



AI capability and product innovation intensity: Driving B2B marketing innovation under varying levels of market turbulence[☆]

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ABSTRACT

In increasingly volatile markets, firms are turning to artificial intelligence (AI) to enhance innovation and maintain a competitive edge. However, many organizations continue to struggle to translate AI investments into meaningful innovation outcomes. This study develops and empirically tests a framework examining how AI capability is transformed into business-to-business (B2B) marketing innovation through organizational agility and product innovation intensity. Drawing on survey data from 239 Chinese firms, the findings reveal that AI capability drives B2B marketing innovation through a theorized sequential relationship, in which organizational agility enables intensified product innovation, which in turn supports market-facing innovation. Furthermore, market turbulence acts as a contingent boundary condition, amplifying the effects of AI capability on product innovation intensity and downstream innovation outcomes, while not significantly affecting its relationship with organizational agility. By conceptualizing AI capability as an enabling capability architecture that activates sensing, seizing, and reconfiguring processes, this research advances dynamic capability theory and provides a more granular explanation of how AI is translated into innovation. It also distinguishes between innovation generation (product innovation intensity) and innovation realization (B2B marketing innovation), offering a process-based account of capability-to-innovation transformation. The study provides actionable insights for managers on developing integrated AI capability, enhancing organizational agility, and strategically intensifying innovation efforts under varying levels of market turbulence.

1. Introduction

Artificial intelligence (AI) is increasingly being adopted by firms seeking to improve productivity, decision-making, and innovation (Cillo and Rubera, 2025; Marzi et al., 2025). Yet investment in AI does not

automatically generate organizational value. Many AI initiatives fail to deliver their anticipated outcomes, highlighting an important distinction between acquiring AI technologies and developing the organizational capability required to deploy them effectively (Ryseff et al., 2024). This challenge is particularly salient in business-to-business

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(B2B) contexts, where firms often operate through complex relationships, customized offerings, and rapidly changing customer requirements. AI may help firms anticipate buyer preferences, process market information, and improve product and marketing decisions, but these benefits depend on how effectively AI-related resources are integrated into organizational processes (Arias-Pérez and Huynh, 2023; Roberts and Candi, 2024).

We therefore focus on AI capability, rather than AI adoption alone. AI capability refers to a firm's ability to utilize and orchestrate complementary AI-related tangible, human, and intangible resources (Mikalef and Gupta, 2021). These resource categories are rooted in established resource-based and technology-capability research (Barney, 2001; Bharadwaj, 2000) and together capture the infrastructure, expertise, and organizational conditions required for effective AI deployment. This conceptualization also distinguishes AI capability from organizational agility. AI capability concerns the underlying capacity to mobilize AI-related resources, whereas organizational agility reflects the realized ability to respond flexibly and rapidly to changing customer, operational, and strategic conditions. A firm may therefore possess substantial AI resources without necessarily being agile if those resources are not translated into organizational action.

This distinction matters because existing research still provides an incomplete account of how AI capability is translated into innovation outcomes (Gama and Magistretti, 2025; Mariani et al., 2023; Petrescu et al., 2022). Prior studies have shown that AI can support B2B marketing capabilities, strategic agility, decision-making performance, and innovation (Liu et al., 2025; Mikalef et al., 2023; Mikalef and Gupta, 2021), while other work has conceptualized AI-enabled dynamic capabilities in specific innovation settings such as circular business-model innovation and digital servitization (Sjödin et al., 2023). However, less is known about how adaptive organizational responsiveness and substantive product-renewal activity may operate together in the progression from AI-related resources to downstream market-facing innovation.

A further source of ambiguity concerns the treatment of innovation itself. Product innovation and marketing innovation are related, but they represent distinct stages of the wider innovation process. Product innovation concerns the development and renewal of what a firm offers, whereas marketing innovation concerns novel approaches through which those offerings are brought to market and value is created and captured from customers. Conflating these stages can obscure the mechanisms through which AI capability contributes to innovation generation versus innovation realization.

Accordingly, this study focuses on B2B marketing innovation as the focal market-facing outcome. Drawing on the Oslo Manual framework, we define B2B marketing innovation as the implementation of a new marketing method or approach that represents a substantive departure from a firm's prior marketing practices in its business-to-business operations (OECD, 2018). Such innovation may involve novel approaches to pricing, distribution, customer engagement, value communication, or product/service presentation. Importantly, routine adjustments in price, promotion, or distribution do not constitute marketing innovation; the defining characteristic is novelty in the marketing method itself. B2B marketing innovation is also distinct from commercialization capability, which refers to the capacity to commercialize effectively, and from product innovation, which concerns novelty in the offering itself.

B2B marketing innovation warrants examination as an outcome because the development of a novel product does not automatically imply that firms will innovate in how that product is presented, priced, distributed, or monetized. In B2B settings, where offerings may be technologically complex, customized, or embedded within long-term relationships, the way innovations are brought to market can materially affect whether their value is realized. Prior research also links marketing innovation and related marketing capabilities to firm survival and superior customer-related performance (Naidoo, 2010; Ngo and O'Cass, 2012). We therefore position this study at the intersection of

innovation and marketing. Our objective is not to explain all antecedents of B2B marketing innovation, but to isolate one theoretically important technology-enabled pathway through which AI-related resources may be transformed into market-facing innovation.

Three related gaps motivate the study. First, there is a conceptual gap in distinguishing innovation generation from innovation realization. Second, there is a process gap concerning how AI capability is transformed through organizational mechanisms into downstream innovation outcomes. Third, there is a contextual gap concerning the role of market turbulence: although market conditions can shape innovation and organizational performance, it remains unclear whether turbulence uniformly affects AI-enabled innovation or differentially alters particular relationships within the capability-to-innovation process (Li, 2022; Tsai and Yang, 2013).

To address these gaps, we examine organizational agility and product innovation intensity as theoretically distinct mechanisms. Because AI capability represents an upstream configuration of AI-related resources, dynamic capability theory suggests that its value depends on how these resources are mobilized through organizational processes and capabilities. Organizational agility, reflecting a firm's strategic flexibility, operational adaptability, and customer responsiveness, serves as the initial channel because it enables firms to sense, interpret, and respond rapidly to environmental developments (Teece, 2018; Warner and Wäger, 2019). Without this first step, AI remains a static resource rather than a driver of innovation. However, agility alone does not indicate that firms are actually intensifying the development and renewal of their offerings.

Product innovation intensity captures this latter element: the pace and continuity of product-development and innovation activity (Ahsan et al., 2023; Sullivan and Fosso Wamba, 2024). Digital technologies can create value not only through efficiency improvements but also by increasing the speed and intensity of innovation activity (Liu et al., 2025). Product innovation intensity therefore serves as the second channel, representing a substantive innovation-generation mechanism, while organizational agility captures adaptive responsiveness. These mechanisms are conceptually distinct but potentially connected: agility may help firms identify where and how innovation effort should be directed, while product innovation intensity reflects the subsequent renewal of the firm's offerings.

Accordingly, we theorize this channeling as an ordered capability-transformation process – informed by dynamic capability theory's temporal logic of sensing, seizing, and reconfiguring – in which AI capability supports organizational agility, agility supports intensified product innovation, and product innovation intensity contributes to downstream B2B marketing innovation (Teece et al., 1997). This ordering provides a distinct process explanation because product-renewal activity undertaken without adequate sensing of market developments may produce poorly aligned offerings, while organizational agility without corresponding innovation activity may generate responsiveness without substantive renewal. Importantly, we do not suggest that alternative pathways identified in prior research are invalid or universally inferior. Rather, studies such as Liu et al. (2025), Mikalef et al. (2023), Mikalef and Gupta (2021), Petrescu et al. (2022) and Sjödin et al. (2023) examine different mechanisms and outcomes. Our study addresses a different theoretical question: how AI capability may be progressively translated into market-facing innovation through adaptive organizational responsiveness and intensified product renewal.

This focus also extends related work by Ameen et al. (2024), which conceptualizes AI capability and strategic agility as a coupled construct fostering product and service creativity. Creativity represents an important aspect of innovation, but does not capture the intensity and continuity of product development activity or explain how AI-enabled responsiveness may subsequently relate to B2B marketing innovation. Similarly, product innovation intensity should not be conflated with B2B marketing innovation: the former concerns the pace and continuity of innovation effort directed at offerings, whereas the latter concerns novel

approaches through which those offerings are brought to market and commercialized (Ahsan et al., 2023; Mooi et al., 2022; Sullivan and Fosso Wamba, 2024).

We further examine market turbulence as a contingent boundary condition, rather than treating turbulence as a prerequisite for B2B marketing innovation to be meaningful. B2B marketing innovation can remain relevant in both relatively stable and highly turbulent markets. What may differ is the strength with which organizational capabilities and innovation processes contribute to it. Higher turbulence increases uncertainty, information-processing requirements, and the need for firms to interpret and respond to changing customer and competitive conditions, suggesting that it may alter the value of AI-enabled sensing, organizational responsiveness, product innovation, and market-facing adaptation (Li, 2022; Tsai and Yang, 2013).

Against this background, the study addresses two research questions: (1) How does AI capability contribute to B2B marketing innovation through organizational agility and product innovation intensity? and (2) How does market turbulence shape particular relationships within this capability-to-innovation process? We address these questions using survey data from managers across 239 firms in China. This study makes three principal theoretical contributions. First, it advances research on AI capability by distinguishing AI capability from AI adoption and from downstream adaptive capabilities such as organizational agility. Second, it advances the AI-innovation literature by distinguishing innovation generation from innovation realization and by theorizing how organizational agility and product innovation intensity may connect AI capability with downstream B2B marketing innovation. This process perspective complements prior work on AI competencies, dynamic-capability micro-foundations (Mikalef et al., 2023; Mikalef and Gupta, 2021), strategic agility, decision-making performance (Liu et al., 2025), and AI-enabled business-model innovation (Sjödén et al., 2023). Third, it develops a contingency perspective on market turbulence by examining turbulence as a boundary condition that may alter specific relationships within the capability-to-innovation process rather than treating it as a uniform environmental background factor.

2. Literature review

2.1. The dynamic capability view

The dynamic capability view is centered on the adaptability and responsiveness of organizations to changing business environments and contexts. Expanding on the resource-based view of the firm, the dynamic capability view implies that a firm's resources and capabilities are its key sources of competitive advantage (Eisenhardt and Martin, 2000). The framework highlights three core mechanisms – sensing (detecting environment changes), seizing (implementing newly identified opportunities), and reconfiguring (adapting resources and skills to recognized possibilities) – through which firms achieve sustained competitive advantage (Khan et al., 2021; Teece et al., 1997). Organizational agility, which emerges as a pivotal facet of dynamic capabilities, is recognized for its potential to drive organizational performance and foster competitive advantage (Weber and Tarba, 2014). Organizational agility refers to an organization's ability to promptly discern and effectively respond to shifts in its environment (Hoonsopon and Puriwat, 2021). It involves the integration, building, and reconfiguration of both internal and external resources to navigate the fluid and evolving dynamics inherent in contemporary business environments (Doz and Kosonen, 2010). The relationship between dynamic capabilities and organizational agility is multidimensional and complex (Teece et al., 1997). Dynamic capabilities enable organizations to develop and enhance their agility by providing the procedures and routines required to sense and respond to changes in the environment. In contrast, organizational agility is a manifestation of dynamic skills in action, reflected in the firm's capacity to rapidly adapt and respond to change (Hoonsopon and Puriwat, 2021; Weber and Tarba, 2014).

Despite its strong explanatory power, the dynamic capability framework provides limited insight into how emerging technological capabilities, particularly artificial intelligence, are operationalized within sensing, seizing, and reconfiguring processes in practice. While prior research acknowledges the importance of these mechanisms, it often remains unclear how specific capability configurations enable firms to enact them under conditions of environmental uncertainty. This limitation is especially salient in the context of AI, where the value of the technology depends not only on its adoption, but on the firm's ability to integrate and deploy AI-related resources in ways that support adaptive and innovation-oriented responses. Yet existing AI capability research has largely established whether AI capability is associated with agility, creativity, innovation, or performance, while offering less explanation of how these organizational responses unfold as an ordered process through which AI resources are converted into innovation outcomes (Ameen et al., 2024; Mikalef and Gupta, 2021).

We address this gap by positioning AI capability as an upstream enabling capability that activates dynamic capability mechanisms rather than as a standalone technological resource. Specifically, we argue that AI capability enhances sensing by enabling firms to process large-scale and real-time data, improving their ability to detect emerging trends and shifts in customer needs (Teece, 2018). It supports seizing by allowing decision-makers to interpret AI-generated insights and translate them into strategic actions, such as prioritizing innovation opportunities and reallocating resources (Mikalef and Gupta, 2021). Furthermore, it facilitates reconfiguring by enabling the diffusion of AI-informed routines across organizational functions, supporting the transformation of processes and innovation activities (Ritala et al., 2024; Warner and Wäger, 2019).

This perspective also clarifies the conceptual relationship between AI capability and organizational agility. While dynamic capabilities provide the underlying processes of adaptation, and organizational agility represents their manifestation in observable organizational responses, AI capability is theorized as an upstream enabling condition that strengthens the firm's ability to enact these mechanisms. In this sense, AI capability and organizational agility are conceptually distinct yet dynamically connected, addressing prior ambiguity regarding their roles within the dynamic capability framework.

Finally, this framing provides a theoretical basis for understanding how AI capability contributes to innovation outcomes beyond operational efficiency. By strengthening opportunity identification, prioritization, and resource allocation under conditions of uncertainty, AI capability enables firms not only to respond to change, but to intensify their innovation efforts. This positions AI capability as a critical mechanism through which dynamic capabilities are translated into sustained innovation activity and market-facing outcomes.

2.2. AI capability

AI capability refers to the firm's capacity to select, integrate, and deploy AI-related resources in a strategically purposeful manner that enables adaptive organizational responses (Mikalef and Gupta, 2021). It has been conceptualized as a multidimensional higher-order construct that comprises human- and AI-specific aspects: (1) tangibles (data, technology, and basic resources), (2) human skills (both technical and business competencies); and (3) intangibles (inter-departmental coordination, organizational change capacity, and risk proclivity) (Mikalef et al., 2022; Mikalef and Gupta, 2021). Together, these dimensions highlight that AI capability is not reducible to technology alone, but depends on the coordinated deployment of AI-relevant resources, human expertise, and organizational support conditions. Notably, what makes this capability specifically AI-related is that these resources and routines are configured to support AI-enabled data processing, prediction, and decision support rather than general digital or IT capability (Mikalef and Gupta, 2021). The three dimensions are best understood as complementary and mutually reinforcing components whose

integration constitutes AI capability, rather than isolated organizational attributes.

From the dynamic capability perspective (Teece et al., 1997; Warner and Wäger, 2019), AI capability can be understood as an enabling capability that activates each core mechanism of the framework through its constituent dimensions. Tangible AI resources support sensing by enabling real-time processing of large-volume market and environmental data that conventional scanning routines cannot match (Teece, 2018). Human skills, through both technical AI expertise and business acumen, support seizing by enabling decision-makers to interpret AI-generated insights and translate them into strategic action (Mikalef and Gupta, 2021). Intangible resources enhance reconfiguring by creating organizational conditions under which AI-informed insights diffuse across functional boundaries and reshape innovation routines (Ritala et al., 2024; Warner and Wäger, 2019). By improving opportunity identification, prioritization, and resource allocation, AI capability creates the conditions for more responsive, intensified innovation activity rather than mere operational improvement (Petrescu et al., 2022; Vallé et al., 2026). This capability-oriented view is particularly significant in B2B settings, where prior research has called for more integrative explanations of how AI-related resources and capabilities are translated into innovation rather than treated as standalone technologies (Mariani et al., 2023).

Accordingly, AI capability is positioned in this research as an enabling capability – an antecedent resource condition that feeds into agile organizational responses, while organizational agility represents the observable organizational behavior that results from the effective activation of these dynamic capability mechanisms. The strategic value of this capability architecture is, however, contingent on environmental conditions, as dynamic capability theory suggests that capability deployment produces differential innovation outputs under varying degrees of market uncertainty (Teece, 2018).

2.3. Product innovation intensity, B2B marketing innovation, and market turbulence

Product innovation intensity refers to the rate and comparative volume of a firm's new product development and introduction relative to its competitors (Ahsan et al., 2023). It captures the generation side of innovation, or how rapidly and continuously a firm commits resources to developing and launching new, unique, or improved offerings (Sullivan and Fosso Wamba, 2024). Firms with higher product innovation intensity maintain a stronger pipeline of new products, indicating that their seizing and reconfiguring routines are actively converting sensed opportunities into tangible new product outputs (Sullivan and Fosso Wamba, 2024; Teece et al., 1997). In this sense, AI capability is expected to strengthen product innovation intensity not simply by merely improving operational efficiency, but by improving opportunity identification, prioritization, and resource allocation in ways that conventional routines cannot sustain (Mikalef and Gupta, 2021; Teece, 2018; Vallé et al., 2026).

B2B marketing innovation entails novelty in the methods through which firms commercialize their offerings and engage business customers (Aas and Pedersen, 2011; Khan et al., 2021). While product innovation intensity addresses what the firm produces, B2B marketing innovation involves how those offerings are brought to market and how value is created with business customers. This distinction reflects the theoretical consequences because in B2B markets – where customized solutions, complex distribution channels, and long-term relational exchange characterize the path from product to market – innovation value is not fully realized at the point of new product creation but depends on the firm's capacity to develop novel commercialization approaches (Calantone et al., 2003; Im et al., 2013). Without innovation in how offerings reach and create value for business customers, even intensive product innovation may fail to translate into competitive advantage. This logic becomes salient under market turbulence, where shifting

customer preferences (Mangus et al., 2020) and competitive instability accelerate the obsolescence of established go-to-market methods (Calantone et al., 2003; Soto-Acosta, 2020; Wilden and Gudergan, 2015). Therefore, B2B marketing innovation is viewed as the focal downstream outcomes construct that directly captures whether firms convert upstream AI capability and product innovation intensity into sustained competitive value in business markets.

Market turbulence is an external condition characterized by the rate and unpredictability of change in the customer composition and preferences, the degree of volatility within an industry, and increasing demand for new products and services (Calantone et al., 2003; Low and Mohr, 2001). Accordingly, market turbulence is treated as a contingent variable that conditions the effectiveness of capability deployment, rather than as a uniform environmental backdrop. Under varying levels of market turbulence, demand patterns shift rapidly, competitor positions are unstable, and customer needs become difficult to forecast, increasing the information-processing burden on firms and intensifying the need for firms to adapt both their innovation processes and their market-facing approaches (Lin et al., 2025; Mangus et al., 2020). The contingent effects of the environmental instability highlight that market turbulence is not merely a contextual descriptor but a boundary condition that shapes the strategic value of capability deployment (Teece, 2018; Wilden and Gudergan, 2015), in turn determining not only a firm's resilience (Lin et al., 2025) but also its innovation performance (Sullivan and Fosso Wamba, 2024). Thus, under conditions of high turbulence, firms face greater urgency to sense emerging shifts, seize fleeting opportunities, and reconfigure routines before competitors do, making AI capability particularly consequential for innovation.

Prior research reports a mixed effects of market turbulence on innovation. While some studies suggest that market turbulence can stimulate product and B2B marketing innovation by revealing unmet customer needs (Li, 2022; Sullivan and Fosso Wamba, 2024), others highlight the challenges and delays it poses to new product development (Z. Su et al., 2013; Tsai and Yang, 2013). Despite the growing body of research on market turbulence organizational agility and AI-enabled innovation, there remains a significant gap in our understanding of how AI capability is translated into B2B marketing innovation through the theorized sequential relationships of organizational agility and product innovation intensity under turbulent environments. This study aims to address this gap by developing and testing a comprehensive model of AI-driven B2B marketing innovation under varying levels of market turbulence.

3. Theoretical framework and hypotheses development

To survive in competitive markets and develop their strategic agility, organizations need to nurture related factors, such as their customer and competitor orientations and their ambidexterity, while remaining aware of the market conditions surrounding them (Ameen et al., 2022). Previous studies suggest that B2B marketing innovation draws on various digital and human skill-related resources, as well as organizational agility (Guo et al., 2023). In addition, we argue that the relationships within this capability-to-innovation process may depend on the market turbulence surrounding organizations. In highly turbulent environments, future developments become more difficult to predict, increasing firms' reliance on external knowledge and adaptive organizational capabilities (Ameen et al., 2022; Eisenhardt and Martin, 2000). Accordingly, our conceptual model integrates AI capability, organizational agility, product innovation intensity, and B2B marketing innovation, with market turbulence conceptualized as a contingent boundary condition on the proposed relationships. Fig. 1 shows our proposed model.

3.1. The impact of AI capability on organizational agility and product innovation intensity

When firms develop the resources required for AI capability, they

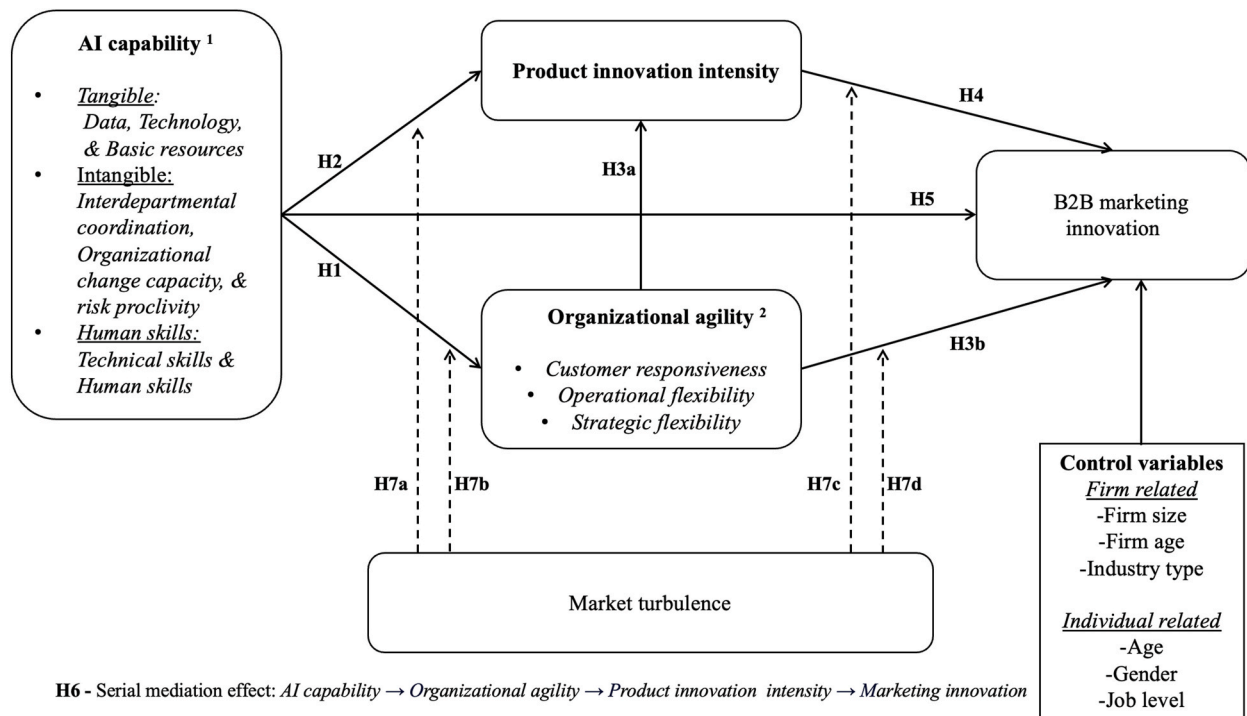


Fig. 1. Proposed model

Note: A value of 1 indicates that AI capability is measured as a third-order construct (formative-formative-formative), while a value of 2 indicates that organizational agility is measured as a second-order construct (reflective-formative).

develop their capacity to respond with speed to environmental changes and opportunities (Mikalef and Gupta, 2021). The reasoning that underpins such claims is that, as a result of the automation of many manual tasks, humans will have more time on their hands to engage in creative activities. Also, through certain applications of AI, human capabilities can be augmented through what is termed augmented intelligence (Ameen et al., 2022b). Specific AI techniques can use large datasets to assist professionals in creative tasks, such as engineering, design, and the arts, by enhancing their input information, and providing suggestions that would otherwise be hard to develop. Accordingly, the development of AI capability can enhance the main components of organizational agility: customer responsiveness, operational flexibility, and strategic flexibility (Mikalef et al., 2022; Ravichandran, 2018). Specifically, the development of the tangible, intangible, and human resources related to AI enables organizations to assess customer needs and preferences, while speedily responding to product and service offerings, streamlining their processes, speeding up their product development, revamping supply chain and logistics processes, identifying and entering new markets, and redefining the scope of their businesses (Ameen et al., 2022; Mikalef et al., 2022; Mikalef and Gupta, 2021). For example, AI can be applied to automate routine cognitive tasks, such as data entry, analytics, and predictions, and creative ones and improve productivity (Moradi and Dass, 2022). AI-based business applications can use algorithms and modeling to turn data into actionable insights into how organizations can optimize a range of functions and business processes.

From a dynamic capability perspective, AI capability translates into enhanced organizational agility by enhancing firms' ability to continuously sense, interpret, and respond to environmental changes in real time. By embedding AI into decision-making and operational routines, firms reduce latency between market signals and strategic action, enabling faster and more coordinated responses. This extends prior research (Teece, 2018; Warner and Wäger, 2019) by conceptualizing AI capability not merely as a decision-support tool, but as an enabling mechanism for real-time adaptive responsiveness. Accordingly, we proposed.

H1. Firms' AI capability has a positive effect on their organizational agility.

The development of AI capability can enhance an organization's ability to launch new products into the market relative to its key competitors. When organizations develop the resources required for AI capability, they can develop both the technology and the ways in which their employees can work effectively with it, e.g., by developing the technical skills required for successful augmentation (Ameen et al., 2022). In addition, AI enables the creation of solutions that are more highly user-centered than those resulting from human-based approaches (i.e., endowed with extreme levels of granularity, designed for every single person), potentially more creative, and continuously updated through learning iterations across the entire product life cycle, thus improving product innovation intensity in organizations (Verganti et al., 2020). For example, supervised ML algorithms are increasingly useful in supporting experts (or accepted sources of truth) in predicting outcomes (Verganti et al., 2020). Organizational AI capability moves digital automation upstream, from manufacturing to design, thus enhancing product innovation intensity.

From a dynamic capability perspective, AI capability enhances product innovation intensity by strengthening firms' ability to identify and act on innovation opportunities under uncertainty. Unlike general digital or operational capabilities, AI capability drives product innovation intensity through its distinctive capacity to process environmental data at scale, identify emerging innovation opportunities, and support resource prioritization in ways that conventional routines cannot sustain (Mikalef and Gupta, 2021; Vallé et al., 2026). By improving opportunity recognition and resource allocation processes, AI capability supports continuous innovation efforts rather than isolated product development outcomes (Teece, 2018). This extends prior research that focuses primarily on efficiency and decision-making benefits of AI (Petrescu et al., 2022; Vallé et al., 2026), by demonstrating its role in accelerating the pace and continuity of innovation activity.

Therefore, we proposed.

H2. Firms' AI capability has a positive effect on their product innovation intensity.

3.2. The roles of organizational agility and product innovation intensity

Previous studies have suggested that enterprises should fully consider the role played by the external market in shaping product innovation intensity and accordingly adjust their internal resources and organizational structures in an agile manner (Cai et al., 2019). As one of the core antecedents of product innovation intensity (Cai et al., 2019; Hoonsopon and Puriwat, 2021), organizational agility encompasses three key dimensions, customer responsiveness, strategic flexibility, and operational flexibility, that enable firms to rapidly identify and respond to evolving market demands (Fosso Wamba, 2022; Ravichandran, 2018). Importantly, the influence of organizational agility on product innovation intensity is not merely direct but is underpinned by knowledge-based mechanisms. Agile firms are better positioned to develop and leverage absorptive capacity (Cohen and Levinthal, 1990), defined as the ability to acquire, assimilate, and apply both external and internal knowledge, which is critical for innovation. In parallel, agility fosters continuous experimentation and strategic learning, enabling firms to recombine knowledge into novel product development efforts. These micro-foundations enhance a firm's ability to translate market insights into intensified innovation activities.

Specifically, market demand serves as a key driver of product innovation intensity (X. Su et al., 2022). In response, an increasing number of enterprises have adopted flexible organizational structures and digital technologies to capture and process large volumes of market data, thereby strengthening their innovation capabilities (Fosso Wamba, 2022; Z. Su et al., 2013). For example, firms such as Apple integrate employees from marketing, R&D, and manufacturing to facilitate cross-functional collaboration in customized innovation processes (Olabode et al., 2022), while Chinese manufacturing firms such as Haier Group leverage AI-enabled cross-functional coordination across R&D, supply chain, and design functions to intensify product innovation efforts (Luo et al., 2026). Such high levels of product innovation intensity often require coordinated efforts across organizational units, further necessitating structural and operational flexibility. Organizational agility also reduces asset specificity through enhanced strategic and operational flexibility (Tarba et al., 2023), allowing firms to reconfigure resources more efficiently. As resources, structures, and processes become more adaptable, firms are better equipped to respond proactively to market changes through intensified product innovation. Thus, organizational agility significantly enhances product innovation intensity (Hoonsopon and Puriwat, 2021). We therefore formulate the following hypothesis.

H3a. Organizational agility has a positive effect on product innovation intensity.

Beyond the effect of organizational agility on production innovation intensity, organizational agility also directly enables B2B marketing innovation, which has hitherto not been articulated (Zahoor et al., 2024). By reconfiguring how firms engage with business customers under varying levels of market turbulence, agility creates the structural conditions for market-facing innovation (Urresta-Vargas et al., 2025). Greater customer responsiveness, one of the three dimensions of organizational agility (Ravichandran, 2018), enables firms to quickly identify shifting customer preferences and optimizing product channels and pricing strategies (Shams et al., 2021; Tallon and Pinsonneault, 2011). In addition, strategic and operational flexibility, two more crucial dimensions of organizational agility, can facilitate the rapid implementation of B2B marketing innovation by allowing firms to reconfigure organizational structure in response to market changes (Ravichandran, 2018). Firm-level flexibility accelerates the interaction between external market opportunities and internal resources, thus providing structural conditions favorable to B2B marketing innovation (Kaiser

et al., 2023).

Beyond product development, organizational agility also enables firms to reconfigure market-facing activities, allowing them to experiment with and implement novel marketing approaches under changing conditions. This extends existing work by positioning agility as a driver of downstream, market-facing innovation rather than solely an internal operational capability. Companies endowed with higher organizational agility are more capable of implementing B2B marketing innovation. Therefore, we proposed the following hypothesis.

H3b. Organizational agility has a positive effect on B2B marketing innovation.

Although product innovation intensity and B2B marketing innovation take on different forms, they are strongly linked. From the strategic management view, B2B marketing innovation (e.g., product price, channel selection, brand design, and packaging) is largely based on product attributes and innovation intensity (Litina et al., 2021). The higher the product innovation intensity of an enterprise, the greater the differences between its products and those of its competitors in the industry, which helps it create higher competition barriers and broadens the boundaries of B2B marketing innovation strategies (Moorman and Slotegraaf, 1999).

In addition, from the business model perspective, product innovation intensity and B2B marketing innovation play important roles in contributing to product value creation and delivery. Specifically, product innovation intensity, which largely reflects the extent to which value is created, is based on the novelty found in the development of product attributes (Qu and Mardani, 2023). B2B marketing innovation, on the other hand, shows how value is delivered, and relies on novel ways to build up customer assets and relationships (Aksoy, 2017). Therefore, higher levels of product innovation intensity can enable firms to respond to changing marketing conditions and stay ahead of the competition, enabling them to pursue novel marketing innovation strategies. For example, the high innovation intensity found in the electric vehicle industry pushes the rapid emergence of new customized B2B marketing innovations (Tang et al., 2021). Thus, intensive product innovation generates new B2B marketing innovation.

This relationship reflects a value realization process in which intensified innovation efforts expand the scope for differentiation, thereby enabling more sophisticated and novel market engagement strategies. In doing so, this study extends prior research by explicitly linking the rate of innovation activity to the breadth of marketing innovation outcomes. Accordingly, we proposed the following hypothesis.

H4. Product innovation intensity has a positive effect on B2B marketing innovation.

While prior research has examined AI capability through its indirect effects on innovation outcomes, its direct influence on B2B marketing innovation remains undertheorized (Liu et al., 2025; Petrescu et al., 2022). AI capability equips firms with the analytical and adaptive means to sense market shifts, interpret evolving customer needs, and reconfigure marketing approaches that go beyond the reach of traditional organizational routines (Mikalef and Gupta, 2021; Vallé et al., 2026). By enabling precise data analysis, predictive insights, and automation, AI supports firms in crafting novel marketing strategies tailored to evolving B2B contexts (Ameen et al., 2022; Bamberger et al., 2025). Under varying levels of market turbulence, where customer needs and competitive dynamics shift rapidly, AI capability enables firms to sense and respond effectively to these changes (Arias-Pérez and Huynh, 2023; Ravichandran, 2018). For instance, firms leveraging AI can optimize supply chains, develop customer-centric solutions, and adapt marketing approaches to sustain their competitive advantage (Arias-Pérez and Huynh, 2023).

Importantly, AI capability enables firms not only to optimize existing marketing practices but also to reconfigure how value is created and

delivered to business customers. This positions AI capability as a direct driver of market-facing innovation, extending prior research that has predominantly focused on its indirect effects through operational and strategic improvements. Therefore, we propose.

H5. AI capability has a positive effect on B2B marketing innovation.

Having established the theoretical and empirical basis for each link in the proposed causal chain (H1, H3a, and H4), the present study argues that organizational agility and the intensity of product innovation jointly function as a theorized sequential pathway in the relationship between AI capability and B2B marketing innovation. According to resource-based theory (Barney, 2001; Eisenhardt and Martin, 2000), many organizations may find the efficient use of AI capability to improve their B2B marketing innovation to be difficult and not straightforward due to the system of logical mechanisms that relate to their agility and direction in relation to their intensity in offering innovative products (Ravichandran, 2018). We assert that the implementation of organizational agility and product innovation intensity may have a theoretically integrated process on the relationship between AI capability and B2B marketing innovation. According to Mikalef and Gupta (2021), capabilities such as those associated with the use of AI technology may help organizations improve their business agility by providing the procedures and routines necessary to perceive and respond to changes in the environment. Subsequently, organizational agility would encourage them to efficiently achieve product innovation intensity. Agile organizations are more flexible in managing their resources, structures, and operations and, as a result, are more likely to react to market demands by increasing their product innovation (Chakravarty et al., 2013; Sullivan and Fosso Wamba, 2024). When organizations strive to create added value in order to meet market demand through product innovation intensity, their B2B marketing innovation tactics will broaden and expand, e.g., by more effectively customizing their product and service offerings, distribution, and building long-term relationships with stakeholders (Aksoy, 2017). This theoretical sequence process reflects a theoretically informed process of dynamic capability by Teece et al. (1997), in which upstream technological capabilities like AI are often used to translate organizations' business strategies into downstream market-facing innovations through intermediate organizational mechanisms. The goal is to promptly respond to adaptations in marketing strategies for business commercialization and value propositions. Drawing on this notion, we hypothesized that, when organizations invest in developing AI capability, they will become more agile in their business operations in order to adapt to the intensity of product innovation. As a result, the impact of product innovation intensity will push organizations to become more B2B marketing innovation-focused.

This theoretical sequential relationship reflects a dynamic capability transformation process in which upstream technological capabilities are progressively translated into downstream innovation outcomes through intermediate organizational processes. This extends prior work by empirically specifying the ordered pathway through which AI capability is converted into market-facing value. Therefore, we proposed the following hypothesis.

H6. The relationship between AI capability and B2B marketing innovation is sequentially mediated by organizational agility and product innovation intensity.

3.3. The moderating effects of market turbulence

Market turbulence reflects dynamic and uncertain market conditions in which customer preferences, competitive pressures, and market requirements change rapidly. From a contingency perspective, the value generated by organizational resources and capabilities depends on the environmental conditions in which they are deployed (Li, 2022; Tsai and Yang, 2013). This reasoning is also consistent with dynamic capability

theory, according to which firms derive value from their ability to sense environmental change, seize emerging opportunities, and reconfigure resources accordingly (Teece, 2018; Teece et al., 1997). Market turbulence should therefore affect the strength of specific relationships within the capability-to-innovation process because heightened uncertainty increases firms' need for rapid information processing, adaptation, and innovation responses. Rather than assuming that turbulence exerts a uniform influence across the model, we theorize its moderating role separately for each focal relationship.

First, AI capability can enhance product innovation intensity by enabling firms to process large-scale and real-time information, identify changes in customer needs, recognize emerging market opportunities, and support innovation-related decision-making (Mikalef and Gupta, 2021; Teece, 2018). AI-enabled resources can also facilitate experimentation and the reconfiguration of organizational processes and innovation activities (Ritala et al., 2024; Warner and Wäger, 2019). Under conditions of high market turbulence, these functions become particularly valuable because existing knowledge and established product configurations can become obsolete more quickly, while firms face greater pressure to detect and respond to changing market requirements. Firms with strong AI capability should therefore be better positioned to convert volatile market information into intensified product-development activity and more rapid product renewal (Mikalef and Gupta, 2021; Yang and Gabrielsson, 2017). By contrast, when turbulence is low, customer preferences and competitive conditions are relatively stable, reducing the incremental need for AI-enabled sensing and rapid product adaptation. Accordingly, the positive effect of AI capability on product innovation intensity should be stronger when market turbulence is high rather than low. This reasoning is also consistent with prior evidence that market turbulence shapes firms' innovation activities and the value generated through digital transformation (Li, 2022; Tsai and Yang, 2013).

H7a. Market turbulence positively moderates the relationship between AI capability and product innovation intensity, such that the relationship is stronger when market turbulence is high.

Second, AI capability can strengthen organizational agility because AI-enabled information processing allows firms to detect environmental changes, evaluate large volumes of information, support faster decision-making, and adjust organizational activities accordingly (Gao et al., 2020; Tallon et al., 2019). More broadly, AI capability strengthens sensing and seizing by helping firms identify emerging developments and translate AI-generated insights into strategic responses (Mikalef and Gupta, 2021; Teece, 2018). These benefits should become more consequential under high market turbulence, when organizations face rapidly changing and less predictable environmental signals and therefore require faster interpretation and response. In such conditions, firms with stronger AI capability should be able to mobilize information and resources more rapidly, strengthening their capacity for organizational agility (Cho et al., 2023; Tallon et al., 2019). Conversely, in relatively stable markets, firms face fewer urgent environmental changes and can rely to a greater extent on established routines and accumulated knowledge, reducing the incremental contribution of AI capability to rapid organizational adaptation. We therefore expect the positive relationship between AI capability and organizational agility to be stronger under high market turbulence.

H7b. Market turbulence positively moderates the relationship between AI capability and organizational agility, such that the relationship is stronger when market turbulence is high.

Third, product innovation intensity reflects the pace and continuity with which firms develop and renew their offerings (Ahsan et al., 2023; Sullivan and Fosso Wamba, 2024). Intensified product innovation can stimulate B2B marketing innovation because new and changing offerings create a need for corresponding adjustments in how firms communicate, price, distribute, configure, and commercialize value for

business customers. Product innovation therefore concerns *what* the firm develops, whereas B2B marketing innovation concerns novel approaches through which those offerings are brought to market and value is realized (Mooi et al., 2022; Sullivan and Fosso Wamba, 2024). This relationship should become stronger under high market turbulence. When customer requirements and competitive conditions change rapidly, newly developed products are more likely to require innovative marketing approaches to remain aligned with evolving market expectations. Turbulence therefore increases the need to translate product renewal into novel market-facing practices, including adaptations in value communication, customer engagement, pricing, and routes to market (Chong et al., 2016). In lower-turbulence environments, established commercialization approaches are more likely to remain effective, meaning that intensified product innovation does not necessarily require a comparable degree of marketing innovation. Consequently, market turbulence should strengthen the positive relationship between product innovation intensity and B2B marketing innovation. This argument is consistent with previous research showing that turbulence affects firms' innovation and marketing responses (Li, 2022; Tsai and Yang, 2013).

H7c. Market turbulence positively moderates the relationship between product innovation intensity and B2B marketing innovation, such that the relationship is stronger when market turbulence is high.

Finally, organizational agility captures firms' ability to recognize environmental changes and rapidly adjust their strategies, structures, and operations in response (Hoonsopon and Puriwat, 2021; Weber and Tarba, 2014). Agile firms are better able to mobilise and reconfigure resources when market requirements change, thereby translating environmental responsiveness into adaptive organizational actions (Doz and Kosonen, 2010; Teece et al., 1997). This capacity should have particularly strong implications for B2B marketing innovation under high market turbulence. When customer preferences, competitive actions, and market conditions shift quickly, firms need to adapt not only their internal operations but also their market-facing practices. Organizational agility enables firms to respond through more rapid changes in customer engagement, value propositions, pricing, communication, and other marketing approaches (Zahoor et al., 2024). Under relatively stable market conditions, however, existing marketing practices are more likely to remain aligned with customer and competitive requirements, reducing the extent to which additional organizational agility translates into marketing innovation. Thus, it is the relationship between organizational agility and B2B marketing innovation, not the moderation effect itself, that we expect to be stronger under high rather than low market turbulence.

H7d. Market turbulence positively moderates the relationship between organizational agility and B2B marketing innovation, such that the relationship is stronger when market turbulence is high.

To avoid any confounding effects from the testing of our hypotheses, firm-related (i.e., size, age, and industry type) and individual-related (i.e., age, gender, and job level) control variables were included in our model (see Fig. 1). Previous studies indicate that employees who are younger, female, and hold top management positions in large older firms from different industry types are more likely to invest and engage in high new product creativity and new service development performance to keep up with changing business environments (Tønnessen et al., 2021).

4. Methods

4.1. Instrumentation

The first part of our questionnaire was focused on gathering information about the participating managers and their respective firms, including details such as firm size, firm age, role/position, gender,

educational background, and other relevant factors. The second part consisted of questions that directly corresponded to the variables specified in our conceptual model. These variables were measured using a 7-point Likert scale ranging from (1) *strongly disagree* to (7) *strongly agree*. The measurement items for all factors incorporated into our proposed model were adapted from existing literature (additional details can be found in Appendix A). In particular, *AI capability*, a formative factor, included human skills (technical and business), tangibles (data, technology, and basic resources), and intangibles (inter-departmental coordination, organizational change capacity, and risk proclivity) were adapted from Mikalef and Gupta (2021), particularly the need to adapt the general context of AI capability to AI capability in B2B marketing and innovation contexts.

Meanwhile, *organizational agility* includes three dimensions: *customer responsiveness* (five items), *operational flexibility* (six items), and *strategic flexibility* (five items) (Ravichandran, 2018). *Market Turbulence* included three items adapted from Calantone et al. (2003), while *B2B Marketing Innovation* included six items adapted from Aas and Pedersen (2011). Finally, *product innovation intensity* included three items adapted from Ahsan et al. (2023). With regard to these constructs, the wording was refined to ensure greater alignment with the B2B context and to facilitate comparability across firms in the sample.

We also used the standard translation/back-translation procedure to translate the survey into Chinese. To reduce the possibility of survey mistakes, we pretested the questionnaire on a panel of experts (i.e., Chinese-speaking managers with expertise in the use of AI in their company operations), proving content validity. For example, we revised our questionnaire and added new questions to sections like 'basic resource', 'technology', 'human skills', and 'business skills'. Subsequently, we invited 57 managers with AI experience to participate in a pilot study to strengthen content validity. Based on feedback from the pre-test stage, we refined some items for greater clarity before moving on to the pilot study and repeated the same process for the pilot study before moving on to the main one.

4.2. Data collection procedure

We identified prospective survey respondents from the Wenjuanxing database (a Chinese platform similar to Qualtrics)¹ using two sampling criteria: 1) the managers had to be employed by firms that adopt AI in their B2B marketing activities, and 2) these firms must also use AI to drive product innovation. These criteria were implemented at the beginning of the survey, and only respondents who satisfied both requirements were permitted to participate. In fact, this screening process was designed to ensure that our respondents possessed sufficient knowledge and direct experience with the organizational practices and capabilities examined in this study. Given that the focal constructs relate to AI-enabled marketing and innovation activities, managers operating within firms actively adopting these technologies were considered the most appropriate informants to provide reliable assessments. While this sampling strategy may exclude firms with limited or no AI adoption, the purpose of the study is to examine the relationships among AI capability, B2B marketing innovation, and firm performance within organizations

¹ Wenjuanxing is a widely used Chinese online survey platform that provides access to a large pool of registered respondents from diverse demographic backgrounds across China (Yin et al., 2026; Zhang et al., 2026). In other words, the demographic distribution of the sample (e.g., age, gender, education, and income) is broadly consistent with profiles reported in prior studies using Wenjuanxing and with national statistics, suggesting an acceptable level of coverage for theory-testing purposes. It is important to note that participants voluntarily join the platform and are invited to surveys based on predefined screening criteria. According to its official statistics, as of April 2026, a total of 356 million questionnaires have been distributed on the Wenjuanxing platform, with 26.526 billion responses collected.

where these phenomena are present and observable. Consequently, prioritizing knowledgeable respondents enhances the validity of the data and the meaningfulness of the theoretical inferences drawn. Upon distribution of the online survey to potential respondents, the invitation contained a concise description of the study's objective and the ethical assurances regarding anonymity and data confidentiality. Participation in the study was voluntary, and respondents were offered an incentive (e.g. monetary compensation) in accordance with standard practice for online survey research.

As all measures used in the study were based on self-reported data collected using the same survey instrument, there was the potential for the presence of common method variance (CMV) in the data. To address this concern, we took several precautions to minimize the likelihood and impact of any CMV resulting from the common method. First, we ensured anonymity and confidentiality by employing personal pseudonym codes (MacKenzie and Podsakoff, 2012). Second, we encouraged participants to express their true opinions and assured them that there were no right or wrong answers. Third, we randomized the order of the survey questions for each participant to avoid any mood states influenced by the context of the specific survey items and other related biases. Fourthly, an attention-check question was included in the survey (i.e., 'What color is the sky?') in order to remove respondents who were careless or inattentive. Finally, we took care to avoid any ambiguous or complex items in the survey (e.g., technical jargon or colloquialisms) by using clear and straightforward language and avoiding item priming effects by varying the wording of the scales (Schwarz et al., 2017).

The data was collected in the first quarter of 2024². During the process, we received responses from managers in 339 companies (one manager per company). We then deleted those from managers of 63 firms due to illogical responses and missing values (e.g. some managers stated that their firms had a good ability to change, but then went on to state that they were unable to anticipate and plan for change), demonstrated straight-lining or invariant response patterns, and those from 37 firms that only provided B2C services. In total, approximately 20% of the initial responses were removed. This exclusion rate is comparable to those reported in previous studies that used online survey panels (Deutschens et al., 2004; Holtom et al., 2022). It reflects the application of conservative quality control criteria rather than deficiencies in item clarity. Additionally, all measurement items were adapted from established scales and pretested to ensure clarity and face validity.

Thus, our final sample included questionnaires completed by managers of 239 firms (see Appendix B), most of which had 101-500 employees (50.6%) and were less than 15 years old (40.6%). In terms of gender, most responding managers were male (73.6%), in terms of education, they had a bachelor's degree (82.0%) and in terms of age, they were between 26 and 35 years old (65.3%). In addition, all our respondents indicated that their respective companies offered services that could be considered AI-enabled (100%), and that they interacted directly and several times a day with AI-enabled platforms in their companies (43.5%). They also reported that the most common uses of AI platforms were for AI analytics (48.1%) and R&D (27.2%) for their product development. Finally, the data showed that many of our sample companies operate in the information and technology sector (38.5%), in addition to other sectors.

² The first quarter of 2024 was the best for data collection due to a significant acceleration in artificial intelligence development in the Chinese market. This period was characterized by increased investment, rapid adoption of generative AI applications, and substantial involvement from technology companies and startups. It is widely regarded as a turning point that signaled the large-scale commercialization and strategic integration of AI across key Chinese industries (Lu et al., 2025).

4.3. Data estimation technique

This study employed partial least squares structural equation modelling (PLS-SEM) to estimate the proposed research model, which incorporates a higher-order reflective-formative construct, mediation effects, and moderation relationships. PLS-SEM was selected because the primary objective of the study was to explain and predict variance in the focal endogenous construct (i.e., B2B marketing innovation), rather than reproduce an observed covariance matrix or assess exact model fit. Such an objective is consistent with the predictive and variance-explanatory orientation for which PLS-SEM was originally developed (Hair et al., 2021).

We acknowledge the methodological concerns raised regarding the use of PLS-SEM for strict confirmatory theory testing. In particular, Rönkkö et al. (2016) questioned the suitability of PLS-SEM for covariance-based model confirmation, citing issues related to parameter estimation, capitalization on chance, and the absence of a traditional global goodness-of-fit assessment. However, subsequent methodological work has argued that these criticisms largely stem from evaluating PLS-SEM against objectives and criteria associated with covariance-based SEM rather than its intended purpose (Hair et al., 2019). Specifically, Hair et al. (2019) emphasized that PLS-SEM should be assessed in relation to its strengths in prediction, variance explanation, and the estimation of complex models involving formative measurement specifications. Consistent with this perspective, the findings of the present study are interpreted from a prediction-oriented and variance-explanatory standpoint rather than as evidence of exact covariance-based model confirmation (Guenther et al., 2023; Hair et al., 2021). In addition, contemporary methodological literature increasingly suggests that the choice between PLS-SEM and CB-SEM should be guided by the research objective, model characteristics, and measurement model specifications, rather than by a presumed methodological hierarchy in which one approach is considered universally superior to the other (Hair et al., 2019; Sarstedt et al., 2024). Given the presence of a higher-order reflective-formative construct, the incorporation of mediation and moderation effects, and the study's emphasis on explaining and predicting B2B marketing innovation, PLS-SEM represents an appropriate analytical approach. Therefore, the use of PLS-SEM in this study is consistent with contemporary methodological recommendations and aligns closely with the predictive orientation of the research design.

5. Results

5.1. Common method variance (CMV)

To ensure the efficacy of the implemented procedural remedies of CMV (stated in section 6.3), we then conducted the full collinearity (FC) test in PLS-SEM and the unmeasured latent factor control approach (Williams et al., 2010). The result in Appendix C shows that all variance inflation factor (VIF) values of FC were well below the threshold value of 3.3 (Hair et al., 2021), suggesting that there is no significant CMV in this study. In relation to the second approach, the R^2 value for organizational agility was 0.538, product innovation intensity was 0.672, and B2B marketing innovation was 0.674 before the addition of the unmeasured latent factor. After the inclusion of unmeasured latent factor control approach, the R^2 increased slightly (less than 0.1) to 0.539 for organizational agility, 0.681 for product innovation intensity, and 0.682 for B2B marketing innovation. Therefore, the addition of this unmeasured latent factor control approach does not result in a substantial alteration to the R^2 value of the endogenous construct. Consequently, these findings collectively indicate that the presence of CMV was unlikely to be a major issue in the present study.

5.2. Measurement model

In the initial phase of the measurement model, we undertook a comprehensive evaluation of the construct measures to ascertain their validity and reliability. All items demonstrated loadings that exceeded the minimum threshold of 0.5, which is acceptable as proposed by Hair et al. (2021) (see Appendix C). Subsequently, the results indicated that all variables had average variance extracted (AVE) values above 0.5 and composite reliability (CR) values above 0.7 (Hair et al., 2021), thus, both convergent validity and internal consistency were established, demonstrating acceptable psychometric properties. Subsequently, the discriminant validity was evaluated using Fornell and Larcker's (1981) criterion and heterotrait-monotrait (HTMT) ratio correlation (Hair et al., 2021). According to Fornell and Larcker's (1981) criterion, the square root of average variance extracted for each construct was higher than the correlations between that construct and all others, indicating that each construct shares more variance with its indicators than with those of other constructs. Additionally, all variables were found to have HTMT ratios below the maximum threshold of 0.90 (Hair et al., 2021), thereby confirming that the discriminant validity was established without any concern (see Appendix D). Collectively, these results indicate a robust and well-specified measurement model.

Furthermore, we assessed the formative construct for AI capability (classified as a third-order construct following the formative-formative type) and organizational agility (classified as a second-order construct following the reflective-formative type) using the approaches delineated by Becker et al. (2023). In the initial stage of the analysis, the VIF values were examined. It was observed that all items and dimensions were distinct, as indicated by the VIF values falling below the maximum threshold of 3.3, thereby indicating no multicollinearity concern (see Appendix E). Subsequently, the statistical analysis indicated that not all items in the first-order constructs of AI capability were statistically significant. Nevertheless, the statistical significance of the second-order constructs (p -value < 0.05) permitted the confirmation of the presence of the third-order construct of AI capability. The third-order construct was also found to demonstrate statistical significance in all its second-order constructs or dimensions of Tangible AI capability, Human AI capability, and Intangible AI capability (p -value < 0.05). In addition, the second-order dimensions of organizational agility (customer responsiveness, operational flexibility, and strategic flexibility) were found to be statistically significant with a p -value < 0.05. Consequently, the third-order construct of AI capability and the second-order construct of organizational agility were successfully established (see Appendix E). To validate this finding, we created and evaluated a global item for AI capability (i.e., "Overall, the company is well equipped with AI capability.") and organizational agility (i.e., "Overall, the company has prioritized organizational agility."). The redundancy analysis yielded path coefficient values of 0.741 and 0.784, which exceeded the minimum threshold of 0.70 (Hair et al., 2021), thereby substantiating the convergent validity of AI capability and organizational agility.

5.3. Structural model

Table 1 reveals that AI capability was found to exert a significant influence on organizational agility (H1: $\beta = 0.733$, $t = 18.967$, p -value = 0.000). Thus, H1 was found to be supported with an explanatory power of 53.8%. Also, AI capability was found to exert a significant influence on product innovation intensity (H2: $\beta = 0.403$, $t = 5.534$, p -value = 0.000) with a medium effect size ($f^2 = 0.205$). Similarly, organizational agility was also found to significantly influence product innovation intensity (H3a: $\beta = 0.477$, $t = 6.895$, p -value = 0.000) but with a large effect size ($f^2 = 0.378$). Thus, H2 and H3a were found to be supported with explanatory powers of 67.2%. Furthermore, organizational agility (H3b: $\beta = 0.364$, $t = 3.568$, p -value = 0.000), product innovation intensity (H4: $\beta = 0.432$, $t = 4.419$, p -value = 0.000), and AI

capability (H5: $\beta = 0.425$, $t = 4.003$, p -value = 0.000) were found to significantly influence B2B marketing innovation with small ($f^2 = 0.123$) and medium ($f^2 = 0.170$) effect sizes, thus both H3b and H5 were found to be supported with explanatory powers of 67.4%, especially after controlling for six variables (i.e., firm size, firm age, industry type, age, gender, and job level) that demonstrated the non-significant result (p -value > 0.05).^{3, 4, 5, 6}

To account for the mediating effects, we employed the mediation approach proposed by Carrión et al. (2017) and Nitzl et al. (2016). We observed that product innovation intensity and B2B marketing innovation have a significant partial sequential mediation effect between AI capability and B2B marketing innovation (H6: $\beta = 0.151$, $t = 3.967$, p -value = 0.000) with a variance accounted for (VAF) of 20.770%. Thus, H6 was found to be confirmed and supported (see Table 1). In addition, we calculated the effect size of this sequential mediation path (Lachowicz et al., 2018) and found that the result exhibited a small effect size ($v = 0.023$). Overall, these findings highlight the crucial roles played by organizational agility and product innovation intensity in the relationship between AI capability and B2B marketing innovation.

Subsequently, we observed that market turbulence plays an important moderator role in the relationships between AI capability and product innovation intensity (H7a: $\beta = 0.099$, $t = 3.166$, p -value = 0.001), product innovation intensity and B2B marketing innovation (H7c: $\beta = 0.076$, $t = 2.114$, p -value = 0.017), and organizational agility and B2B marketing innovation (H7d: $\beta = 0.073$, $t = 2.237$, p -value = 0.013) with small effect sizes ranging from 0.031 to 0.054. In contrast, we found that market turbulence does not moderate the relationship between AI capability and organizational agility (H7b: $\beta = 0.024$, $t = 0.587$, p -value = 0.279) with a trivial effect size of 0.002. Thus, H7a, H7c, and H7d were found to be supported, but H7b was not (Table 1).⁷

6. Discussion

Drawing on dynamic capability theory, this study examines how AI capability contributes to B2B marketing innovation through

³ The descriptive statistics and bivariate correlations among the study constructs are reported in Appendix F.

⁴ Appendix G provides further elaboration on the assessment of collinearity and endogeneity tests, to ensure the robustness of our structural model results.

⁵ Our proposed model exhibits an excellent approximate fit, as indicated by an SRMR value of 0.051, which is well below the recommended threshold of 0.08 (Hair et al., 2026). Additionally, the NFI value of 0.880 indicates an acceptable level of improvement in fit over the null model according to the naïve benchmark from PLS-SEM (see (Hair et al., 2026)). These results suggest that the proposed model adequately represents the observed data structure. However, model evaluation in PLS-SEM should rely on predictive and measurement quality criteria rather than on global fit indices alone. Therefore, Appendix H provides further elaboration on assessing predictive validity.

⁶ To ensure the robustness of our structural model findings, a comparison was made between our proposed model and an alternative model. This enabled the selection of correctly specified models when comparing predictive generalizability. In particular, we reverse the relationship between innovation intensity and organizational agility as the alternate model and compare it to the original model. The structural model findings demonstrate significant value for all direct paths, with R2 values of 0.660 for organizational agility, 0.553 for product innovation intensity, and 0.674 for B2B marketing innovation. However, the model selection criteria result shows that the proposed model (AIC: 0.498 and BIC: -259.995) produces a better result than the alternative model (AIC: 0.502 and BIC: -259.977). It should be noted that the AIC is known as Akaike Information Criteria and the BIC is known as Bayesian Information Criteria. If the proposed model achieves lower AIC and BIC values compared to an alternative model, this indicates a better model fit and preferred model than the alternative model.

⁷ To corroborate these findings, we also examined the interaction plot of the significant moderator effects (see Appendix I).

Table 1
Structural model.

Relationship						BCa CI		VIF	f^2/ν^2	VAF	R ²	Q ² _{predict}
		Std Beta	Std Error	t-value	p-value	LB	UB					
Direct effect	H1: AI capability → Organizational agility	0.733	0.039	18.967	0.000	0.655	0.773	1.000	NA		0.538	0.513
	H2: AI capability → Product innovation intensity	0.403	0.073	5.534	0.000	0.269	0.484	2.130	0.205		0.672	0.491
	H3a: Organizational agility → Product innovation intensity	0.477	0.069	6.895	0.000	0.403	0.608	2.130	0.378			
	H3b: Organizational agility → B2B marketing innovation	0.364	0.102	3.568	0.000	0.196	0.508	2.655	0.123		0.674	0.546
	H4: Product innovation intensity → B2B marketing innovation	0.432	0.098	4.419	0.000	0.266	0.570	2.626	0.170			
	H5: AI capability → B2B marketing innovation	0.425	0.106	4.003	0.000	0.250	0.599					
Indirect effect	H6: AI capability → Organizational agility → Product innovation intensity → B2B marketing innovation	0.151	0.038	3.967	0.000	0.091	0.234		0.023	20.770%		
Moderator effect	H7a: AI capability x Market turbulence → Product innovation intensity	0.099	0.041	3.166	0.001	0.058	0.152		0.054			
	H7b: AI capability x Market turbulence → Organizational agility	0.024	0.154	0.587	0.279	−0.032	0.103		0.002			
	H7c: Product innovation intensity x Market turbulence → B2B marketing innovation	0.076	0.036	2.114	0.017	0.012	0.128		0.035			
	H7d: Organizational agility x Market turbulence → B2B marketing innovation	0.073	0.031	2.237	0.013	0.018	0.119		0.031			
Control variables	Type of service offered → B2B marketing innovation	−0.061	0.037	1.616	0.106	−0.139	0.022					
	Age → B2B marketing innovation	−0.099	0.065	1.523	0.059	−0.182	0.019					
	Education → B2B marketing innovation	0.063	0.042	1.480	0.069	−0.009	0.132					
	Firm age → B2B marketing innovation	0.004	0.041	0.108	0.914	−0.045	0.093					
	Firm size → B2B marketing innovation	−0.040	0.042	0.958	0.338	−0.112	0.015					
Endogeneity test	GC (AI capability → Organizational agility) → Organizational agility	0.217	0.152	1.428	0.085	−0.044	0.632					
	GC (AI capability → Product innovation intensity) → Product innovation intensity	−0.137	0.154	0.892	0.373	−0.489	0.130					
	GC (Organizational Agility → Product innovation intensity) → Product innovation intensity	−0.188	0.152	1.238	0.216	−0.549	0.071					
	GC (Product innovation intensity → B2B marketing innovation) → B2B marketing innovation	−0.208	0.173	1.202	0.121	−0.449	0.015					
	GC (Organizational agility → B2B marketing innovation) → B2B marketing innovation	−0.163	0.149	1.095	0.274	−0.393	0.129					
	GC (AI capability → B2B marketing innovation) → B2B marketing innovation	−0.178	0.112	1.584	0.113	−0.388	0.029					

Note: BCa: bias-correlated and accelerated; LB: lower bound; UB: upper bound; VAF: variance accounted for; NA: not applicable; GC: endogeneity test using Gaussian Copula.

organizational agility and product innovation intensity under varying levels of market turbulence. Positioned at the intersection of innovation and marketing, this study addresses an underexplored gap in the innovation literature by examining how AI capability can be transformed through organizational capability-building into marketing innovation. This represents the commercialization phase of the innovation process, a phase innovation scholars have long identified as critical yet often neglected (Naidoo, 2010; Ngo and O'Cass, 2012). We identify a novel theorized sequential relationship, where organizational agility and product innovation jointly bridge the link between AI and B2B marketing innovation (Ahsan et al., 2023). The findings further indicate that environmental turbulence does not uniformly strengthen this process, but conditions particular relationships within it.

Importantly, these findings both align with and extend prior research on AI-enabled innovation. Consistent with Liu et al. (2025), our results confirm that AI capability enhances organizational responsiveness and innovation outcomes. However, our findings go beyond this work by providing evidence consistent with a theorized capability-transformation pathway involving organizational agility and product innovation intensity, rather than focusing solely on strategic

agility or decision-making performance. This provides a more granular explanation of how AI capability is translated into market-facing innovation. Similarly, while Petrescu et al. (2022) conceptualize AI-enabled innovation through interdisciplinary mechanisms, our findings extend this work by empirically distinguishing between innovation generation and innovation realization and providing evidence consistent with the theorized linkage between these distinct stages.

Our findings offer several important insights that extend current understanding in the areas of product innovation, AI capability and B2B marketing innovation. *First*, our study reveals a novel theorized sequential relationship, where the relationship between AI capability and B2B marketing innovation is sequentially mediated by organizational agility and product innovation intensity. This finding suggests that when organizations develop their AI capability, they also need to enhance their flexibility in responding to customer needs, adapt to new strategies and operations, and develop the ability to launch new products into the market relative to their key competitors (Ahsan et al., 2023; Chakravarty et al., 2013). This finding both supports and refines prior work on innovation pathways. While earlier studies (e.g., Ahsan et al., 2023) emphasize the role of innovation processes in driving

competitive outcomes, our results provide evidence consistent with the theorized sequential structure, in which organizational agility is associated with the translation of AI capability into intensified innovation effort, which is subsequently associated with market-facing innovation. This provides a more precise articulation of the mechanisms linking capability development to innovation outcomes.

Second, our study clarifies the theoretical rationale for focusing on B2B marketing innovation as the focal downstream dependent variable. While prior research has often conflated innovation generation with innovation realization, we argue that B2B marketing innovation, the novelty of commercialization approaches, is a strategically critical outcome in its own right because it captures the value realization phase of the innovation process. Product innovation without effective commercialization may fail to generate market impact, whereas innovative commercialization can enhance the success of even incremental product innovations. Thus, B2B marketing innovation is not merely a "supporting activity" but a necessary complement to product innovation, representing the final step in the capability-to-outcome pathway. This distinction matters theoretically because it isolates the precise stage at which AI capability generates market-facing value, and practically because it guides managers on where to invest beyond product development.

Third, our study provides novel insights into the relationships between organizational agility, product innovation intensity, and B2B marketing innovation. While previous studies have empirically tested the effects of organizational agility on production innovation (e.g., Cai et al., 2019; Ganguly et al., 2024), our research extends this by demonstrating that both organizational agility and product innovation intensity significantly influence and shape B2B marketing innovation, extending the role of agility beyond internal innovation processes to downstream marketing innovation. In doing so, we respond to recent calls to better understand how agility contributes to market-facing outcomes in dynamic environments. This finding suggests that all components of organizational agility facilitate the rapid implementation of B2B marketing innovation. Moreover, greater product innovation intensity has been shown to expand the scope of B2B marketing innovation strategies by enhancing product differentiation from competitors (Moorman and Slotegraaf, 1999). It is noteworthy that while the mediating effects of organization agility and innovation intensity are statistically significant, their effect sizes are relatively modest. We interpret this not as evidence of model misspecification, but as an indication that B2B marketing innovation is multiply determined by various factors, including marketing-specific antecedents such as marketing expertise, creativity, and market-sensing capabilities (Morgan et al., 2009; Ngo and O'Cass, 2012). Our model identifies one theoretically important and previously overlooked pathway, not a complete explanation of all variance in marketing innovation. The influence of AI capability on the innovation of B2B marketing may therefore operate through additional mechanisms, such as knowledge integration, customer co-creation, and enhanced market sensing, which extend beyond the examined pathways.

Fourth, our results demonstrate that AI capability significantly enhances organizational agility, supporting prior research on the role of AI capability in improving organizational flexibility (e.g., Mikalef and Gupta, 2021). Our findings further suggest that AI capability operates not merely as a driver of organizational flexibility, but as an enabler of adaptive organizational responses central to dynamic capability processes, thereby extending its role beyond context-dependent performance enhancement. Specifically, AI-related resources can support firms' customer responsiveness, operational flexibility, and strategic flexibility, in turn strengthening their capacity for organizational adaptation (Mikalef et al., 2022; Ravichandran, 2018).

Finally, our research offers new and nuanced insights into the role of market turbulence in determining the strategic value of AI capability for various organizational outcomes. Specifically, we find that, under conditions of heightened market turbulence characterized by intensified

competition and rapidly shifting customer and technological demands, AI capability becomes particularly consequential in enhancing the intensity of product and B2B marketing innovation. This suggests that AI capability functions as a mechanism for absorbing uncertainty, enabling firms to transform volatile and fragmented market signals into actionable insights that stimulate experimentation, learning, and innovation. In turbulent environments where traditional routines and historical knowledge may become less reliable guides for decision-making, AI-driven analytics enable firms to identify emerging opportunities, adjust their offerings, and develop more adaptive marketing practices. Thus, environmental volatility amplifies the strategic value of AI by increasing firms' information-processing requirements. This extends prior work highlighting how market turbulence shapes firms' innovation and marketing investments (Li, 2022; X. Su et al., 2022; Tsai and Yang, 2013). Interestingly, our findings indicate that market turbulence does not moderate the relationship between AI capability and organizational agility. This suggests that the positive association between AI capability and organizational agility remains comparatively stable across different levels of turbulence. Consistent with prior research (Mikalef and Gupta, 2021; Powell et al., 2018), AI capability can support sensing, decision-making, and operational coordination, functions that remain relevant across different levels of environmental turbulence. However, the innovation-related benefits of AI capability become more pronounced as environmental uncertainty intensifies.

6.1. Theoretical contributions

This study makes several theoretically distinct contributions to the literature on dynamic capability theory, AI-enabled innovation, and B2B marketing.

First, this research advances dynamic capability theory by reconceptualizing AI capability as an enabling and integrative capability architecture through which sensing, seizing, and reconfiguring processes are enacted in data-rich and uncertain environments. While prior research has largely treated AI as a technological input or decision-support tool (e.g., Liu et al., 2025; Petrescu et al., 2022), this study moves beyond input-output logics by theorizing how the multidimensional structure of AI capability, comprising tangible, human, and intangible components, activates core dynamic capability mechanisms in practice (Teece et al., 1997; Warner and Wäger, 2019). Specifically, AI capability enhances sensing through large-scale data processing and environmental scanning (Teece, 2018), strengthens seizing through AI-enabled interpretation and decision-making (Mikalef and Gupta, 2021), and facilitates reconfiguring through the diffusion of AI-informed routines across organizational functions (Ritala et al., 2024). By explicitly mapping these mechanisms, this study shifts the role of AI capability from a passive technological resource to an active mechanism of capability orchestration, providing a precise and process-based account of how firms translate technological investments into adaptive responsiveness and sustained innovation.

Second, this study advances the AI-innovation literature by theorizing and empirically testing a two-stage capability-to-innovation pathway. Specifically, we distinguish between innovation generation (product innovation intensity) and innovation realization (B2B marketing innovation) as well as providing evidence consistent with their theoretically ordered and interconnected roles. This extends prior work (e.g., Liu et al., 2025; Petrescu et al., 2022), which does not explicitly differentiate between internal innovation effort and downstream market-facing innovation. By modelling these constructs as distinct yet interconnected stages, this study provides a more granular and theoretically precise explanation of how AI capability is translated into market-level value.

Third, this study advances the organizational agility literature by positioning agility as a manifestation of dynamic capability that operates through underlying knowledge-based micro-foundations. Rather than treating agility as a direct and immediate driver of innovation, we

demonstrate that its effect on product innovation intensity is underpinned by mechanisms such as absorptive capacity and strategic learning (Cohen and Levinthal, 1990). This process-based perspective moves beyond prior work that conceptualizes agility as a structural or cultural attribute, offering a more nuanced explanation of how agility translates into intensified and continuous innovation activity.

Fourth, this research extends the literature on environmental contingency by theorizing market turbulence as a boundary condition that shapes the value of capability deployment. While prior studies often treat turbulence as a contextual variable, this study demonstrates that it amplifies the impact of AI capability on innovation outcomes by increasing firms' information-processing requirements and the urgency of adaptive responses (Teece, 2018; Wilden and Gudergan, 2015). This positions market turbulence as an analytically integrated construct within the dynamic capability framework, clarifying when and why AI capability becomes more consequential for innovation.

Taken together, these contributions move beyond input–output explanations of AI and provide a process-based theoretical account of how AI capability is transformed into market-facing innovation under conditions of environmental turbulence.

6.2. Managerial implications

Our research offers several important implications for managers, particularly those in B2B firms seeking to leverage AI for B2B marketing innovation in turbulent environments. *First* and foremost, managers should adopt a holistic approach when implementing AI capability. Our findings emphasize that AI capability is not just about technology, but encompasses tangible resources (data, technology, basic resources), intangible assets (inter-departmental coordination, change capacity, risk proclivity), and human skills (technical and business). Managers should ensure balanced and integrated development across these dimensions to fully realize the potential of AI. For example, firms can implement cross-functional data governance structures to ensure that marketing, IT, and operations share and standardize data effectively. In parallel, managers should invest in structured AI training programs that combine technical instruction with business-oriented analytics training, enabling employees to translate AI outputs into marketing insights. Such practices help firms build an AI capability that combines data infrastructure, organizational coordination, and employee expertise.

Second, our research highlights the critical role of organizational agility in translating AI capability into B2B marketing innovation. Managers should focus on enhancing their firm's customer responsiveness, operational flexibility, and strategic flexibility. For instance, firms can establish cross-functional innovation teams that integrate marketing, product development, and data science personnel to rapidly interpret AI-generated insights and respond to customer needs. Managers may also adopt modular product and service architectures that allow components to be modified or recombined quickly in response to changing market demands. Additionally, implementing short planning cycles supported by AI-driven dashboards can enable firms to respond more rapidly. The goal should be to create an organization that can quickly adapt to changing market conditions and customer needs, leveraging AI insights to drive decision-making.

Third, our findings underscore the importance of product innovation intensity as a key link between AI capability and B2B marketing innovation. Managers should use AI-driven insights to identify new product opportunities, implement AI in the product development process to accelerate innovation, and foster a culture of continuous innovation supported by AI capability. For instance, AI-based market analytics can be used to identify unmet customer needs or emerging application areas, while predictive modeling can guide product design decisions and reduce development cycles. Establishing formal processes that integrate AI insights into stage-gate product development systems can ensure that data-driven insights consistently inform innovation decisions. This focus on product innovation can help firms differentiate themselves in

competitive B2B markets and respond more effectively to changing customer needs.

Fourth, given the strong influence of market turbulence on the effectiveness of AI and innovation processes, managers should develop adaptive marketing strategies that can quickly respond to market changes. One practical approach is to deploy AI-based market sensing systems that continuously analyze customer feedback, competitor activity, and demand signals. Managers can then incorporate these insights into regular strategic review meetings, allowing marketing strategies and resource allocations to be adjusted more frequently. Scenario-based planning supported by AI simulations can also help firms prepare for multiple market contingencies. In highly turbulent markets, the ability to quickly pivot marketing strategies based on AI-generated insights can be a significant competitive advantage.

6.3. Limitations and future research

While our findings make several theoretical contributions and have numerous practical implications, our study has some limitations, which we encourage researchers to address in future research. We collected cross-sectional survey data from Chinese firms. The use of primary survey data is appropriate in this study because the focal constructs are perceptual and latent in nature (e.g., organizational capabilities and innovation-related behaviors) and are not readily observable through secondary data sources, which typically capture archival or objective indicators rather than the underlying cognitive and behavioral mechanisms of interest. While we controlled for firm size and age, future studies could undertake more detailed examinations of these factors by comparing how AI capability development and B2B marketing innovation evolve across firms of different sizes and stages of organizational maturity. At the same time, the cross-sectional nature of the data imposes important limitations. Although the hypothesized model specifies a theoretically grounded sequence of relationships among focal constructs, the analyses cannot establish that these effects unfold in the proposed temporal order. Accordingly, the findings should be interpreted as evidence consistent with the theorized process rather than definitive proof of causal or temporal sequencing. Future research could extend this work by employing longitudinal, multi-wave, panel, or experimental designs in China and other institutional contexts. Such approaches would enable researchers to track the development of AI capability and innovation activities over time, provide stronger evidence regarding causal ordering, and more rigorously examine the sequential mediation process proposed in this study. These designs would offer deeper insights into the dynamic evolution of organizational capabilities and innovation mechanisms, which lie beyond the scope of the present cross-sectional investigation.

Additionally, future studies could systematically compare alternative model specifications to further refine the understanding of the relationships among AI capability, organizational agility, product innovation intensity, and B2B marketing innovation. Specifically, contrasting parallel and sequential mediation structures would help determine whether these mechanisms operate independently or as part of a temporally ordered process. This would allow us to disentangle the relative explanatory power of competing theoretical perspectives, such as process-based versus configurational logics. Furthermore, our findings show that market turbulence does not moderate the relationship between AI capability and organizational agility. We also found that, when market turbulence intensifies, the relationships between AI capability and product innovation intensity, product innovation intensity and B2B marketing innovation, and organizational agility and B2B marketing innovation become stronger. Future research could go beyond our findings by relying on case studies to explore the impact of market turbulence in greater depth and compare various cases according to their specific conditions.

Also, we acknowledge that B2B marketing innovation is influenced by other factors beyond our model, particularly marketing-specific

resources such as expertise, creativity, and market sensing (Morgan et al., 2009; Ngo and O'Cass, 2012). However, our focus on AI capability is intentional: we examine an underexplored technology-driven pathway through a dynamic capability lens, not a marketing competency one. Future research should incorporate marketing-specific controls and explore how these factors interact with or substitute for AI capability in driving commercialization novelty.

Finally, despite implementing procedural and statistical remedies (e.g., the FC test in PLS-SEM and the unmeasured latent factor control approach) to address potential CMB, this study has limitations that warrant acknowledgment. Notably, the study did not employ a marker variable approach (Lindell and Whitney, 2001), as this technique requires the inclusion of a theoretically unrelated construct in the initial survey design, a step that was not taken in this study. Therefore, future research may enhance methodological rigor by incorporating a marker variable at the instrument design stage or adopting multi-respondent/multi-source research designs to further strengthen construct validation and reduce perceptual bias.

CRediT authorship contribution statement

Nisreen Ameen: Writing – review & editing, Writing – original draft, Project administration, Data curation, Conceptualization. **Jun-Hwa Cheah:** Writing – review & editing, Formal analysis. **Senmao Xia:** Writing – review & editing, Data curation. **Tippayanet Sorosrungruang:** Writing – review & editing. **Vera Hoelscher:** Writing – review & editing, Formal analysis. **Shlomo Tarba:** Writing – review & editing.

Ethical approval

An ethical approval has been obtained from Royal Holloway, University of London and the university's ethical guidelines have been followed.

Availability of supporting data

Can be made available on request.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.technovation.2026.103737>.

Data availability

Data will be made available on request.

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