jackson et al., 2024). These resources, when "*rare, valuable, and difficult to imitate*", enable firms to plan more effectively, predict outcomes, and execute supply chain operations more efficiently (Dey et al., 2024; Li et al., 2025).

Dynamic capability (DC) theory complements this vision by emphasizing that, in an uncertain logistics environment (supply disruptions, demand volatility, ecological crises), performance does not depend solely on available resources, but above all on the ability to adapt them quickly (Evrard Samuel & Ruel, 2013; Rojo et al., 2018). The DC theory highlights an organization's capability to integrate, build, and reconfigure its resources in response to environmental changes (Teece, 2007; Teece et al., 1997). Many different perspectives converge in this theory, which highlights the significant role environmental change plays in shaping the company's history (Teece, 2007; Teece et al., 1997). Moreover, from a more managerial and strategic perspective of the RBV, the DC theory focuses on modifying resources to enhance competitive advantage and impact on organizational performance (Teece, 2007; Teece et al., 1997). DC theory also focuses on the trend of innovation concerning flexibility in rapidly changing environments and the identification of new opportunities (Teece, 2007; Teece et al., 1997). Researchers have used this theory to understand either the resilience, supply chain performance, supply chain environmental performance, or the importance of innovative technologies on the supply chain (Chowdhury & Quaddus, 2017; Dubey et al., 2023; Irfan et al., 2019; Kähkönen et al., 2023; Kazmi & Ahmed, 2022; Kumar et al., 2018; Shahzadi et al., 2024). However, prior research drawing on RBV and DC theory in supply chain contexts has predominantly examined AI either as a set of capabilities or as a standalone technological innovation (Felsberger et al., 2022). In contrast, the IS and IT literature provides growing empirical evidence that AI technologies create value only when they are strategically leveraged through firm-specific competencies and organizational capabilities, such as AI competency (Gama & Magistretti, 2023; Mikalef et al., 2023) and absorptive capacity (Bag et al., 2023; Zhang & Yang, 2024; Zhang et al., 2025).

Indeed, AI competency is defined as a multidimensional organizational capability encompassing functional expertise in data and AI systems, cybersecurity management, and ambidextrous capacity to exploit existing knowledge while exploring new AI-driven opportunities, enabling firms to effectively deploy and continuously adapt AI technologies (Gama & Magistretti, 2023; Mikalef et al., 2023). At the firm level, AI competencies are viewed as a strategic resource within the RBV framework (Mikalef et al., 2023), as they encompass valuable, rare, and hard-to-imitate technological and organizational capabilities (Li et al., 2025). However, the traditional RBV is static and does not account for the rapidly changing contexts of the supply chain environment (Mohsin et al., 2025; Stentoft et al., 2023). This is why we draw on DC theory, which complements the RBV by explaining how firms must capture and reconfigure their resources to adapt to uncertainty (Mohsin et al., 2025; Stadtfeld & Gruchmann, 2023). According to DC theory, simply possessing a resource (in this case, AI competencies) is not enough; firms must be able to transform and deploy it dynamically. In this context, absorptive capacity plays a central role. Absorptive capacity is conceptualized as a dynamic capacity that enables the acquisition, assimilation, transformation, and exploitation of new knowledge (Zahra & George, 2002). In other words, absorptive capacity serves as a link between RBV and DC theory (Neirotti et al., 2021), because it transforms the AI resource (competencies) into a dynamic lever for resilience and environmental performance (Felsberger et al., 2022; Zhang et al., 2025). In concrete terms, absorptive capacity does not merely filter information passively; it activates the AI competencies by facilitating the integration of external AI-related knowledge and by continuously adapting practices (Neirotti et al., 2021; Zhang et al., 2025). Therefore, our framework posits that AI competency (resource) and absorptive capacity (dynamic capability) interact in a complementary manner (Zhang et al., 2025). For example, when AI investments are high, a strong level of absorptive capacity is necessary to transform these resources into concrete benefits. Conversely, beyond a certain threshold of AI competency, the additional impact of absorptive capacity may diminish, suggesting the existence of threshold effects or non-linearity (Li et al., 2025; Zhang & Yang, 2024).

Furthermore, according to DC theory, dynamic capabilities such as absorptive capacity enable companies to reconfigure their logistics processes, integrate innovations, and respond effectively to disruptions (Chowdhury & Quaddus, 2017; Flatten et al., 2011; Teece, 2007; Zahra & George, 2002).

This capacity enables the organization to capture external knowledge, transform it, and leverage it to enhance the resilience and sustainability of its supply chain (De Benedittis et al., 2018; Mouakhar & Benkeltoum, 2020). Moreover, while RBV helps explain why AI competencies can be treated as a valuable organizational resource (Mikalef et al., 2023), it is insufficient on its own to explain how value is generated in supply chains. In this study, we therefore position AI competencies not as a static inventory of digital assets, but as an enabling base that supports the reconfiguration of information flows, decision routines, and coordination processes across the supply chain (Gama & Magistretti, 2023; Mikalef et al., 2023). This move is consistent with DC logic, which emphasizes sensing, seizing, and reconfiguring in response to changing conditions (Stadtfeld & Gruchmann, 2023). In supply chain management, such reconfiguration is reflected in enhanced visibility, faster information processing, and tighter coordination among actors, rather than in technology ownership alone (Jackson et al., 2024; Stadtfeld & Gruchmann, 2023). Our model, therefore, assumes that AI competencies become valuable when they are mobilized through organizational mechanisms that alter how information is interpreted, shared, and translated into coordinated action. Thus, combining RBV and DC theory is relevant for: (a) linking strategic resources (AI competencies) to performance, (b) explaining how these resources produce value through the activation of DC (absorptive capacity), and (c) understanding their effect on the resilience and environmental performance of the supply chain (Dubey et al., 2023; Gölgeci & Kuivalainen, 2020; Kumar et al., 2018; Liu et al., 2013; Shahzadi et al., 2024; Singh et al., 2019). **Table 1** presents the definition of the four key constructs of our research model.

Construct	Definitions	Reference
AI competency	"*An AI competency is not merely the technology used to support it, or the technical ability to leverage it effectively, but the creative bundling of such technologies, organizational knowledge, and institutions as a harmonious whole*". In this study AI competence refers to a cross-functional and hard-to-imitate organizational capability that enables the effective deployment, integration, and strategic use of AI technologies across processes.	(Mikalef et al., 2023, p. 3)
Absorptive capacity	Absorptive capacity refers to an organization's dynamic capability to systematically identify valuable external	(Zahra & George, 2002)

Construct	Definitions	Reference
	knowledge, assimilate it through internal learning processes, and transform it into actionable insights that drive innovation, adaptation, and strategic performance.	
Supply chain resilience	Supply chain resilience refers to a supply chain's ability to anticipate, absorb, and adapt to unexpected disruptions while maintaining or rapidly recovering its core functions and performance.	(Gölgeci & Kuivalainen, 2020)
Supply chain environmental performance	Supply chain environmental performance refers to the extent to which a supply chain integrates environmentally responsible practices, such as resource efficiency, pollution control, and waste reduction, across its operations and partnerships to minimize ecological impact and comply with stakeholder and regulatory expectations.	(Fosso Wamba, Queiroz, & Trinchera, 2024)

Table 1: Constructs definition.

Figure 1 illustrates the conceptual model along with the corresponding research hypotheses. Indeed, the research model links three levels. First, AI-related competencies form the enabling base that does not mechanically affect outcomes. Second, these competencies are transformed through organizational capabilities and coordination routines (absorptive capacity). Indeed, AI competency operates through organizational transformation mechanisms that enable the firm to absorb information, coordinate across functions, and reconfigure decisions and processes. Third, these transformation processes generate performance outcomes (supply chain resilience and environmental performance). The conceptual model, therefore, explains not only whether AI matters, but also through which organizational pathway it is expected to matter. This logic allows the research model to move beyond the simple proposition that AI resources (competencies) improve organizational outcomes (Li et al., 2025; Zhang et al., 2025) and instead specifies how value is created within the organization.

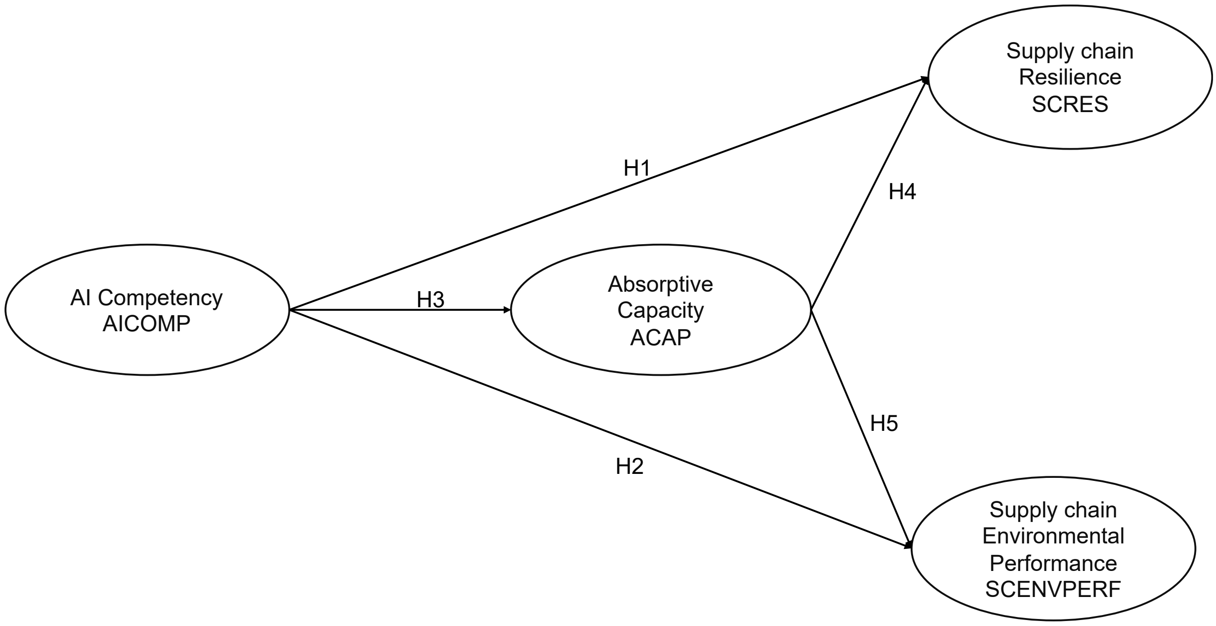

Figure 1: Research model.

2.2. AI competencies, supply chain resilience, and supply chain environmental performance

First, this study adopts a systemic view of AI-enabled value creation and organizational performance (Li et al., 2025; Zhang & Yang, 2024). The focal issue is not whether firms possess AI-related resources, but whether these resources help redesign information-processing and coordination patterns (Jorzik et al., 2023; Mikalef et al., 2023; Tippins & Sohi, 2003). AI competencies are therefore theorized as a higher-order enabling condition that supports supply chain adaptation by improving how firms structure data flows, integrate signals, and coordinate decisions across organizational boundaries. In this sense, the research model extends RBV with a DC theory interpretation centered on reconfiguration rather than possession (Huang et al., 2023). Indeed, while prior research often treats AI as part of the broader domain of IT capabilities, recent work suggests that AI competencies should be conceptualized as a distinct, higher-order organizational construct (Mikalef et al., 2023). Traditional IT capabilities primarily refer to a firm's ability to deploy and manage IS/IT to support operational efficiency and information processing. In contrast, AI competencies extend beyond technical deployment to embed AI into the firm's core strategic and organizational fabric (Gama & Magistretti, 2023; Jorzik et al., 2023). Building on Mikalef et al. (2023, p. 3), AI competencies encompass three key characteristics that differentiate it from conventional IT capabilities. First, it involves the ability to orchestrate AI technologies to enable competitive differentiation, rather than merely improve efficiency. Second, it spans multiple organizational functions and processes, reflecting its cross-functional and integrative nature. Third, it is inherently difficult to imitate, as it relies on continuous experimentation, learning, and proactive adaptation. Therefore, unlike IT capabilities, which are often operational and support-oriented, AI competency represents a core organizational capability that shapes strategic positioning and long-term value creation. This distinction is critical for understanding how firms can leverage AI not just as a technological tool, but as a source of sustained competitive advantage. For example, Jorzik et al. (2023) show that the require AI competencies to help firm innovate their business model are knowledge and understanding of AI technology, AI mindset, AI leadership capabilities, ability to navigate AI abstraction, ability to make AI-based decisions. For Gama and Magistretti (2023), when firms rely on AI for innovation their need build some competencies such functional competency (ability of team to manage end embed different AI technology bricks into products, services, or process), cybersecurity management, ambidextrous competence (ability to simultaneous deliver high-quality services at a lower cost, sense and seize opportunities made possible AI technologies). AI competencies differ from traditional IT capabilities, which primarily focus on the management and governance of technology. According to Berente et al. (2021), "*managing AI involves communicating, leading, coordinating, and controlling an ever-evolving frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems" (p. 1433).*

In contrast, according to exiting studies, AI competencies extend beyond technical domains to include end users, who must develop not only technical knowledge but also critical thinking, ethical awareness, and evaluative skills [e.g., (Annapureddy et al., 2025), (Chandra et al., 2022), (Gupta & Jaiswal, 2024), (Kim & Kwon, 2023), (Lee & Zhou, 2026), and (Russell et al., 2023)]. This distinction is particularly important in the context of GenAI technologies, as such technologies are no longer confined to IT departments but are increasingly accessible and used across all organizational levels (Gama & Magistretti, 2023; Jorzik et al., 2023; Mikalef et al., 2023). The concept of AI competency has been increasingly framed not merely as a set of technical skills but as a core organizational capability with strategic implications. According to Mikalef et al. (2023, p. 3) AI competencies must include three key features: (a) "*it must address the technical ability to effectively orchestrate the technology in an effective manner and have the potential for competitive differentiation*"; (b) "*it must transcend a single business unit and cover a range of operations and processes*"; and (c) "*it must hard for competitors to imitate, which requires a focus on continuous experimentation and proactiveness*". Organizations with strong AI competencies can have better predictive tools, greater real-time adaptability, and increased decision-making agility (Jorzik et al., 2023; Mikalef et al., 2023). These competencies enable supply chains to respond more quickly to disruptions (resilience) and better manage resources, thereby reducing their ecological footprint (environmental performance) (Riad et al., 2024; Shawon et al., 2025; Tuo et al., 2024).

First, several studies have shown that AI competency can enhance supply chain resilience by improving visibility, risk forecasting, and operational responsiveness. For example, Belhadi et al. (2022), Jackson et al. (2024), Riad et al. (2024), Shawon et al. (2025), Singh and Goyal (2023), and Wong et al. (2024) emphasize that the integration of AI technologies (e.g., machine learning, fuzzy systems, deep learning, wavelet neural networks, predictive analytics, or GenAI) improves preparedness, response, and recovery in the supply chain, with a particularly pronounced effect on the readiness phase. Furthermore, an empirical study in Ghana demonstrates that AI capabilities directly strengthen supply chain resilience, which then acts as a mediator to improve the overall performance of the supply chain (Shawon et al., 2025; Tuo et al., 2024). Therefore, we hypothesize that.

H1. *AI competency has a positive and significant influence on supply chain resilience.*

Second, recent research has established a positive relationship between the use of AI and environmental performance (Fosso Wamba, Queiroz, & Trinchera, 2024; Shahzadi et al., 2024). This existing research empirically confirms that adopting AI improves supply chain environmental performance by using predictive and optimization AI models and techniques on logistics data to reduce carbon emissions, to optimize travel routes, to minimize distance and travel time, and to forecast future deliveries to plan the most efficient routes (Shahzadi et al., 2024; Shawon et al., 2025). Therefore, we hypothesize that.

H2. *AI competency has a positive and significant influence on supply chain environmental performance.*

2.3. AI competencies and absorptive capacity

In this study, absorptive capacity is not treated as a black-box mediator. It is understood as the set of routines through which firms identify, interpret, transform, and exploit AI-generated information (Neirotti et al., 2021). In AI-enabled settings, this process requires more than information access. It depends on data governance rules, cross-functional interfaces, human interpretation of model outputs, and operational routines that convert algorithmic signals into actionable decisions (Bag et al., 2023; Neirotti et al., 2021; Zhang & Yang, 2024). Absorptive capacity, therefore, represents the organizational mechanism that links AI competencies to coordinated action.

AI competency is defined here as the set of knowledge, expertise, and organizational routines that enable the understanding, exploitation, and adaptation of AI-based systems to specific strategic objectives (Mikalef et al., 2023). These competencies serve as catalysts for organizational capabilities (e.g., absorptive capacity), facilitating the identification of relevant knowledge sources, their assimilation, and subsequent transformation into innovations or improved processes (Liu et al., 2013; Mikalef et al., 2023; Neirotti et al., 2021). Besides, when traditional IT mainly improves information availability, AI can also reshape organizational cognition by changing how signals are prioritized, how alternatives are generated, and how decision rights are distributed between human actors (employees) and algorithmic systems (Boussioux et al., 2024; Pascal et al., 2026). Accordingly, the expected effect of AI competencies on performance is not purely informational; it is also cognitive and coordinative. Specifically, in the case of GenAI, unlike conventional analytics systems, GenAI produces probabilistic outputs that may vary across prompts, contexts, and interaction settings. Its organizational value, therefore, depends not only on model access but also on prompt formulation, task framing, and human oversight. In this sense, GenAI is better understood as a prompt-sensitive and generative system whose outputs are contingent rather than fixed. This also suggests that variation in prompt capability and human oversight may explain heterogeneous outcomes across firms. Therefore, the more competent an organization is in the strategic use of AI, the more capable it will be of quickly converting complex digital signals into organizational learning. More specifically, AI competency improves performance only when algorithmic outputs are absorbed through organizational routines. For example, this can involve several steps: (i) AI-generated signals (insights or contents) must be rendered understandable and credible; (ii) they must be combined with contextual and operational knowledge held by managers and frontline actors; and (iii) they must be embedded into decision routines, coordination protocols, and execution processes (Neirotti et al., 2021). Absorptive capacity captures this sequence of interpretation, transformation, and integration. Existing studies show that firms' competencies influence their organizational capabilities (absorptive capability) in innovative technology (e.g., big data, AI, digital technologies) (Bag et al., 2023; Liu et al., 2013; Mikalef et al., 2023; Neirotti et al., 2021; Rubbio & Bruccoleri, 2023; Srivastava et al., 2015). Therefore, we hypothesize that.

***H3**. AI competency has a positive and significant influence on absorptive capacity.*

2.4. Absorptive capacity, supply chain resilience, and supply chain environmental performance

Absorptive capacity is a key dynamic capability that enables organizations to detect, assimilate, transform, and exploit external knowledge to respond effectively to environmental changes (Flatten et al., 2011; Rojo et al., 2018; Zahra & George, 2002). In the context of supply chain management, where operational uncertainties, healthcare crises, AI-driven competitiveness, and sustainability pressures are on the rise, this capability is a strategic lever for building both organizational resilience and sustainable environmental performance. Indeed, absorptive capacity serves as a strategic learning mechanism that translates information from the external environment, whether related to logistical risks, technological developments, or environmental requirements, into effective organizational responses (Abourokbah et al., 2023; Dubey et al., 2023; Dzhengiz & Niesten, 2020; Rojo et al., 2018). It thus contributes simultaneously to making the supply chain more resilient to disruptions and more environmentally responsible.

First, several studies highlight that absorptive capacity strengthens companies' ability to anticipate and absorb disruptions, whether they are minor (such as delays or shortages) or significant (like pandemics or geopolitical crises) (Abourokbah et al., 2023; Dubey et al., 2023; Kähkönen et al., 2023; Roh et al., 2022; Rojo et al., 2018). Gölgeci and Kuivalainen (2020) demonstrate that organizations with strong absorptive capacity can quickly transform external information into adaptive operational responses, thereby improving their ability to maintain critical flows. In times of crisis, this ability allows companies to reconfigure their networks, innovate in processes, and coordinate partners in an agile manner

(Abourokbah et al., 2023; Dzhengiz & Niesten, 2020; Roh et al., 2022). Thus, absorptive capacity serves as a fundamental facilitator of supply chain resilience in unstable environments (Dzhengiz & Niesten, 2020). Therefore, we hypothesize that.

H4. *Absorptive capacity has a positive and significant influence on supply chain resilience.*

Second, absorptive capacity also significantly influences the enhancement of supply chain environmental performance (Dzhengiz & Niesten, 2020; Kumar et al., 2018). It enables companies to capture knowledge related to green technologies, sustainable practices, or regulatory requirements, and then transform it into operational innovations that reduce emissions, waste, or energy consumption (Dzhengiz & Niesten, 2020; Kumar et al., 2018). This ability to integrate external environmental knowledge is becoming essential in a supply chain faced with growing expectations from stakeholders (NGOs, governments, consumers) (Dzhengiz & Niesten, 2020; Gölgeci & Kuivalainen, 2020). By facilitating continuous learning around responsible practices, absorptive capacity strengthens an organization's ability to respond proactively to environmental issues (Dzhengiz & Niesten, 2020; Kumar et al., 2018). Thus, we hypothesize that.

H5. *Absorptive capacity has a positive and significant influence on supply chain environmental performance.*

2.5. The mediation effect of absorptive capacity

First, supply chain resilience is defined as the ability of a logistics system to withstand disruptions, recover quickly, and maintain its critical functions in an uncertain environment (Evrard Samuel & Ruel, 2013; Ponomarov & Holcomb, 2009; Shahzadi et al., 2024). With the emergence of global crises (pandemics, supply disruptions, geopolitical conflicts), this concept has become central to modern logistics strategies. Studies have shown that AI-based technologies can strengthen logistics resilience through predictive tools, real-time visibility, and adaptive flow optimization (Dubey et al., 2023; Shahzadi et al., 2024). However, the ability to leverage these technologies largely depends on an organization's capacity to interpret, contextualize, and integrate digital signals into its decision-making processes (Rojo et al., 2018; Srivastava et al., 2015; Wang et al., 2019). Furthermore, absorption capacity plays a fundamental role in rapid adaptation to logistical disruptions. It enables dynamic reconfiguration of resources and partnerships in response to exogenous shocks (Flatten et al., 2011; Zahra & George, 2002). In this study, we argue that supply chain resilience is influenced by both AI competency (a strategic resource) and absorptive capacity (a dynamic capacity that facilitates agility) (Shahzadi et al., 2024). Similarly, this resilience is indirectly promoted by AI competency through the mediation of absorptive capacity, which acts as a conversion mechanism between informational resources (AI competency) and operational results (resilience).

***H6**. Absorptive capacity mediates the relationship between AI competency and supply chain resilience.*

Second*,* supply chain environmental performance refers to a company's ability to mitigate the negative environmental impacts of its operations through sustainable practices, such as eco-design, waste reduction, CO_2 emission reduction, and the responsible use of resources (Fosso Wamba, Queiroz, & Trinchera, 2024; Kumar et al., 2018; Zhang et al., 2025). AI technologies are playing an increasingly important role in this area, enabling route optimization, energy demand prediction, real-time inventory adjustments, and the identification of opportunities for a circular economy (Shahzadi et al., 2024; Shawon et al., 2025). However, as with resilience, these benefits largely depend on the organizational capacity to absorb technological innovations and apply them to ecological purposes (Zhang et al., 2025). Therefore, based on the existing literature, we argue that environmental performance is indirectly promoted by AI competency through the mediation of absorptive capacity, which conditions the appropriation of these technologies in sustainability practices.

***H7**. Absorptive capacity mediates the relationship between AI competency and Supply chain environmental performance.*

3. Methodology

Data were collected through an online survey administered by Bilendi, a professional market research provider. The survey targeted mid-level, managerial, and senior executives engaged in supply chain activities within organizations that had already implemented artificial intelligence (AI) and business analytics (BA) initiatives to enhance operational and organizational performance. All respondents indicated that they possessed a solid understanding of both the technical and managerial capabilities required for successful AI and BA deployment in their firms. In total, 351 usable responses were obtained, yielding a 8.6% response rate. This rate is consistent with prior studies employing comparable online survey methods, such as Delic and Eyers (2020) and Li et al. (2020). For example, Li et al. (2020) reported a response rate of 3.4% in their study of digital technologies and firm performance in Chinese manufacturing, while Delic and Eyers (2020) achieved a response rate of 9.8% in their investigation of additive manufacturing adoption within European automotive supply chains.

Variables	**Factors**	***N*=351**	**Percentage (%)**
Segment	Banking/finance	30	8.55
	Retailing	16	4.56
	Other	34	9.69
	Computers/software	64	18.23
	Consulting	22	6.27
	Insurance	21	5.98
	Manufacturing	88	25.07
	Medicine/health	24	6.84
	Publishing/communications	13	3.70
	Hotel/restaurants	11	3.13
	Transportation	20	5.70
	Energy	3	0.85
	Telecommunication	5	1.42
Age	18–24	12	3.42
	25–34	64	18.23
	35–49	165	47.01
	50–64	106	30.20
	>65	4	1.14
Gender	Male	199	56.70
	Female	151	43.02
	NA	1	0.28
Education	High School	55	15.67

Variables	Factors	*N*=351	Percentage (%)
	Bachelor	128	36.47
	Master	86	24.50
	Postgraduate	54	15.38
	Ph.D.	28	7.98
Position	Directors of Operations	64	18.23
	Vice Presidents	47	13.39
	Operations Managers	38	10.82
	Project Manager	38	10.82
	Business Analyst	15	4.27
	Distribution Manager	13	3.70
	Director of Logistics & Distribution	9	2.56
	Logistics Analyst	8	2.28
	Supply Chain Manager	7	1.99
	Director of Global Procurement	7	1.99
	Purchasing Manager	7	1.99
	Other positions	98	27.92

Table 2: Sample description (n=351).

From an industry perspective, manufacturing was the most represented sector (25.1%), followed by computer/software-related activities (18.2%). On average, respondents reported nine years of experience in their current role (median = 7 years). Concerning job positions, 18% identified as Directors of Operations, 13% as Vice Presidents, 11% as Operations Managers, and 11% as Project Managers. Regarding respondents' demographic characteristics, the largest age group was 35-49 years (47%), followed by 50-64 years (30%) and 25-34 years (18.2%). A small proportion of respondents were under 25 (3.4%) or over 65 (1.1%). The sample comprised 56.7% male and 43.3% female participants. In terms of education, 36.5% of respondents held a bachelor's degree, while 24.5% had completed a master's degree. A comprehensive overview of respondents' demographic characteristics and additional descriptive statistics is provided in **Table 2**.

3.1. Measures

The constructs used in this study were derived from existing literature and measured via validated seven-point Likert scales, with responses ranging from 1 ("*strongly disagree*") to 7 ("*strongly agree*"). Descriptive statistics for all items are reported in **Table 3**.

AI competency (AICOMP). This construct captures a cross-functional organizational capability that is difficult to imitate and that supports the effective deployment, integration, and strategic use of AI technologies across business processes, ultimately contributing to sustained competitive advantage (Mikalef et al., 2023, p. 3). We operationalize AI competency as a second-order reflective construct with three first-order reflective dimensions: AI objects, AI operations, and AI knowledge. The measurement scale includes 15 items adapted from prior validated instruments (Tippins & Sohi, 2003; Wang et al., 2019), ensuring consistency with established approaches in the literature.

Absorptive capacity (ACAP). Absorptive capacity is conceptualized as a dynamic organizational capability that enables firms to identify and acquire valuable external knowledge, assimilate it through internal processes, and transform it into actionable insights that support innovation, adaptation, and improved performance (Zahra & George, 2002). In line with prior research, ACAP is modeled as a second-order reflective construct encompassing four first-order reflective dimensions: Acquisition, Assimilation, Transformation, and Exploitation. The construct is measured using 14 items adapted from established scales (Flatten et al., 2011; Jaklič et al., 2018). These items capture the firm's ability to assimilate AI-based insights, translate them into shared understanding, and integrate them into operational and managerial decisions for the supply chain. This includes routines such as data governance, cross-functional dialogue, interpretation of algorithmic recommendations, and the incorporation of AI-generated information into ongoing coordination processes.

Supply chain environmental performance (SCENVPERF). Supply chain environmental performance reflects the extent to which supply chain activities incorporate environmentally sustainable practices - such as efficient resource utilization, emissions reduction, and waste management - across operations and inter-organizational relationships, with the aim of reducing environmental impact and meeting regulatory and stakeholder expectations (Fosso Wamba, Queiroz, & Trinchera, 2024). This construct is operationalized using four reflective items adapted from prior literature (Huang & Li, 2017), consistent with existing measures of environmental performance in supply chain contexts.

Supply chain resilience (SCRES). Supply chain resilience refers to the capability of a supply chain to anticipate potential disruptions, absorb shocks, and adapt effectively in order to maintain or quickly restore its operational performance (Gölgeci & Kuivalainen, 2020). The construct is modeled as a first-order reflective latent variable and measured using four items adapted from Shin and Park (2021).

3.2. Data Analysis

To assess the proposed theoretical model, we applied Covariance-Based Structural Equation Modeling (CB-SEM) (Bollen, 1989). The analyses were conducted in R version 4.3.0, using the *lavaan* package (version 0.6–18) (Rosseel, 2019), in combination with *semTools* (version 0.5–6) (Jorgensen et al., 2019) and *semoutput* (version 1.0.2) (Tsukahara, 2023). Data normality was examined using Mardia's test for multivariate skewness (Mardia, 1970). As the test revealed a significant deviation from multivariate normality (Mardia's multivariate skewness = 1603.724; *p-value* < 0.001), we employed the maximum likelihood estimator with robust standard errors and a mean- and variance-adjusted test statistic (MLMV) to account for non-normality (Asparouhov & Muthén, 2010; Rosseel, 2019). Model fit was evaluated using robust indicators in line with recommendations by Guide Jr and Ketokivi (2015), including the Satorra-Bentler scaled chi-square ($SB\chi^2$), the robust Root Mean Square Error of Approximation (RMSEA), the robust Comparative Fit Index (CFI), and the robust Standardized Root Mean Square Residual (SRMR). We also considered the null hypothesis test for a RMSEA < 0.05 and its 90% confidence interval as additional evidence of model adequacy. In accordance with established criteria, a satisfactory model fit was defined by CFI > 0.95, RMSEA < 0.06, and SRMR < 0.05 (Hu & Bentler, 1999; Satorra & Bentler, 1994; Steiger, 2007). Furthermore, model fit was assessed using the chi-square to degrees of freedom ratio, following the guidelines of Jöreskog and Sörbom (1993).

We assessed the internal consistency of each first-order construct using Cronbach's alpha and its 95% confidence interval (Trinchera et al., 2018), focusing on the lower bound. In addition, we computed the

Omega reliability coefficient (Raykov, 2001) and Average Variance Extracted (AVE) to further evaluate a scale reliability. To assess whether AICOMP and ACAP are adequately represented as second-order latent constructs, we estimated two Confirmatory Factor Analysis (CFA) models. In the hypothesized model, each construct is specified as a second-order reflective factor manifested through its corresponding first-order dimensions. In contrast, the alternative model treats each construct as a single first-order latent variable directly measured by all items across its dimensions. Model comparisons were conducted using the chi-square difference test (likelihood ratio test, LRT) and the Root Mean Square Error of Approximation associated with the chi-square difference ($RMSEA_D$), following the guidelines proposed by Savalei et al. (2024). As advocated by Gaskin et al. (2025), discriminant validity was assessed using the procedures outlined by Rönkkö and Cho (2022) and the HTMT2 values (Roemer et al., 2021). Finally, to address potential Common Method Bias (CMB) that could affect structural model results, we followed the approach suggested by Malhotra et al. (2006).

Constructs	**First order dimensions**	**Items**	**Mean**	**SD**	**Median**	**Min**	**Max**	**Skew**	**Kurtosis**
AICOMP	AI_KNOW	AIKNOW1	5.228	1.542	5	1	7	-0.820	0.090
		AIKNOW2	4.980	1.667	5	1	7	-0.750	-0.120
		AIKNOW3	5.094	1.587	5	1	7	-0.710	-0.200
		AIKNOW4	5.179	1.567	5	1	7	-0.860	0.210
	AI_OBJECT	AIOBJECT1	4.644	1.872	5	1	7	-0.570	-0.780
		AIOBJECT2	5.083	1.736	5	1	7	-0.900	0.020
		AIOBJECT3	5.006	1.545	5	1	7	-0.720	0.000
		AIOBJECT4	4.974	1.716	5	1	7	-0.840	-0.080
		AIOBJECT5	4.989	1.571	5	1	7	-0.730	-0.020
	AI_OPER	AIOPER1	4.775	1.871	5	1	7	-0.650	-0.580
		AIOPER2	5.154	1.651	5	1	7	-0.860	0.030
		AIOPER3	5.063	1.652	5	1	7	-0.800	0.030
		AIOPER4	5.291	1.551	6	1	7	-0.950	0.480
		AIOPER5	5.202	1.625	6	1	7	-0.920	0.240
		AIOPER6	5.259	1.569	6	1	7	-0.990	0.470
ACAP	ACQUIS	ACQUIS1	5.464	1.360	6	1	7	-0.870	0.470
		ACQUIS2	5.672	1.306	6	1	7	-1.170	1.480
		ACQUIS3	5.151	1.520	5	1	7	-0.780	0.130
	ASSIMIL	ASSIMIL1	5.379	1.394	6	1	7	-0.920	0.620
		ASSIMIL2	5.430	1.434	6	1	7	-0.950	0.500
		ASSIMIL3	5.416	1.379	6	1	7	-0.880	0.520
		ASSIMIL4	5.416	1.409	6	1	7	-0.980	0.690

Constructs	First order dimensions	Items	Mean	SD	Median	Min	Max	Skew	Kurtosis
	EXPLOIT	EXPLOIT1	5.368	1.412	6	1	7	-0.930	0.570
		EXPLOIT2	5.573	1.292	6	1	7	-1.050	1.120
		EXPLOIT3	5.707	1.187	6	1	7	-1.080	1.490
	TRANSFOR	TRANSFOR1	5.635	1.232	6	1	7	-1.120	1.420
		TRANSFOR2	5.544	1.326	6	1	7	-1.090	1.100
		TRANSFOR3	5.598	1.186	6	1	7	-0.900	0.900
		TRANSFOR4	5.712	1.178	6	1	7	-1.170	1.870
SCENVPERF		SCENVPERF1	4.991	1.541	5	1	7	-0.620	-0.190
		SCENVPERF2	5.530	1.385	6	1	7	-1.130	1.180
		SCENVPERF3	5.097	1.531	5	1	7	-0.820	0.150
		SCENVPERF4	5.140	1.474	5	1	7	-0.840	0.320
SCRES		SCRESILI1	5.425	1.188	6	1	7	-0.990	1.580
		SCRESILI2	5.368	1.262	6	1	7	-0.900	0.880
		SCRESILI3	5.425	1.228	6	1	7	-0.840	0.830
		SCRESILI4	5.433	1.159	6	1	7	-0.900	1.350

Table 3: Descriptive statistics for the observed measures (n=351).

4. Results

4.1. Measurement model assessment

Table 4 presents the reliability indicators for all first-order constructs, including Cronbach's alpha with associated 95% confidence intervals, coefficient omega (CR), and Average Variance Extracted (AVE). For every first-order construct, the lower bound of the Cronbach's alpha confidence interval exceeds 0.78, indicating satisfactory internal consistency. The coefficient omega and AVE values further corroborate the reliability of the scales.

Construct	First order dimension	Cronbach's Alpha [CI][1]	AVE	CR
AICOMP	AI_OBJECT	0.902 [0.880 — 0.924]	0.654	0.904
	AI_OPER	0.936 [0.920 — 0.951]	0.709	0.935
	AI_KNOW	0.947 [0.936 — 0.958]	0.820	0.948
ACAP	ACQUIS	0.787 [0.732 —0.842]	0.555	0.788
	ASSIMIL	0.893 [0.868 —0.919]	0.679	0.894

[1] 95% Confidence Interval limits computed according to Trinchera et al., 2018 are reported in bracket.

Construct	First order dimension	Cronbach's Alpha [CI][1]	AVE	CR
	TRANSFOR	0.913 [0.891 —0.935]	0.731	0.915
	EXPLOIT	0.837 [0.796 — 0.878]	0.640	0.841
SCENVPERF	SCENVPERF	0.899 [0.872 — 0.926]	0.691	0.899
SCRES	SCRES	0.891 [0.866 —0.916]	0.691	0.896

Table 4: Construct reliability (n=351).

Standardized factor loadings and their 95% confidence intervals, obtained from the model shown in **Figure 1**, are reported in **Table 5**. All point estimates for factor loadings exceed 0.62, with upper confidence bounds well above 0.70 and no lower bound falling below 0.50. These results confirm that each indicator appropriately reflects its intended latent construct.

The nested model comparison results reported in **Table 6** provide strong support for representing AICOMP and ACAP as second-order latent constructs. For both constructs, the CFA results indicate that the model specifying a second-order model fits the data significantly better (*p-value* < 0.001) than the alternative model in which each construct is modeled as a single first-order latent variable directly measured by all associated items. Consistent with these findings, the RMSEA associated with the chi-square difference ($RMSEA_D$) further supports the superiority of the second-order specification. Overall, these results provide robust empirical justification for modeling AICOMP and ACAP as higher-order reflective constructs.

Inter-construct correlations and the upper bounds of their respective confidence intervals are shown in **Table 7**. Following the guidelines by Rönkkö and Cho (2022), we examined discriminant validity by evaluating the 95% confidence interval for each correlation estimate. In addition, we computed HTMT2 values for all pairs of focal constructs (Roemer et al., 2021). The highest HTMT2 value observed was 0.74, corresponding to the relationship between the exploitation dimension of absorptive capacity and supply chain resilience. This value remains well below the more conservative threshold of 0.85, thereby providing additional evidence supporting discriminant validity. Furthermore, a series of nested model comparisons was conducted by constraining the correlation between each pair of latent constructs to 0.90. Discriminant validity is supported when the unconstrained model provides a significantly better fit relative to the constrained models. As all upper bounds of the 95% confidence intervals for inter-construct correlations are below 0.86, this suggests minimal concern regarding discriminant validity, in line with Rönkkö and Cho (2022) recommendations. Furthermore, **Table 8** presents model comparisons, showing that the unconstrained model consistently outperforms the constrained counterparts, thus providing further evidence in favor of discriminant validity between all the constructs.

Constructs	First order dimensions	Items	Standardized Loadings	95% CIs	SEs	p-values
AICOMP	AI_KNOW	AIKNOW1	0.897	0.872 — 0.922	0.013	<0.001
		AIKNOW2	0.925	0.901 — 0.949	0.012	<0.001
		AIKNOW3	0.899	0.850 — 0.949	0.025	<0.001
		AIKNOW4	0.897	0.870 — 0.925	0.014	<0.001
	AI_OBJECT	AIOBJECT1	0.778	0.718 — 0.838	0.030	<0.001
		AIOBJECT2	0.851	0.806 — 0.895	0.023	<0.001
		AIOBJECT3	0.819	0.766 — 0.873	0.027	<0.001
		AIOBJECT4	0.794	0.736 — 0.853	0.030	<0.001
		AIOBJECT5	0.801	0.735 — 0.867	0.034	<0.001
	AI_OPER	AIOPER1	0.787	0.733 — 0.841	0.027	<0.001
		AIOPER2	0.878	0.839 — 0.916	0.020	<0.001
		AIOPER3	0.848	0.804 — 0.892	0.022	<0.001
		AIOPER4	0.866	0.818 — 0.913	0.024	<0.001
		AIOPER5	0.874	0.835 — 0.914	0.020	<0.001
		AIOPER6	0.826	0.763 — 0.890	0.032	<0.001
ACAP	ACQUIS	ACQUIS1	0.784	0.705 — 0.864	0.041	<0.001
		ACQUIS2	0.846	0.799 — 0.893	0.024	<0.001
		ACQUIS3	0.618	0.501 — 0.736	0.060	<0.001
	ASSIMIL	ASSIMIL1	0.872	0.833 — 0.911	0.020	<0.001
		ASSIMIL2	0.807	0.731 — 0.883	0.039	<0.001
		ASSIMIL3	0.800	0.729 — 0.870	0.036	<0.001
		ASSIMIL4	0.816	0.769 — 0.864	0.024	<0.001
	EXPLOIT	EXPLOIT1	0.783	0.728 — 0.839	0.028	<0.001
		EXPLOIT2	0.857	0.798 — 0.915	0.030	<0.001
		EXPLOIT3	0.752	0.663 — 0.842	0.046	<0.001
	TRANSFOR	TRANSFOR1	0.876	0.839 — 0.912	0.018	<0.001
		TRANSFOR2	0.884	0.852 — 0.917	0.017	<0.001
		TRANSFOR3	0.808	0.726 — 0.891	0.042	<0.001
		TRANSFOR4	0.840	0.779 — 0.902	0.031	<0.001
SCENVPERF		SCENVPERF1	0.849	0.805 — 0.892	0.022	<0.001
		SCENVPERF2	0.678	0.589 — 0.767	0.045	<0.001
		SCENVPERF3	0.884	0.844 — 0.924	0.020	<0.001

Constructs	First order dimensions	Items	Standardized Loadings	95% CIs	SEs	p-values
		SCENVPERF4	0.875	0.837 — 0.914	0.020	<0.001
SCRES		SCRESILI1	0.848	0.806 — 0.889	0.021	<0.001
		SCRESILI2	0.801	0.733 — 0.870	0.035	<0.001
		SCRESILI3	0.842	0.796 — 0.889	0.024	<0.001
		SCRESILI4	0.839	0.790 — 0.888	0.025	<0.001

Table 5: Standardized factor loadings and associated inferential measures (n=351).

Construct	Model	χ^2	Df	Robust RMSEA	$\Delta\ \chi^2$[2]	*p-value*	*$RMSEA_D$*
AICOMP	Second-order model	272.25	87	0.061	193.26	<0.001	0.773
	Single-factor model	902.84	90	0.150			
ACAP	Second-order model	82.545	73	0.001	88.359	<0.001	0.425
	Single-factor model	339.030	77	0.085			

Table 6: Nested model comparison for second-order constructs (n=351)

Constructs	AICOMP	ACAP	SCENVPERF	SCRES
AICOMP		0.796	0.581	0.688
ACAP	UL: 0.861		0.563	0.763
SCENVPERF	UL: 0.685	UL: 0.670		0.628
SCRES	UL: 0.769	UL: 0.839	UL: 0.732	

Note: The upper section contains estimated correlations between pairs of latent factors, the lower section displays the upper limits (UL) of the associated 95% confidence intervals, and square root of AVE values are presented on the diagonal.

Table 7: Correlation among the latent factors (n=351).

[2] Scaled Chi Square Difference as defined by Satorra & Bentler, 2001.

Model	χ^2	Df	Model Comparison	$\Delta\ \chi^2$[3]	*p-value*
1. Unconstrained model	301.53	616	- - - - - - - -	- - - - -	- - - - - -
2. Constrained model cor(SCRES,SCENVPERF)=0.90	324.84	617	2 vs. 1	56.889	<0.001
3. Constrained model cor(SCRES, AICOMP)=0.90	556.84	617	3 vs. 1	44.997	<0.001
4. Constrained model cor(SCRES, ACAP)=0.90	452.12	617	4 vs. 1	21.672	<0.001
5. Constrained model cor(SCENVPERF, AICOMP)=0.90	417.82	617	5 vs. 1	80.128	<0.001
6. Constrained model cor(SCENVPERF, ACAP)=0.90	376.31	617	6 vs. 1	91.986	<0.001
7. Constrained model cor(AICOMP, ACAP)=0.90	406.42	617	7 vs. 1	13.131	<0.001

Note: The unconstrained model refers to the Confirmatory Factor Analysis (CFA) model, in which all correlations among the factors are freely estimated. This corresponds to the model that generates the correlation coefficients included in Table 7.

Table 8: Likelihood ratio test results to evaluate discriminant validity.

4.2. Structural model assessment

The structural model in **Figure 1** demonstrates an overall good fit to the data (n = 351; SBχ^2= 648.978, df = 616; SBχ^2/df= 1.05; Robust CFI = 0.98; SRMR = 0.05; Robust RMSEA = 0.03 with a 95% confidence interval of [0.00, 0.05]; *p-value* for RMSEA < 0.05 = 0.90). Standardized path coefficients for the structural relationships are reported in **Table 9**. All hypothesized relationships are statistically significant at the 0.05 level. In line with the proposed hypotheses, AI competency (AICOMP) has a significant and positive direct effect on supply chain resilience (SCRES; β = 0.221, *p-value* = 0.03), supply chain environmental performance (SCENVPERF; β = 0.363, *p-value* = 0.01), and absorptive capacity (ACAP; β = 0.796, *p-value* < 0.001), providing support for H1, H2, and H3.

[3] Scaled Chi Square Difference as defined by Satorra & Bentler, 2001.

Hypothesis	Path	Beta	SE	t-statistic	*p-value*
H1	AICOMP → SCRES	0.221	0.100	2.208	0.027
H2	AICOMP → SCENVPERF	0.363	0.133	2.727	0.006
H3	AICOMP → ACAP	0.796	0.035	22.866	<0.001
H4	ACAP → SCRES	0.587	0.101	5.786	<0.001
H5	ACAP → SCENVPERF	0.273	0.136	2.012	0.044
H6	Indirect effect of AICOMP on SCRES	0.467	0.089	5.242	<0.001
H7	Indirect effect of AICOMP on SCENVPERF	0.218	0.109	2.004	0.045

Note: Standard errors (SE) and *p-values* are obtained via bootstrap.

Table 9: Standardized path coefficients (*n*=351).

The results also indicate that ACAP exerts a significant positive influence on both SCRES (β = 0.587, *p-value* < 0.001) and SCENVPERF (β = 0.273, *p-value* = 0.04), confirming H4 and H5. Our findings further confirm significant indirect effects of AICOMP on SCRES (β = 0.467, *p-value* < 0.001) and SCENVPERF (β = 0.218, *p-value* < 0.05) via ACAP, supporting the mediating role of ACAP in the relationships described in H6 and H7. The model accounts for 63.4% of the variability in ACAP, 60% of the variability in SCRES, and 36.5% of the variability in SCENVPERF.

4.3. Common method bias assessment

Consistent with the procedure described by Malhotra et al. (2006), we assessed the potential impact of common method variance (CMV) using a marker variable technique. Rather than introducing a dedicated marker construct, this approach relies on the smallest observed correlation in the dataset as a proxy for CMV. In our case, the lowest correlation (between AIOPER1 and SCENVPERF2, r = 0.246) was identified and used to adjust the item correlation matrix. This adjusted matrix was then used to re-estimate the structural model with *lavaan*. **Table 10** presents the standardized path coefficients obtained from both the original and CMB-adjusted covariance structure. The results indicate that the size and statistical significance of the structural paths remain stable after accounting for CMB. These findings suggest that common method bias does not substantially influence the relationships identified in our model.

Hypothesis	Path	Original estimates	CMB corrected estimates
H1	AICOMP → SCRES	0.221*	0.211*
H2	AICOMP → SCENVPERF	0.363***	0.358***
H3	AICOMP → ACAP	0.796***	0.799***
H4	ACAP → SCRES	0.587***	0.599***
H5	ACAP → SCENVPERF	0.273*	0.285***
H6	Indirect effect of AICOMP on SCRES	0.467***	0.478***
H7	Indirect effect of AICOMP on SCENVPERF	0.218*	0.227***

Notes: **p-value* <0.05; ***p-value* <0.01; ***p-value <0.001.

Table 10: Standardized path coefficients before and after correcting for CMB (n =351).

5. Discussion

The results of this study advance the literature and debate on AI competency, absorptive capacity, supply chain resilience, and supply chain environmental performance. **Table 11** compares the existing literature in the field with the present study.

References	Theory	Data	Main results
(Abdul Wahab & Radmehr, 2024)	Dynamic capability	Based on 417 SMEs in Lebanon.	Absorptive capacity partially mediating the link between AI assimilation and firm performance.
(El Bhilat et al., 2024)	Dynamic capability view and organizational information-processing theories	348 responses collected from executives and managers in the Moroccan agri-food industry.	AI adoption influences agri-food supply chain efficiency, which in turn influence organizational performance.
(Gölgeci & Kuivalainen, 2020)	Social capital	Based on 265 Turkish firms.	While absorptive capacity influences supply chain resilience, absorptive capacity mediates the relationship between social capital and supply chain resilience.

References	Theory	Data	Main results
(Guo et al., 2026)	Operations and supply chain management perspective	Chinese A-share listed companies from 2017 to 2022.	GenAI enhances the supply chain resilience.
(Lu et al., 2026)	Dynamic capability	Data from 232 senior supply chain executives in China.	Resilience is maximized when AI capabilities and supply chain integration are congruent and mutually reinforcing.
(Wang et al., 2019)	Information technology assimilation, the resource-based view, and dynamic capability	Data were collected from 600 companies across six countries.	Organizational absorptive capacity plays a crucial mediating role between Business analytics competency and Business analytics assimilation
(Zhang et al., 2025)	Absorptive capacity theory	Based on data drawn from 361 Chinese firms.	AI capabilities significantly contribute to Green Innovation, whereas potential absorptive capacity and realized absorptive capacity serve as key mediators between AI capabilities and Green Innovation.
This study	Resource-based view theory and the dynamic capability theory.	351 individuals	AI competency significantly improves the supply chain resilience and environmental performance, and that high absorptive capacity reinforces these effects. The study highlights the complementary role of AI competency and organizational capabilities (absorptive capacity) in supply chain resilience and environmental performance.

Table 11: Comparison between the existing literature in the field and the present study.

Furthermore, the findings offer valuable insights for managers, practitioners, and policymakers seeking to understand the dynamic relationships between AI competency and absorptive capacity, as well as their impact on supply chain resilience and environmental performance. Accordingly, while the literature on supply chain performance (flexibility, resilience, or environmental performance) has been reporting absorptive capacity mainly as one of the predictor variables (Abourokbah et al., 2023; Dzhengiz & Niesten, 2020; Liu et al., 2013; Zhang et al., 2023), we validated absorptive capacity as a dependent variable and a mediator in the relationship between AI competency and supply chain resilience and supply chain environmental performance. Globally, our results are aligned with existing studies, which demonstrated the importance of absorptive capacity in the transformation, exploitation, application, and assimilation of the capabilities, resources (e.g., big data analytics, IT infrastructure), which are part of the AI competencies [e.g., (Bag et al., 2023), (Fosso Wamba et al., 2020), (Liu et al., 2013), (Rubbio & Bruccoleri, 2023), (Wang et al., 2019), and (Zhang et al., 2025)]. However, it is important to acknowledge an epistemological boundary between our theoretical characterization of AI and our empirical approach. While we theorize AI as a probabilistic and contingent system, our CB-SEM model inherently captures the average tendency of AI-enabled mechanisms rather than their full variability or non-linear dynamics. Although this methodological choice is rigorous and appropriate for testing the proposed mediation structure, future research employing other approaches will be essential to fully map the erratic and complex nature of these relationships.

First, rather than merely restating that AI capabilities or AI technologies improve firm (supply chain) performance (environmental, social, economic) and resilience (Li et al., 2025; Singh & Goyal, 2023; Zhang & Yang, 2024), we reconceptualize AI competency as a generative resource that actively builds a firm's knowledge base (De Benedittis et al., 2018). The findings therefore support a view of AI as a distinct organizational technology that affects not only information processing but also the allocation of attention, inference, and coordination authority. In particular, there is concern about the organizational use of a probabilistic system such as GenAI, whose outputs are shaped by prompting, contextualization, and evaluation routines (Wang et al., 2026). This also suggests that variation in prompt capability, Large Language Model (LLM) appropriation, and human oversight may explain heterogeneous outcomes across firms. In our research model, treating absorptive capacity as an outcome of AI competency highlights this shift. Unlike much prior supply chain management research, where absorptive capacity is a predictor of performance, our findings show that strong AI competency can enhance a firm's absorptive capacity [consistent with Neirotti et al. (2021) and Zhang et al. (2025)], effectively making absorptive capacity a conduit through which firms' AI resources are assimilated. This framing is not merely a methodological convenience; it reflects a theoretical move, implying that AI-driven competencies can reshape how organizations acquire and exploit knowledge in turbulent supply chain management contexts (Zhang et al., 2025).

Second, our findings show that AI competency directly boosts supply chain resilience, and supply chain environmental performance aligns with studies showing AI's positive impact on supply chains (Belhadi et al., 2022; Riad et al., 2024; Shahzadi et al., 2024). However, by focusing specifically on AI competency, rather than generic IT (technology), big data, or AI capabilities, we extend these works. We show that AI's effects depend on an organization's learning processes; firms with higher AI competency must concurrently develop absorptive capacity to realize performance gains. This extends the studies of Li et al. (2025), Zhang and Yang (2024), and Zhang et al. (2025) which demonstrated that AI technology or AI capabilities can influence innovation (green) and organizational performance (social, environmental, and economic) if they develop absorptive capacity. However, our findings should also be interpreted with caution from an environmental perspective. While the results are consistent with the idea that AI can enhance environmental performance through efficiency and improved decision-making, they do not imply that AI is environmentally beneficial in all cases. Recent research shows that AI can generate direct environmental costs through computing power, data infrastructure, and energy consumption (Cheng et al., 2024; Nishant et al., 2020). The environmental effect of AI is therefore better understood as the outcome of two competing mechanisms: operational optimization versus infrastructure footprint (Cheng et al., 2024; Nishant et al., 2020). Accordingly, the environmental value of AI should be understood as conditional rather than automatic. AI may improve environmental performance when optimization effects dominate, but the same technology may weaken or offset these gains when computational intensity, infrastructure expansion, and associated energy consumption become substantial. This suggests that AI-related environmental effects may involve threshold, trade-off, or even non-linear dynamics rather than a purely positive relationship.

Third, the mediation analysis offers new insights. We find that absorptive capacity partially mediates the impact of AI competency on both resilience and environmental performance. This echoes prior evidence on the importance of absorptive capacity for exploiting digital innovations (Bag et al., 2023; Liu et al., 2013; Rubbio & Bruccoleri, 2023) and emerging technologies (Li et al., 2025; Zhang & Yang, 2024; Zhang et al., 2025). Indeed, the main value of AI technologies lies in supporting a mechanism-based explanation. Consistent with recent research, the findings suggest that AI competency improves outcomes by reshaping intermediate organizational processes, especially decision routines, coordination, and transformation mechanisms (Neirotti et al., 2021; Zhang et al., 2025). This is important because it clarifies that performance gains stem less from possession of technology than from the firm's ability to embed AI in organizational action (Bag et al., 2023; Mikalef et al., 2023; Wang et al., 2026). This mediation should therefore be interpreted as processual rather than purely statistical, because AI competencies do not directly improve outcomes. It first produces algorithmic signals/insights, which must then be interpreted, contextualized, and integrated through organizational routines. This clarifies why absorptive capacity is central to the mechanism that turns data-based inference into coordinated managerial and operational action for supply chain function. This interpretation is consistent with recent integrative work on dynamic capabilities(De Benedittis et al., 2018), which emphasizes that capabilities are context-sensitive in their expression but generalizable in their mechanisms (Huang et al., 2026; Stadtfeld & Gruchmann, 2023).

Besides, our findings provide depth by demonstrating that the strength of this mediation differs by outcome. Absorptive capacity more strongly mediates the AI competency–supply chain resilience relationship (p-value < 0.001) than the AI competency–supply chain environmental performance relationship (p-value = 0.045), suggesting that absorptive capacity is especially critical for resilience. This nuance can help to refine the literature by indicating that context and outcome matter when considering knowledge processes. For example, absorptive capacity plays a stronger mediating role in resilience, as it facilitates rapid, coordinated responses to internal disruptions (Leoni et al., 2022; Li et al., 2025). Indeed, supply chain resilience often depends on immediate operational decisions (e.g., reorganizing workflows, reallocating resources, reducing risks, and compliance with evolving ESG regulations), areas where absorptive capacity excels by quickly organizing and leveraging internal information (Boone et al., 2025; Leoni et al., 2022). In contrast, supply chain environmental performance is driven by external constraints and long-term strategies (e.g., regulations, customer pressure), and involves slower collaborative processes (e.g., eco-design, green partnerships/innovation) (Li et al., 2025; Zhang et al., 2025). Absorptive capacity, focused on the internal knowledge acquisition of knowledge, plays a less direct role here. In other words, absorptive capacity effectively stimulates rapid detection and adaptation (sensing/seizing phases), thereby increasing resilience; however, for the environment, external mechanisms (e.g., sustainable investments, cross-functional governance), less tied to information absorption, are also required, resulting in a smaller indirect effect. Moreover, the differences observed between supply chain resilience and supply chain environmental performance suggest that these mechanisms are outcome-dependent. The stronger mediation effect for supply chain resilience indicates that knowledge assimilation and coordination processes are particularly critical for responding to disruptions. In contrast, supply chain environmental performance appears to depend not only on AI competency and absorptive capacity, but also on complementary capabilities such as environmental management routines, knowledge management, inter-organizational collaboration, and sustainability-oriented dynamic capabilities [e.g., (Geyi et al., 2020), (Kumar et al., 2018), (Leoni et al., 2022), (Li et al., 2025), and (Yuan & Pan, 2023)]. This finding refines the existing literature by showing that the effectiveness of AI competency in enabling AI capabilities (Mikalef et al., 2023) varies across performance dimensions. In addition, our results help shed light on the microfoundations of AI competency. Rather than treating it as a black-box construct or as an IT/AI capabilities shadow construct, our results suggest that its influence operates through a combination of organizational mechanisms, including data management practices, governance routines, skill development, and human–AI interaction processes. These microfoundations enable firms to continuously experiment, learn, and adapt AI applications, thereby strengthening their absorptive capacity and performance outcomes.

6. Implications

6.1. Theoretical implication

While the existing technology-based supply chain literature has focused on advancing the perspective of capabilities of digital and emerging technologies, primarily in the context of big data, AI, and digital technologies, our study builds upon this by validating a model that utilizes AI competency as the main variable and the main predictor of absorptive capacity, supply chain resilience, and supply chain environmental performance. Overall, this study provides a more precise explanation of how AI competency and absorptive capacity jointly shape supply chain resilience and supply chain environmental performance. Specifically, it highlights that the value of AI does not reside solely in technological deployment, but in the organization's ability to embed AI within learning processes and coordinated actions. This perspective offers a more nuanced explanation of why some firms can translate AI investments into tangible performance gains while others cannot. In this regard, our study presents the following contributions.

First, we emphasize that AI is not merely a technical tool that mechanically generates performance gains. Unlike existing research, which merely explores the direct effect of technological capabilities on resilience or environmental impact, our results show that the effect of AI depends heavily on the specific AI competencies developed and their implementation through knowledge absorption (absorptive capacity). In other words, it is not investment in AI technologies alone that matters, but how this resource is leveraged by specific competencies (knowledge, routines, training) and integrated through absorptive capacity. For example, one might naively assume that deploying AI technology is sufficient to improve supply chain resilience; our results suggest instead that without strong absorptive capacity to assimilate and apply the information generated by AI technologies, the gains remain limited. This result indicates that AI alone creates value only to the extent that the organization develops "AI competencies" that are then leveraged by dynamic capabilities such as absorptive capacity.

Second, integrating the RBV and DC theory enriches existing AI-based supply chain management. The RBV accounts for the extent of AI's competency impact on performance as a scarce, difficult-to-imitate strategic resource, while dynamic capabilities explain how this resource is utilized through absorptive capacity. This study's contribution is to show that absorptive capacity is not merely a passive mediator: it is a genuine dynamic capability that shapes the assimilation of AI contributions and modulates performance. In other words, absorptive capacity acts as an active mechanism that continuously transforms AI competency to enhance supply chain resilience and supply chain environmental sustainability. For example, studies in IS have shown that advanced IT/AI capabilities without corresponding learning processes can remain ineffective (Bag et al., 2023; Dey et al., 2024; Leoni et al., 2022). In our context, this means that strong AI competency without a solid absorptive capacity is insufficient to deliver the expected benefits, underscoring the importance of their complementarity.

Third, grounding of our findings, rather than simply reiterating that AI skills and capabilities "improve performance," we explain why and how this occurs in an uncertain context. We demonstrate, following and extending the lead of Leoni et al. (2022), Neirotti et al. (2021), Wang et al. (2019), and Zhang and Yang (2024) that organizations equipped with both a robust technology resource (e.g., AI competency) and a developed absorptive capacity can more effectively reconfigure their processes in the face of disruptions. This combination creates a competitive advantage: AI competency provides the technological foundation (Mikalef et al., 2023), and absorptive capacity enables the processing and application of generated data to support coordinated decision-making (Neirotti et al., 2021). Our contribution is therefore conceptual, as it clarifies that AI alone is limited unless the company can continuously learn and adapt through absorptive capacity.

6.2. Practical implications

Based on our findings, we have identified four key practical implications: (a) leveraging AI as a specific strategic tool; (b) enhancing knowledge absorption through targeted initiatives; (c) adopting a resilience strategy tailored to the supply chain context; and (d) proactively integrating environmental considerations.

First, regarding leveraging AI as a specific strategic lever, managers must stop viewing AI as merely a technical tool or a technological panacea and instead see it as a scarce strategic resource. This means investing in dedicated expertise (at both the strategic and operational levels) and in AI governance, rather than simply passively adopting technological solutions. In practice, this could involve creating cross-functional teams dedicated to AI (Mikalef et al., 2023) or implementing continuing education programs to raise teams' awareness of the challenges and opportunities AI presents. In practice, for example, a manufacturing company could train its production managers to use AI for predictive maintenance while directly involving operators in the algorithm learning process. These measures help transform technological capabilities into genuine organizational AI competencies. For example, at the BMW Group, the deployment of a global AI platform, an internal "AI Lab" in Landshut, and an enterprise AI platform. BMW has trained dedicated teams (data scientists, AI engineers) to integrate AI into all its processes, from design to production and after-sales service (Steven, 2026). More concretely, managers should not launch AI solely through isolated pilots. They should implement a staged roadmap with three operational gates: (1) business-case validation, (2) data-readiness assessment, and (3) AI technologies governance assignment. This means that every AI initiative should be tied to one clearly measurable use case, one accountable owner, and one expected operational KPI (e.g., forecast accuracy, downtime reduction, service level, or scrap reduction). This also requires recognizing real organizational constraints such as budget limits, legacy systems, fragmented data, and employee resistance. Firms should therefore prioritize a small number of high-value use cases before scaling, rather than trying to diffuse AI across all functions at once. This is because AI value is highly dependent on work-practice redesign, line involvement, and formalized routines rather than on technology deployment alone (Li et al., 2025; Neirotti et al., 2021; Zhang & Yang, 2024).

Second, companies must strengthen their knowledge absorption through targeted actions. Our findings highlight that to reap the benefits of AI; companies must develop robust knowledge absorption capabilities. This requires very concrete actions: forming cross-functional, self-organized teams (e.g., combining IT specialists, logistics experts, and R&D personnel), creating knowledge repositories (shared databases, internal wikis), and establishing technology watch processes (information on AI innovations and environmental regulations). For example, a retailer could establish monthly meetings between its logistics department and IT experts to collaboratively develop AI use cases and document lessons learned in an accessible repository. These practices enable more effective capture of external information (market trends, regulations, customer feedback) and its transformation into operational solutions, thereby improving the ability to anticipate disruptions and respond to environmental challenges. For example, at "*Agiloft*", initiatives such as weekly AI showcases, where employees demonstrate workflows, automations, prompts, and agents they have built, have shifted AI from isolated experimentation to peer-led, repeatable practice (Tom, 2026). Consequently, "*Agiloft*" Teams across customer success, professional services, people operations, and IT now leverage AI to unify data, surface insights faster, and reduce manual effort, fostering a culture of compounding learning (Raguseo & Vitari, 2016; Tom, 2026). The main challenge here is that cross-functional integration, decentralization, formalization, and socialization routines are essential for converting data into relevant knowledge with AI (Leoni et al., 2022; Neirotti et al., 2021). To make these initiatives actionable, firms should formalize at least several routines: (1) develop GenAI prompts and AI use-case documentation, (2) post-project learning reviews, (3) escalation rules for low-confidence AI outputs, and (4) cross-functional validation meetings before operational deployment. Managers should also be able to distinguish between data access and knowledge absorption (Neirotti et al., 2021). Having dashboards or models alone is not enough, as firms need mechanisms to translate AI outputs into shared understanding and coordinated decisions. In practice, this means assigning liaison roles between technical experts and business users and embedding AI reviews into recurring operating meetings.

Third, companies must adopt a resilience strategy tailored to the supply chain context. Indeed, the positive role of absorption capacity means that strategic supply chain decisions must incorporate a learning dimension. Depending on the level of turbulence and the sector's AI maturity, companies can, for example, diversify their suppliers (to reduce the risk of disruption) by leveraging collaborative AI platforms for joint planning, or invest in intelligent redundancy (algorithm-optimized safety stock). In highly regulated industries (e.g., pharmaceuticals, food, and agriculture), managers can use AI to improve product traceability and environmental compliance while leveraging absorption capacity to absorb and interpret new regulatory standards. In contrast, in more flexible sectors (e.g., retail, e-commerce), the focus could be on the operational agility enabled by AI (e.g., demand forecasting, rapid workflow adaptation) and on cross-functional team training to maintain this agility. For example, in the automotive industry, "Catena-X," an open and collaborative data ecosystem that relies heavily on AI in its core operations, enables partners across value chains to address resilience, sustainability, and regulatory compliance through digital collaboration (Steven, 2026). Managers should therefore avoid a one-size-fits-all resilience strategy. A practical decision rule is to align AI deployment with several variables: the level of supply chain uncertainty and the level of process codifiability. When uncertainty is high and processes are codifiable, AI can support predictive planning and dynamic reallocation. When uncertainty is high, but processes are weakly codified, firms should first invest in data discipline, escalation routines, and human override mechanisms before relying heavily on AI. In addition, resilience investments should be reviewed through scenario-based exercises. Especially, what should managers always ask: what happens if the AI model fails, if supplier data are delayed, or if external conditions shift faster than the system can learn? This will make the resilience strategy more realistic and more operational. Besides, evidence from green supply chain and AI adoption studies suggests that adoption costs and contextual conditions can moderate the net benefits of digital technologies, reinforcing the need for selective and context-sensitive deployment.

Finally, regarding proactively integrating environmental considerations, the implications for environmental performance go beyond simply using AI to be greener (Trid et al., 2019). It's about reinventing business processes with AI. For example, a logistics company can deploy route optimization algorithms to reduce fuel consumption, but this also requires training drivers on the new tools and adjusting fleet management practices (e.g., absorption capacity). Similarly, cross-company collaborations (e.g., partnership-based eco-design) can be strengthened through joint AI projects that leverage shared data platforms. These concrete measures illustrate that AI must be integrated into a comprehensive environmental strategy, supported by the company's capacity to absorb and leverage knowledge on sustainable development. For example, BMW participates in "Catena-X," an open data ecosystem where AI calculates the carbon footprint of each product from start to finish (from raw material to finished product) (Steven, 2026). More specifically, firms should track two families of indicators in parallel: supply chain operational environmental gains (e.g., energy saved, waste reduced, transport emissions avoided) and AI-induced environmental costs (e.g., computing energy, storage load, model retraining frequency, and cloud-related emissions) (Cheng et al., 2024; Trid et al., 2019). This dual-measurement system is critical because recent work shows that AI can simultaneously produce environmental benefits and burdens. Managers should therefore require that each major AI sustainability project include an ex-ante environmental business case and an ex-post footprint review. Where data allows, firms should prioritize lighter AI architectures, reduce unnecessary retraining cycles, and favor use cases where optimization gains are likely to outweigh infrastructure costs.

7. Conclusion, Limits, and future avenues of research

This study makes substantial contributions to the literature by moving forward the nascent AI competency literature, supply chain resilience, and supply chain environmental performance. Indeed, the results suggest that, from an RBV and a DC perspective, AI competency is essential for supporting absorptive capacity, supply chain resilience, and supply chain environmental performance. Existing studies on AI, big data, or digital technologies focused on absorptive capacity as the main predictor of supply chain resilience, supply chain agility, supply chain flexibility, and supply chain environmental performance. Furthermore, our findings suggest that absorptive capacity is a key element of supply chain environmental performance and supply chain resilience, where a dynamic perspective combined with organizational key resources is necessary to acquire, assimilate, transform, and apply key resources (i.e., AI competencies) to support and address supply chain resilience and supply chain environmental performance challenges. Besides, the results are therefore applicable beyond the immediate empirical context at the level of explanatory logic. What should be generalized is not a universal direct effect of AI, but rather the capability-based mechanism by which AI competencies translate into organizational outcomes. Future studies should test this mechanism across industries, institutional settings, and forms of AI use to refine its boundary conditions.

However, this study has some limitations. First, this study relies on cross-sectional quantitative data from a single survey to examine relationships among complex constructs such as AI competency, absorptive capacity, supply chain resilience, and environmental performance. While this approach allows for statistical testing of the proposed model, it does not capture the dynamic and evolving nature of these constructs. In particular, AI competency and absorptive capacity develop over time through learning, experimentation, and organizational adaptation. Future research could adopt longitudinal designs to better understand how these capabilities co-evolve and how their impact on performance unfolds over time. Second, the use of self-reported data raises potential concerns about common method bias and perceptual bias. Although standard statistical remedies were applied, respondents may have overestimated their firm's capabilities/competencies or performance. In addition, the relatively high mean values observed across several constructs and the limited dispersion in responses may indicate a degree of range restriction, likely reflecting the focus on organizations that have already invested in AI and business analytics initiatives. While this targeted sampling strategy is consistent with the study's objectives, it may reduce variability and limit the generalizability of the findings to less mature firms or those at earlier stages of AI adoption. Additionally, because our sample targets firms already invested in AI technologies, the individual respondents within these organizations are likely to be those most enthusiastic about AI adoption. While this self-selection dynamic creates a range restriction that typically attenuates observed effects, rendering our statistical estimates conservative, it is also important to acknowledge that it may skew subjective perceptions toward higher enthusiasm. Future studies could address this limitation by using multi-source data (e.g., combining survey data with objective performance indicators or archival data) to strengthen the robustness of findings. Third, the study focuses on firms located in two developed countries, which may limit the generalizability of the results. AI adoption, organizational capabilities, and supply chain structures may differ significantly across institutional and economic contexts. Future research could extend this work by employing multi-group and cross-country analyses to examine potential unobserved heterogeneity and assess whether the observed relationships hold across different institutional and organizational contexts.

Fourth, the research design remains static and does not fully capture the potential non-linearities, threshold effects, or path dependencies between AI competency and absorptive capacity. As our findings suggest, the value of AI may depend on the level of organizational learning and prior experience. Future studies could explore these dynamics using configurational approaches (e.g., fsQCA) or mixed-method designs to better capture complex interactions between resources and capabilities.

Finally, although this study conceptualizes AI competency at the organizational level, it does not explicitly explore its microfoundations. Future research could investigate in greater depth the underlying mechanisms, such as data governance practices, human–AI interaction routines, and skill development processes, through which AI competency affects absorptive capacity and supply chain outcomes. Similarly, the environmental implications of AI should not be treated as unidirectional. Most studies emphasize an “AI-for-Green” logic, according to which AI improves environmental performance through better forecasting, energy efficiency, process optimization, and pollution reduction. However, a more complete view must also incorporate a “Green-AI” perspective, because AI systems rely on energy-intensive computing infrastructure, data centers, model training, and digital equipment that themselves generate environmental burdens. The net environmental contribution of AI is therefore not necessarily linear. It may reflect a trade-off between efficiency gains and environmental costs associated with infrastructure (Cheng et al., 2024). Future studies should acknowledge and explore this duality and interpret environmental performance in light of these potentially competing effects.

CRediT author statement

Samuel Fosso Wamba: Conceptualization, Data curation, Supervision, Validation, Writing – original draft, Writing- Reviewing and Editing. **Laura Trinchera**: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing- Reviewing and Editing. **Serge-Lopez Wamba-Taguimdje**: Methodology, Project administration, Writing – original draft, Writing- Reviewing and Editing.

Declaration of Generative Artificial Intelligence Technologies

During the preparation of this manuscript, the authors used Grammarly (version 1.169.1.0) and ChatGPT (GPT-5.5, OpenAI) to assist with proofreading and language editing. After using these tools, the authors have revised and edited the content to ensure its accuracy, originality, and compliance with scholarly and ethical standards. No generative AI tools were used for conceptualization, literature review, data analysis, statistical modeling, or the generation or interpretation of research results. The authors assume full responsibility for the content of the publication.

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