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Navigating technological disruptions: the interplay of AI-based stakeholder engagement, marketing agility, and firm performance

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Abstract

Purpose – This study aims to examine how artificial intelligence (AI)-based stakeholder engagement can enhance marketing agility and improve firm performance, particularly in environments with high technological turbulence.

Design/methodology/approach – Data were collected through a survey of 335 companies across diverse industries in Australia, using validated scales for AI-based stakeholder engagement, marketing agility, firm performance and technology turbulence. Partial least squares structural equation modelling was used to analyse the data.

Findings – The results indicate that engaging stakeholders through AI technologies positively influences marketing agility, which in turn enhances firm performance. These effects are amplified in conditions of high technology turbulence.

Research limitations/implications – This study focuses solely on technological turbulence as a moderating factor. Future research should replicate these findings and explore additional moderating factors to enhance understanding of AI's impact on marketing dynamics.

Practical implications – Businesses should invest in and leverage AI to improve interaction with stakeholders, as it can enhance their ability to respond swiftly to market changes and significantly boost overall performance. These implications are especially crucial for firms operating in environments highly disrupted by technological advancements.

Originality/value – This study bridges literature gaps by highlighting how firms can use AI as a tool to engage suppliers, employees and other stakeholders effectively. This engagement enhances their capabilities to respond to changes in dynamic and disrupted markets. Additionally, this study sheds light on the boundary conditions of these relationships.

Keywords Artificial intelligence, Stakeholder engagement, Marketing agility, New-age technologies, Technology turbulence

Paper type Research paper

1. Introduction

Disruption has become a persistent companion to the global economy. Disruptions, whether exogenous – stemming from external factors such as technological breakthroughs – or endogenous – originating within firms such as marketing-mix innovation – fundamentally transform the business landscape (Nagy *et al.*, 2016; Buckley *et al.*, 2020). Technological

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disruptions driven by new age technologies (NATs), such as artificial intelligence (AI) and machine learning (ML), are particularly transformative (Gupta *et al.*, 2020b; Cui *et al.*, 2022; Roy *et al.*, 2025a). On one hand, NATs generate critical market intelligence that can refine firms' decision-making processes (Chen *et al.*, 2012). On the other hand, these same technologies can render firms' existing systems inefficient or even obsolete (Kumar *et al.*, 2021). This paradox necessitates a comprehensive understanding of how firms can strategically manage marketing activities within their value chains to enhance agility and navigate, or even capitalise on, these disruptions (Huang and Rust, 2021; Rana *et al.*, 2022).

One solution lies in leveraging AI to enhance how firms interact and engage with their stakeholders. AI technologies offer a plethora of opportunities for firms to deepen stakeholder engagement through personalised interactions (Kumar *et al.*, 2021), enhanced communication channels, real-time feedback analysis (Davenport *et al.*, 2020) and improved decision-making (Bag *et al.*, 2021). Prior research has examined the positive effects of engaging stakeholder through firms' AI initiative – referred to as AI-based stakeholder engagement – on various marketing dynamics, such as customer loyalty (Prentice and Nguyen, 2020), trust (Yin *et al.*, 2023) and value co-creation (Gao *et al.*, 2023). AI-based stakeholder engagement facilitates real-time market sensing, data-driven decision-making and personalised interactions, allowing firms to remain agile and responsive to industry shifts (Davenport *et al.*, 2020; Huang and Rust, 2021). Rather than merely replacing outdated systems, AI can act as a strategic enabler that helps firms overcome inefficiencies and reconfigure business models to navigate disruption with greater agility and responsiveness to market changes (Roy *et al.*, 2025b). Such responsiveness is a critical determinant of business success, particularly in dynamic and technologically disrupted environments (Tallon and Pinsonneault, 2011; Kalaignanam *et al.*, 2021). Firms that fail to adapt quickly to market shifts often face competitive disadvantages, revenue loss or strategic misalignment (Teece *et al.*, 2016). However, despite growing interest in marketing agility and responsiveness, existing research primarily focuses on internal agility factors, such as product innovation and process optimisation, while overlooking the role of AI-driven stakeholder engagement in fostering external market responsiveness (e.g. Zhou *et al.*, 2019).

Moreover, despite the growing adoption of AI in marketing and stakeholder engagement, many companies struggle with fragmented AI implementation, leading to inconsistencies in customer engagement and decision-making (Prentice *et al.*, 2020). Additionally, firms operating in highly dynamic industries, such as financial services and retail, find it increasingly difficult to adapt to rapid technological shifts while maintaining effective stakeholder relationships (Pappas *et al.*, 2023; van Zeeland and Pierson, 2024). Without a nuanced understanding of how leveraging AI for stakeholder engagement impact business success in different conditions, companies risk losing agility and responsiveness, which can negatively impact their market positioning and financial performance (Bag *et al.*, 2021). For example, industries such as telecommunications and consumer goods have seen significant disruption due to AI-driven automation and other NATs, yet many firms lack the agility to fully capitalise on these advancements (Felipe *et al.*, 2020).

While internal firm capabilities are widely recognised as critical drivers of agility, external market forces also play a significant role in shaping firms' ability to respond effectively to disruptions (Teece *et al.*, 2016). Yet, research on marketing agility (especially in the context of AI implementation) has largely focused on internal enablers, such as organisational learning and dynamic capabilities, with less attention to how exogenous factors – such as technology turbulence – moderate agility-driven performance outcomes (e.g. Zhou *et al.*, 2019; Wamba, 2022). Given that firms increasingly operate in environments characterised by rapid technological change, investigating how AI-based stakeholder

engagement interacts with external conditions (i.e. technology turbulence) to influence firm responsiveness and performance is important. By addressing this gap, we contribute to a more holistic understanding of marketing agility as a function of both internal and external dynamics, advancing both theoretical perspectives and practical applications. We, therefore, examine how AI-based stakeholder engagement functions as a capability that enhances marketing agility and ultimately contributes to firm performance. Through a survey conducted in Australia, we collected data from 335 top- and middle-level managers across diverse industries. For data analysis, we used partial least square structural equation modelling (PLS-SEM) using SmartPLS software. Our findings offer empirical support for the hypothesised relationships.

Building on knowledge-based theory (Grant, 1996) and stakeholder theory (Freeman, 1984; Donaldson and Preston, 1995), our study sheds light on how AI can be effectively implemented to engage stakeholders, thereby enhancing firms' agility and responsiveness to dynamic markets. We also confirm that marketing agility significantly enhances firm performance, especially under conditions of technological turbulence. These findings extend existing research on the importance of agility in fast-changing markets (e.g. Tallon and Pinsonneault, 2011; Asseraf *et al.*, 2019; Zhou *et al.*, 2019), while identifying the boundary conditions that amplify its effectiveness.

From a managerial perspective, our findings offer several important implications. This study contributes to practice by demonstrating how AI-based stakeholder engagement can enhance marketing agility, equipping firms with data-driven insights, real-time responsiveness and adaptive decision-making capabilities to thrive in technologically turbulent environments. By clarifying these relationships, we offer practical strategies for firms to optimise their AI-driven engagement and improve business performance in increasingly disrupted markets. Managers should strategically invest in AI technologies not only to enhance marketing agility but also to actively engage stakeholders. This capability is particularly important in industries marked by rapid technological advancements, such as telecommunications and financial services, where agility provides a competitive edge. In addition, this study opens several fruitful avenues for future research.

2. Literature review

2.1 Disruption and technological advancements in marketing

Today's business environment is characterised by constant disruption, largely driven by rapid technological advancements (Christensen, 1997; Christensen *et al.*, 2018). Disruption in marketing, as defined by Christensen (1997), refers to the significant changes that necessitate firms to alter their traditional approaches. Christensen laid the groundwork for understanding disruption in marketing, emphasising how disruptive innovations can reshape industries and compel firms to adapt their strategies to stay competitive. Disruptive business model innovations, whether technology-driven or market-driven, plays a critical role in reshaping industries and markets (Habtay, 2012). Disruptive innovations alter performance metrics and business models, which challenge established norms and create new value propositions (Gasparin *et al.*, 2019). With a focus on disruptions stemming from technological advancement, Sood and Tellis (2011) define three domains for disruption: technology, firm and demand. Technological disruption happens when a new technology outperforms the current leading technology. Firm disruption occurs when a company using a new technology surpasses the market share of the largest firm using the existing leading technology. Demand disruption takes place when products based on the new technology exceed the market share of those based on the current leading technology. Sood and Tellis (2011) consider

technological advancement as the primary source of market disruption. This study primarily focuses on NATs, particularly AI, as the main driver of market disruption.

Technological advancements usually disrupt markets by introducing new products, services and business models that redefine customer expectations and value propositions (Lee *et al.*, 2023). Over time, these innovations can disrupt established players by offering greater value or convenience to a broader customer base. However, AI-driven disruptions are altering industries in ways that extend beyond traditional notions of technological change. In financial services, for example, AI-powered robo-advisors are reshaping wealth management by automating investment decisions, challenging the dominance of human advisors (Baek and Kim, 2023). Unlike previous disruptions in financial services – such as online banking, which primarily improved accessibility – AI enables entirely new modes of service delivery by personalising investment strategies in real time, making disruption theory less applicable in its conventional form (Zhang *et al.*, 2021). In the health-care industry, the rise of telemedicine has transformed patient care delivery, enabling remote consultations and personalised treatment plans, which challenges the conventional health-care model (Fernandes, 2022). This represents a fundamental shift from expert-driven to algorithm-driven decision-making, where AI augments or even replaces human expertise. These examples illustrate that AI-driven disruptions often operate through mechanisms distinct from traditional technology displacement. Rather than simply replacing incumbents, AI is embedded into existing systems, augmenting rather than displacing human roles in some cases, while entirely redefining service delivery in others.

NATs, specifically, act as significant technological disruptors in markets by fundamentally altering how value is created and delivered to customers (Kumar *et al.*, 2021). NATs include, but are not limited to, AI, big data analytics, machine learning, blockchain, Internet of Things, quantum computing and extended reality. These technologies empower businesses to develop innovative products and services that redefine customer expectations (Kumar *et al.*, 2021; Lee *et al.*, 2023). NATs present both challenges and opportunities for marketers navigating disruptions. For example, AI-powered tools can personalise customer experiences, automate repetitive tasks and provide insights into customer behaviour (Ameen *et al.*, 2021). Also, big data analytics enables firms to analyse vast amounts of customer data, identify trends and predict future behaviour, enabling more targeted marketing campaigns (Nickerson and Rogers, 2014; Nair *et al.*, 2017). However, effectively using these technologies demands a shift in marketing and management skillsets to address challenges such as vague objective functions, impractical learning settings, biases and the lack of explainability inherent in NATs (De Bruyn *et al.*, 2020). NATs can also potentially render existing business models obsolete, forcing established firms to adapt their marketing strategies or risk losing market share (Gupta *et al.*, 2020b; Kumar *et al.*, 2021).

Among NATs, AI is uniquely positioned as one of the most transformative forces in marketing (Huang and Rust, 2021). While other NATs, such as blockchain and big data analytics, contribute to operational efficiency and data management (Gupta *et al.*, 2020a; Bai *et al.*, 2024), AI fundamentally reshapes consumer experience and engagement with firm (Perez-Vega *et al.*, 2021; Suraña-Sánchez and Aramendia-Muneta, 2024). AI's ability to process vast amounts of unstructured data, predict consumer behaviour and personalise marketing strategies in real time gives firms an unprecedented level of responsiveness and adaptability (Davenport *et al.*, 2020). These capabilities are particularly crucial in disrupted environments, where firms must rapidly adjust their marketing strategies to shifting consumer expectations (Prentice *et al.*, 2020). By contrast, while big data analytics provides insights into past trends, AI uniquely enables adaptive, real-time decision-making, making it a more potent driver of marketing agility. While disruptive innovation theory

(Christensen, 1997) traditionally explains how novel technologies displace incumbents by introducing new value propositions at lower costs or improved efficiency, AI-driven disruptions do not always follow this classical pattern. Unlike conventional disruptive innovations that typically start in niche markets before challenging dominant firms (Christensen and Raynor, 2013), AI technologies are often adopted by incumbent firms alongside existing technologies, leading to co-evolution rather than outright displacement (Jacobides *et al.*, 2021; Bonetti *et al.*, 2023). Furthermore, AI's impact extends beyond cost reduction or efficiency gains – it fundamentally reshapes decision-making, stakeholder engagement and market responsiveness, altering competitive dynamics in ways that traditional disruption models may not fully capture (Huang and Rust, 2021; Katsikeas *et al.*, 2023). Given this distinction, AI-driven disruptions require a more nuanced theoretical lens that accounts for their simultaneous integration and transformation of business processes. In this study, we particularly focus on AI technologies as an enabler of stakeholder engagement and marketing agility.

2.2 Marketing agility

Marketing agility is a crucial capability for organisations to effectively navigate the disruptive markets. Kalaignanam *et al.* (2021) define marketing agility as "the extent to which an entity rapidly iterates between making sense of the market and executing marketing decisions to adapt to the market" (p. 36). It involves rapidly interpreting market signals and promptly implementing marketing decisions to adapt to changing market conditions (Kalaignanam *et al.*, 2021). Within the broader scope of organisational agility, marketing agility plays a significant role alongside operational agility. Marketing agility is specifically focused on meeting customer needs by continuously monitoring and improving products or services, as well as quickly responding to market changes or seizing emerging opportunities (Tang *et al.*, 2022). The ability to swiftly adjust marketing strategies and tactics is essential for organisations to maintain competitiveness and relevance in disruptive business environments (Zhou *et al.*, 2019).

Moreover, the concept of marketing agility goes beyond just reacting to market changes; it encompasses the strategic execution of growth initiatives through streamlined processes, quick decision-making and a culture of experimentation and learning (Homburg *et al.*, 2020). Studies have identified key dimensions that define an agile marketing capability, including adaptability to market changes, collaborative work environments, innovative culture and strong emphasis on anticipating and meeting market needs (Moi and Cabiddu, 2021). Zhou *et al.* (2019) describe the components of marketing agility as follows: proactiveness, which refers to a firm's ability to anticipate and stimulate demand by identifying early indicators of market changes and seizing new opportunities; responsiveness, which involves quickly recognising and reacting to shifts in market demands and opportunities by swiftly adjusting resources and strategies; speed, which highlights how rapidly a firm can respond to market opportunities and threats; and flexibility, which denotes the capability to efficiently and effectively produce and market a variety of products that meet evolving market needs. This comprehensive approach to marketing agility not only enables organisations to respond effectively to unforeseen events but also empowers them to proactively shape their strategies during different crises and market disruptions (Moi and Cabiddu, 2022).

Marketing literature is rich with studies examining the antecedents and consequences of marketing agility. Antecedents of marketing agility involve various factors that contribute to an organisation's ability to swiftly adapt to market changes. These factors include market sensing, adaptability, ambidextrous capabilities and organisational practices such as internal integration within firm, external integration with key stakeholders and external flexibility

(Braunscheidel and Suresh, 2009; Del Giudice *et al.*, 2021). Del Giudice *et al.* (2021) found that by fostering a culture of learning, innovation and collaboration, organisations can enhance their marketing agility. On the other hand, the consequences of marketing agility are far-reaching. Agile firms are better equipped to identify market opportunities, predict trends and respond effectively to customer needs (Panda and Rath, 2018; Rialti *et al.*, 2018). Marketing agility not only enhances competitiveness but also leads to sustainable competitive advantages and improved firm performance (Zhou *et al.*, 2019).

Therefore, marketing agility is deemed critical in enabling firms to sense and respond to market changes quickly, ensuring sustained competitive advantage (Kalaignanam *et al.*, 2021). Traditionally, agility has been driven by human decision-making, real-time market analysis and adaptive strategies (Tallon and Pinsonneault, 2011). However, the increasing complexity of data-driven marketing and rapidly changing consumer behaviours necessitate technological enablers that enhance firms' ability to process, interpret and act upon market signals at scale.

AI-based stakeholder engagement has emerged as a key technological enabler that enhances marketing agility by automating real-time market sensing, optimising customer interactions and enabling adaptive decision-making (Bag *et al.*, 2021; Katsikeas *et al.*, 2023). Against this backdrop and recognising that achieving agility requires firms to actively monitor customer and stakeholder needs while remaining responsive to market signals (Kalaignanam *et al.*, 2021; Tang *et al.*, 2022), we propose that to enhance their marketing agility, firms should prioritise strong engagement with stakeholders which is facilitated through the integration of AI.

2.3 Artificial intelligence-based stakeholder engagement

Although the concept of stakeholder engagement dates back to Freeman's (1984) seminal work, the field of AI-based stakeholder engagement is still emerging (Katsikeas *et al.*, 2023). Stakeholders are specified as all individuals who can impact or be impacted by a firm (Freeman, 1984), including but not limited to customers, partners, employees and governments. Stakeholder engagement is defined as "a stakeholder's [cognitive, emotional, and behavioural] resource endowment in his/her role-related interactions, activities, and/or relationships" (Hollebeek *et al.*, 2022: p. 328). Stakeholder engagement is an important component of organisational success (Menguc *et al.*, 2017). Incorporating AI systems has the potential to transform the way firms interact with their stakeholders (Prentice *et al.*, 2020). AI-based stakeholder engagement is described as the incorporation of AI to interact and engage with a firm's stakeholders, which involves leveraging AI tools and techniques to enhance interactions, activities and relationships with stakeholders (Katsikeas *et al.*, 2023).

AI-based stakeholder engagement is more than a communication tool; it serves as a strategic response to technological disruptions that challenge existing business models. Prior studies highlight that AI-driven engagement enables firms to extract valuable insights from vast stakeholder interactions, predict market trends and dynamically adjust marketing strategies (Prentice and Nguyen, 2020; Gao *et al.*, 2023). This adaptability is particularly vital in disruptive environments where traditional engagement mechanisms may fail to keep pace with evolving consumer expectations and technological shifts (Singh *et al.*, 2021).

Firms that integrate AI into stakeholder engagement can offset obsolescence by leveraging predictive analytics, automation and real-time feedback systems to refine their value propositions (Bag *et al.*, 2021). For instance, AI-powered chatbots and sentiment analysis tools identify emerging customer needs faster than conventional methods, allowing firms to innovate proactively rather than reactively (Davenport *et al.*, 2020). This capability

ensures that firms remain agile and competitive, rather than being rendered inefficient by rapid technological evolution.

AI technologies can enable more personalised and targeted engagement strategies by analysing extensive data to comprehend stakeholder preferences, behaviours and needs (Perez-Vega *et al.*, 2021). Additionally, as discussed by Buah *et al.* (2020) in a study in the context of project management, AI can aid in the identification of key stakeholders, prioritisation of engagement efforts and automation of routine tasks, which allows organisations to focus on establishing meaningful relationships with stakeholders, while addressing their concerns. Similarly, Syam and Sharma (2018) demonstrate how AI-powered chatbots and virtual assistants can improve customer engagement and service delivery. Table 1 presents a selection of studies on the interaction between AI and stakeholders' engagement in the organisational realm. However, the implications of AI in stakeholder engagement and the impact of rapid AI-driven interactions with stakeholders on achieving marketing agility have not yet been explored.

2.4 Theoretical lenses and hypothesis development

Our theoretical framework integrates stakeholder theory and knowledge-based theory, providing a comprehensive perspective on how AI-based stakeholder engagement influences marketing agility and ultimately enhances firm performance. Stakeholder theory posits that firms must consider the interests and influences of all stakeholders – such as customers, employees, suppliers and the community – to achieve long-term success (Freeman, 1984). This theory can be categorised into descriptive, instrumental and normative perspectives (Donaldson and Preston, 1995). The descriptive perspective explains how firms currently manage stakeholders, the instrumental perspective examines the link between stakeholder management and firm performance and the normative perspective asserts that firms have an intrinsic ethical duty to consider stakeholder interests beyond profit maximisation (Donaldson and Preston, 1995).

In the context of AI-based stakeholder engagement, the instrumental perspective is particularly relevant, as firms can deploy AI-driven strategies to optimise stakeholder interactions in ways that boost performance (Bosse *et al.*, 2023). However, AI also introduces ethical considerations, such as transparency and fairness in algorithmic decision-making, aligning with the normative perspective (John-Mathews *et al.*, 2022). Therefore, while we primarily adopt an instrumental lens – examining how AI-based stakeholder engagement improves firm responsiveness and performance – we acknowledge that firms must balance performance-oriented objectives with ethical AI deployment to maintain stakeholder trust.

Stakeholder engagement through advanced AI tools allows organisations to tap into different stakeholders essential insights and knowledge and align their strategic objectives with stakeholder expectations (Kujala *et al.*, 2022). This engagement is especially critical in dynamic environments, where regular interactions with stakeholders, including customers, suppliers and the wider community, enable organisations to leverage their resources and benefit from their insights (Donaldson and Preston, 1995; Mitchell *et al.*, 2022). This engagement also fosters collaboration, co-creation and knowledge sharing, which are essential for organisations to adapt quickly to changing market conditions and consumer demands (Secundo *et al.*, 2020). Additionally, stakeholder engagement helps build strong relationships with key external parties, such as customers, suppliers and communities, facilitating the exchange of information and resources vital for agile marketing strategies (Kujala *et al.*, 2022). Engaged stakeholders offer valuable input and support, enabling

Table 1. Select studies on the interaction between AI and stakeholder engagement

Authors and Year	Type of AI studied	Study theme	Key findings
Hollebeek *et al*. (2021)	RPA, ML, DL	Customer engagement	AI has the potential to transform customer engagement in automated service interactions
Prentice and Nguyen (2020)	Not specified	Customer engagement	Both employee and AI service experiences significantly influence customer engagement and loyalty
Dutta *et al*. (2023)	AI-based chatbots	Employee engagement	AI-based chatbots improve employee engagement by enhancing a climate for trust
Hui *et al*. (2023)	Not specified	Customer engagement	Anthropomorphism and responsiveness in human−AI interactions can enhance service quality, customer engagement and satisfaction
Sung *et al*. (2021)	AI, ML, MR	Customer engagement	High-quality AI, like advanced speech recognition and synthesis via machine learning, enhances mixed reality immersion, enjoyment and novelty perception, boosting consumer engagement
Kang and Lou (2022)	AI-powered social media	User engagement	Collaboration between AI and users on TikTok has a substantial impact on medium engagement and interactive social engagement
Yin *et al*. (2023)	Not specified	Customer engagement	Customers with higher technology readiness optimism engage more and trust more in AI environments (versus traditional environment) where they perceive ideal self-congruity and lower anthropomorphism
Prentice *et al*. (2023)	AI-powered tools	Employee engagement	AI performance improves employees' job engagement, especially when they feel their jobs are secure
Gao *et al*. (2023)	Not specified	Customer engagement	The perceived interactivity of AI-driven interactions significantly boosts value co-creation, while customer readiness enhances the positive relationship between AI interactions and customer engagement

Source(s): Authors' own work

organisations to respond swiftly to market dynamics, innovate effectively and enhance their competitive position (Murphy *et al.*, 2005).

Moreover, knowledge-based theory (Grant, 1996) posits that firms' ability to create, integrate and apply knowledge is a key determinant of sustained competitive advantage. Marketing agility relies heavily on the firm's knowledge resources (Roberts and Grover, 2012; Kalaignanam *et al.*, 2021). AI-driven stakeholder engagement enhances this process by automating knowledge acquisition, structuring unstructured stakeholder data and enabling real-time insights that improve firms' responsiveness and speed (Bag *et al.*, 2021).

AI's ability to process large volumes of stakeholder interactions – such as customer feedback, social media sentiment and behavioural data – expands firms' market knowledge and predictive capabilities, enabling more responsive and adaptive marketing strategies (Mikalef *et al.*, 2019; Hajli *et al.*, 2020). This aligns with the knowledge-based theory's assertion that firms compete based on their ability to manage and exploit knowledge resources effectively (Grant, 1996). Through AI-powered analytics, firms can detect emerging trends, optimise resource allocation and enhance decision-making agility in ways that were previously limited by human cognitive constraints (Dwivedi *et al.*, 2021).

To sum up, stakeholder theory emphasises that firms must actively engage with stakeholders to stay responsive to market changes, while knowledge-based theory asserts that firms' ability to acquire and apply knowledge is a key determinant of agility. AI-powered stakeholder engagement serves as a critical link between these two perspectives by transforming stakeholder interactions into actionable knowledge that firms can use to sense market changes, optimise resource allocation and drive agile decision-making. Therefore, AI-based stakeholder engagement, which involves the use of AI technologies to interact with and understand stakeholder needs, is expected to significantly improve marketing agility:

H1. AI-based stakeholder engagement has a positive influence on marketing agility.

We also hypothesise that the relationship between AI-based stakeholder engagement and marketing agility is moderated by technology turbulence, which refers to the rate of technological change and innovation within an industry (Jaworski and Kohli, 1993). In highly turbulent technological environments, marked by rapid changes and uncertainties, AI-based stakeholder engagement becomes particularly advantageous. These environment offers more opportunities for innovation and responsiveness (Tushman and Anderson, 2018; Shen *et al.*, 2020), thereby AI can swiftly analyse vast amounts of data generated from interaction with stakeholders. This analysis help firms predict trends and adapt marketing strategies accordingly (Huang and Rust, 2021). Conversely, in stable environments where technological changes occur less frequently and predictably, the impact of AI-based stakeholder engagement on marketing agility may be less significant due to fewer immediate pressures necessitating rapid adaptation. This discussion drives the following hypothesis:

H2. Technology turbulence positively moderates the relationship between AI-based stakeholder engagement and marketing agility.

Marketing agility, in turn, has a positive influence on firm performance. This capability allows firms to quickly respond to market dynamics, seize new opportunities and mitigate potential threats, leading to improved performance outcomes (Kalaignanam *et al.*, 2021). Agility in marketing allows for more effective allocation of resources, better customer satisfaction and increased competitive advantage (Teece *et al.*, 2016). The influence of marketing agility on firm performance has been explored in numerous

studies (e.g. Zhou *et al.*, 2019; Khan, 2020). In line with these studies, we corroborate their findings and replicate testing the following hypothesis:

H3. Marketing agility has a positive influence on firm performance.

We also hypothesise that technology turbulence plays a moderating role in the relationship between marketing agility and firm performance. In environments characterised by high technology turbulence, firms with high marketing agility can better navigate uncertainty and capitalise on technological advancements, leading to superior performance (Zhou *et al.*, 2019). In contrast, in stable environments, the benefits of agility on performance may be less substantial, as there are fewer opportunities in the environment that can be seized through marketing agility. Therefore, we hypothesise:

H4. Technology turbulence positively moderates the relationship between marketing agility and firm performance.

Figure 1 presents the proposed research model, which will be tested in the subsequent sections.

3. Method

3.1 Sampling design

To investigate the hypothesised relationships, we collected data through an online survey targeting top and middle-level managers in Australia using the panel provider Octopus Group. Octopus Group is a well-known Australian panel provider with access to participants at managerial level. The targeted members were sent an introductory email including a link to our survey. We provided participants with a concise overview of the study, a definition of AI and what it means in the business context.

We used a purposive sampling approach, ensuring that only managers meeting specific criteria were included in the study. Respondents were screened based on their managerial level and involvement in their organisation's AI-related decision-making. Only those at or above the middle management level and actively participating in AI-related decisions were included, resulting in a 68% response rate. We also asked managers to specify which department(s) in their firm use AI, allowing us to confirm their awareness of AI implementation within their organisation. We then asked them to rate questionnaire items using a five-point Likert type scale from 1 ("strongly disagree") to 5 ("strongly agree"), based on their firms' practices. The initial response pool consisted of 339 completed responses. Four responses were flagged for quality issues and subsequently excluded, leaving a final sample size of 335 participants. Data collection was completed over a five-day

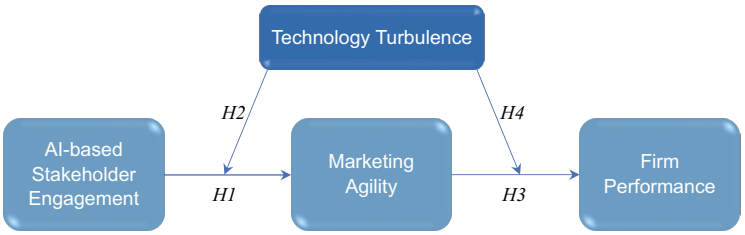

Figure 1. Research model
Source: Authors' own work

period. Before the main data collection, we conducted a pilot test with 12 participants, including four academic staff members, seven PhD candidates and one business owner. This process helped refine the screening questions and data recording procedures.

To further validate the robustness of our sample, we conducted a nonresponse bias assessment by comparing responses gathered on the first day of data collection with those gathered on the last day, focusing on study variables and managers' demographics (Armstrong and Overton, 1977). This test showed no significant concerns regarding nonresponse bias. Our sample includes managers from various major sectors in Australia, such as retailing, health care, IT and ICT, financial services, hospitality and construction. Participants represented companies of diverse sizes, ranging from those with fewer than 10 employees to those with over 2,500 employees. Approximately 67% of the participants have between 1 and 10 years of experience in their current positions, with 62% holding a university degree. The gender distribution was 36.6% men and 62.8% women. Table 2 provides a detailed summary of the sample characteristics.

3.2 Measurement

In this study, we used several established scales to measure the key variables: AI-based stakeholder engagement, marketing agility, firm performance and technology turbulence. Table 3 shows the details of all the measures used in this study. AI-based stakeholder engagement was measured using an 11-item scale adapted from the stakeholder engagement scale developed by Hughes *et al.* (2022), which was further tailored by Tehrani *et al.* (2025) to fit the context of interactions with stakeholders through AI. This scale effectively captures stakeholder engagement facilitated by AI technologies.

Marketing agility was assessed using a 15-item scale from Zhou *et al.* (2019). This scale measures a firm's capability to quickly adjust its marketing strategies and operations in response to market changes and emerging opportunities, capturing dimensions comprising proactiveness, responsiveness, flexibility and speed. To evaluate firm performance, we used a well-established scale from Jaworski and Kohli (1993), which demonstrated a Cronbach's α of 0.86, indicating high reliability. This scale focuses on two dimensions of the overall performance of the firm and the performance of the firm relative to its major competitors. Technology turbulence was measured using a four-item scale also from Jaworski and Kohli (1993). This scale assesses the extent of technological change and its impact on the firm, capturing the degree of technological unpredictability and innovation within the industry. All scales demonstrated high levels of reliability, as detailed in Tables 3 and 4. Additionally, we controlled for firm characteristics such as firm size and firm age to ensure that these variables do not confound our results. Firm size was measured by the number of employees, and firm age was measured by categories shown in Table 2.

3.3 Data analysis

For data analysis, we used PLS-SEM using the SmartPLS 4 software. This analytical technique is highly regarded in the realm of marketing (Guenther *et al.*, 2023) and is particularly suited for examining intricate models that include multiple pathways and interaction effects (Hair *et al.*, 2019). Additionally, we incorporated recent enhancements in PLS-SEM, notably the heterotrait-monotrait ratio test (HTMT) for assessing discriminant validity, and the bootstrapping technique for determining significance levels (Benitez *et al.*, 2020).

To assess the internal consistency and reliability of the measures, we calculated Cronbach's alpha (α) and composite reliability indices, as shown in Table 4. Results support the internal consistency of the measures, with Cronbach's alpha and CR much exceeding 0.8 mark, respectively. We also calculated the average variance extracted (AVE) for the measures, all of which exceeded the 0.5 threshold. To check for multicollinearity among the

Table 2. Demographic details of respondents and firms ($n = 335$)

Respondent details		Distribution (%)
Gender	Male	36.6
	Female	62.8
	Non-binary	0.6
Age	18–25	8.9
	26–34	38.5
	35–44	31
	45–54	14.5
	55-64	5.9
	65 or over	1.1
Education	PhD	2.8
	Master's degree	17
	Bachelor's degree	41.9
	Other	38.3
Occupation	Business Owner	20.7
	C level (CEO, CIO, etc.)	5.9
	Director / Senior Manager / Supervisor / Assistant Manager / Section Head / Team Lead	73.5
Designation	Chairperson / President	5
	C-suite	15.4
	VPs / SVPs	4.2
	Middle management	62.8
	Executive director / Managing director	12.6
Experience in the current designation	Less than 1 year	7.3
	1 to 5 years	40.5
	5 to 10 years	27.9
	10 to 15 years	10.9
	More than 15 years	13.4
Reporting status	Report to CEO	24
	1 level to CEO	15.6
	2 levels to CEO	20.7
	More than 2 levels to CEO	19.3
	There is no level higher than me	20.4
Firm details		
Number of employees	Under 10	24.9
	10 to 19	8.4
	20 to 49	10.9
	50 to 99	7.3
	100 to 199	8.7
	200 to 499	8.4
	500 to 999	6.4
	1,000 to 2,500	8.7
	Over 2,500	16.5
Firm age	Less than 1 year	2.2
	1 to 3 years	11.5
	3 to 5 years	10.1
	More than 5 years	76.3
Industry type	Manufacturing and production	14.8
	Services	78.2
	Both/other	7

(*continued*)

Table 2. Continued

Respondent details		Distribution (%)
Firm type	Private	64.5
	Public	33.5
	Other	2
Industry	IT and ICT	12.3
	Health care	12
	Retail	20.1
	Wholesale	4.2
	Financial services	14
	Construction	8.4
	Hospitality	5.3
	Education	5.3
	Entertainment	3.6
	Other	14.8

Source(s): Authors' own work

latent constructs and their items, the variance inflation factors (VIF) were assessed. The highest VIF is 1.47, which is below the 3.3 threshold (Kock, 2015; Hair *et al.*, 2019), indicating no multicollinearity issues.

To ensure validity of the measurement model, we verify content validity by using established and validated measures when possible. Additionally, discriminant validity was assessed using the HTMT test, with the highest ratio being 0.556, well below the 0.85 threshold, thereby strongly supporting this type of validity (Henseler *et al.*, 2015). To further explore discriminant validity, we compared inter-factor correlations with the square root of AVE values for each factor. Our analysis confirms that none of these correlations exceeded the respective square roots of AVE values, providing additional evidence of discriminant validity. Moreover, all items significantly loaded onto their intended constructs at the 0.05 significance level, with no problematic cross-loadings detected, thereby confirming convergent validity (Anderson and Gerbing, 1988).

3.4 Common method bias

To mitigate potential common method bias, we implemented procedural remedies and conducted statistical analyses following established guidelines (Podsakoff *et al.*, 2012). Participants were assured of the confidentiality of their responses and were informed that their participation was strictly for research purposes. To minimise response bias, we ensured clarity in our survey questions and separated items related to independent and dependent variables into distinct sections within the online questionnaire.

Furthermore, we conducted statistical tests to assess common method bias. We primarily relied on the marker variable approach (Lindell and Whitney, 2001), which is considered more robust than traditional techniques. We used "respondents' years of experience in their current role" as a marker variable, as it is theoretically unrelated to our focal constructs. Analysis incorporating this marker variable indicated no significant increase in variance in the dependent variable. The correlations between latent constructs and the marker variable ranged from −0.09 to 0.04 with an average significance level of 0.25, which is above the conventional threshold of 0.05. Additionally, we conducted Harman's single-factor test as a supplementary analysis. A

Table 3. Details of measures used in this study

Scale/item	Loading	Source
Marketing agility		Zhou *et al*. (2019)
Proactiveness		
1. We can spot the first indicators of new market threats	0.848	
2. We are often the first to seize new market opportunities	0.879	
3. We can anticipate new opportunities for market growth	0.878	
4. We create new preferences by informing customers about new benefits of our products	0.831	
Responsiveness		
5. We can respond to changes in demand without overstocking or losing sales	0.815	
6. We can respond quickly to supply volume fluctuations by having suppliers in many regions of the world	0.815	
7. When an unexpected threat emerges, we are able to adjust through resource reconfiguration	0.802	
8. We can react to fundamental changes with respect changing the competitor landscape	0.825	
Flexibility		
9. We can market a wide variety of products within our portfolio	0.849	
10. We can offer different products through minor modifications to existing ones	0.883	
11. We can adjust what we offer to match market needs	0.857	
Speed		
12. We can meet customer's changing needs faster than our competitors	0.852	
13. We compress time from product concept to marketing to respond quickly to the changes in customer needs	0.868	
14. We can quickly change our product mix in response to changing market opportunities	0.879	
15. We are fast at changing activities that do not lead to the desired effects	0.816	
Technology Turbulence		Jaworski and Kohli (1993)
1. The technology in our industry is changing rapidly	0.825	
2. Technological changes provide big opportunities in our industry	0.803	
3. A large number of new product ideas have been made possible through technological breakthroughs in our industry	0.851	
4. Technological developments in our industry are rather major	0.810	
AI-based stakeholder engagement		Tehrani *et al*. (2025), adapted from Hughes *et al*. (2022)
1. We strive to develop an empowered workforce that is able and committed to adopting AI	0.800	
2. Authority is decentralised and delegated so that our partners, vendors and suppliers can get involved in our decisions about AI's use	0.821	
3. Top management and staff work in partnership to solve AI-related problems together	0.786	
4. We guide and support AI implementation for our partners, vendors and suppliers	0.826	
5. We generate and enhance AI implementation opportunities and encourage our partners, vendors and suppliers to experiment and reflect on those	0.861	
6. Our partners, vendors and suppliers actively seek information from us regarding our AI applications and provide their ideas and inputs on that	0.835	

(*continued*)

Table 3. Continued

Scale/item	Loading	Source
7. Our partners, vendors and suppliers are emotionally involved in our AI initiatives	0.839	
8. Our partners, vendors and suppliers actively participate in our AI projects	0.849	
9. Engaging partners, vendors and suppliers is maximised through our AI management plans and AI strategies	0.891	
10. We participate in joint AI-related activities/interactions with our partners, suppliers and vendors	0.867	
11. Our partners, vendors and suppliers actively seek partnership opportunities with our firm that involve our AI initiatives	0.869	
Firm performance		Jaworski and Kohli (1993)
1. Overall performance of the business unit last year	0.936	
2. Overall performance relative to major competitors last year	0.940	

Source(s): Authors' own work

single factor accounted for only 42% of the variance, which supports the validity of our multivariate model. However, as highlighted by Baumgartner *et al.* (2021), the Harman one-factor test has serious limitations, making it an insufficient standalone test. Specifically, it has low sensitivity and specificity, meaning it may fail to detect common method variance when present (false negatives) and may falsely suggest CMV when it is absent (false positives). These issues arise due to measurement unreliability, the dependence of the test on the number of variables analysed and its incorrect assumption that all common variance is attributable to method bias. We therefore rely primarily on the marker variable approach, which is more suited for identifying subtle common method variance effects in survey-based research.

Ultimately, the structural findings of our study reveal moderating effects, and previous research indicates that moderating effects are genuine and not due to common method bias (Siemsen *et al.*, 2010). These results suggest that common method bias is unlikely to affect our findings significantly. For detailed statistical results, refer to Table 4, which includes the correlation matrix, descriptive statistics, reliability measures, AVEs and square root AVE.

4. Results

We tested the structural model using PLS-SEM with bootstrapped replications with 5,000 subsamples. To evaluate the model's predictive relevance, we examined the R^2 values as suggested by Sarstedt *et al.* (2019). The R^2 value for the ultimate dependent variable, firm performance, is 0.267, which is within acceptable range (Hair *et al.*, 2019). The R^2 values for other endogenous variable, marketing agility ($R^2 = 0.339$), is also within acceptable limits. Additionally, we used the $PLS_{predict}$ algorithm to confirm the structural model's predictive power (Shmueli *et al.*, 2019). The results showed that the Q^2 predicted values are greater than zero for the model's constructs, indicating that our structural model surpassed the most naïve benchmark of the sampled indicator means. Moreover, Table 5 illustrates that the $PLS_{predict}$ analysis for the model's ultimate dependent variable, firm performance, showed lower RMSE values from the PLS-SEM analysis compared to the naïve LM benchmark model, indicating strong predictive power.

The structural model demonstrates a good fit, indicated by SRMR = 0.055, d_ULS = 1.583 and d_G = 0.778. The results show positive associations between AI-based stakeholder

Table 4. Correlational matrix, reliability and AVE ($n = 335$)

Construct	AI-based stakeholder engagement	Marketing agility	Firm performance	Technology turbulence
AI-based stakeholder engagement	*0.840*			
Marketing agility	0.531**	*0.746*		
Firm performance	0.326**	0.507**	*0.937*	
Technology turbulence	0.486**	0.450**	0.256^{ns}	*0.822*
Mean	3.066	3.442	3.575	3.784
Standard deviation	0.966	0.817	0.960	0.846
Composite reliability (rho_c)	0.964	0.949	0.936	0.892
Composite reliability (rho_a)	0.959	0.944	0.874	0.862
Cronbach's alpha	0.958	0.943	0.863	0.841
AVE	0.707	0.556	0.879	0.675

Note(s): Significance level = *$p < 0.05$; **$p < 0.01$; ns not significant; numbers in *bold* are square roots of AVEs
Source(s): Authors' own work

Table 5. Predictive power of structural model

Firm performance indicators	Q^2 predict	PLS-SEM RMSE	LM RMSE
Firm_perf1	0.106	0.943	0.967
Firm_perf2	0.103	0.997	1.028

Source(s): Authors' own work

engagement and marketing agility ($R^2 = 0.339$, $\beta = 0.401$, $p < 0.001$, t-value = 7.13), and between marketing agility and firm performance ($R^2 = 0.267$, $\beta = 0.496$, $p < 0.001$, t-value = 10.27), providing support for *H1* and *H3*. Our analysis found no significant effect of control variables on the dependent variable. We also explored the moderating effect of technology turbulence on the relationship between AI-based stakeholder engagement and marketing agility ($\beta = 0.089$, $p = 0.049$, t-value = 1.97), and on the relationship between marketing agility and firm performance ($\beta = 0.081$, $p = 0.041$, t-value = 2.04). The later interaction is shown to be significant and positive, which supports *H4*. However, the former interaction might be small, as the p-value and t-value suggest that the moderating effect is statistically significant, but the confidence interval includes zero, which suggests it might not be. Given the conflicting evidence, the result is borderline significant. In such cases, the p-value is often given more weight in determining statistical significance, so we can cautiously consider this result as statistically significant. However, further investigation is needed. Table 6 reports the test results.

To better understand the true dynamics of the interaction effect, we used a proper visualisation method (Aiken *et al.*, 1991) rather than relying solely on the statistics of the interaction effect. The interaction effects slopes are displayed in Figures 2 and 3.

Figure 2 shows the positive moderating effect of technology turbulence on the relationship between stakeholder engagement and marketing agility. The interaction plot indicates that the relationship between AI-based stakeholder engagement and marketing agility is stronger under conditions of high technology turbulence. Specifically, when technology turbulence is high, firms that engage stakeholders through AI show greater improvements in marketing agility compared to firms operating in low technology turbulence conditions. All the test statistics, except confidence intervals, suggest the same interaction effect.

Table 6. Results of hypotheses testing ($n = 335$)

Hypothesised path	Path coefficient	*t*-values	*p*-values	LCI (2.5%)	UCI (97.5%)	Hypothesis result
[*H1*] AI-based stakeholder engagement → marketing agility	0.401	7.135	0.000	0.289	0.513	*H1*: Supported
[*H3*] Marketing agility → firm performance	0.496	10.276	0.000	0.402	0.593	*H3*: Supported
[*H2*] Technology turbulence * AI-based stakeholder engagement → marketing agility	0.089	1.966	0.049	−0.002	0.176	*H2*: Partially supported
[*H4*] Technology turbulence * marketing agility → firm performance	0.081	2.044	0.041	0.001	0.157	*H4*: Supported

Source(s): Authors' own work

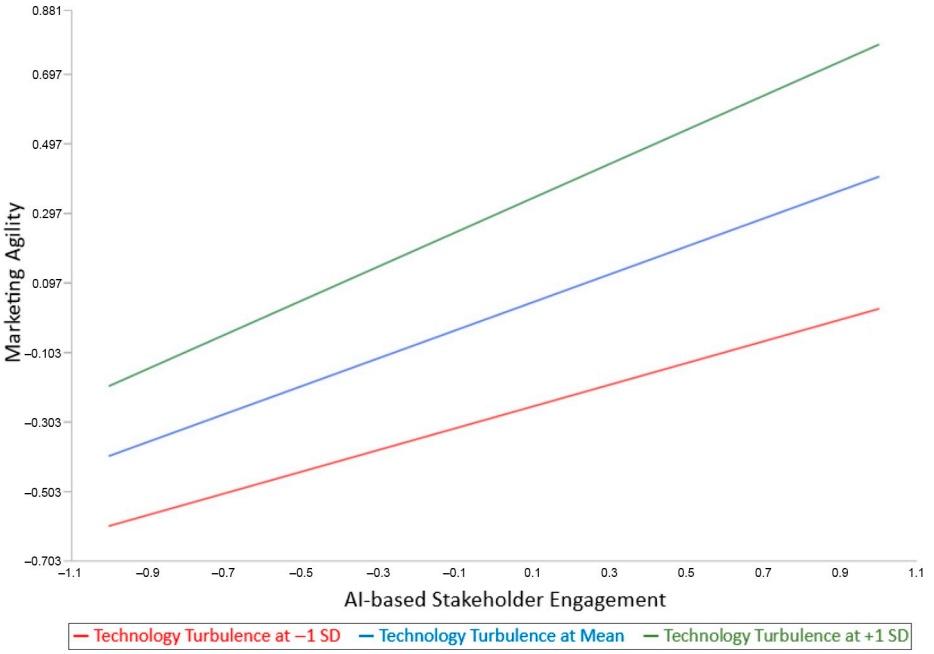

Figure 2. Interaction effect of technology turbulence and AI-based stakeholder engagement on marketing agility
Source: Authors' own work

Figure 3 shows the positive moderating effect of technology turbulence on the relationship between marketing agility and firm performance. The plot reveals that the positive impact of marketing agility on firm performance is amplified under conditions of high technology turbulence. Specifically, firms that exhibit high levels of marketing agility achieve significantly better performance outcomes in environments characterised by fast technological changes. Figure 4 illustrates a summary of our study results.

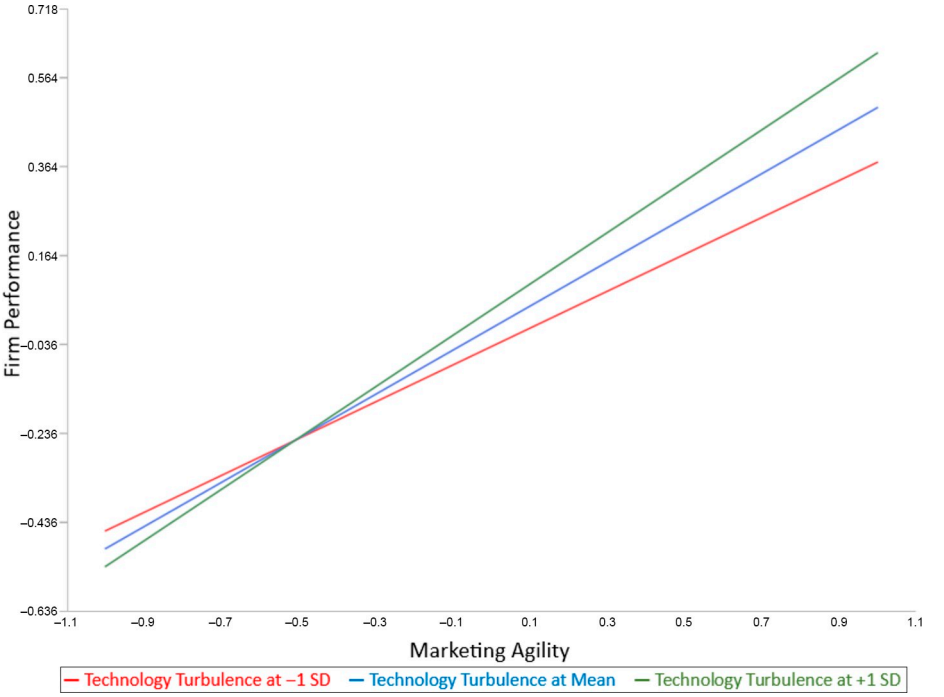

Figure 3. Interaction effect of technology turbulence and marketing agility on firm performance
Source: Authors' own work

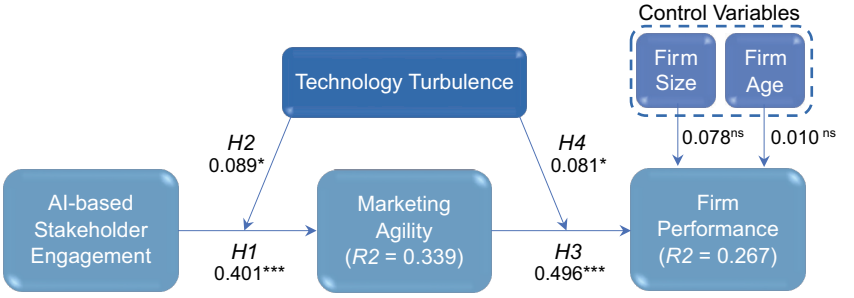

Figure 4. Study results
Note(s): *$p < 0.05$, **$p < 0.01$ and ***$p < 0.001$, ns = non-significant
Source: Authors' own work

4.1 Test of endogeneity

To examine potential endogeneity concerns in our model, we used the Gaussian copula approach, a robust diagnostic technique recommended for use in PLS-SEM frameworks (Park and Gupta, 2012; Hult *et al.*, 2018; Sarstedt *et al.*, 2020). We tested the key endogenous variables, marketing agility and firm performance, for endogeneity relative to their main

predictors: AI-based stakeholder engagement and marketing agility, respectively. The copula terms were found to be statistically non-significant ($p > 0.05$) across all individual and combined models (see Table 7). These results suggest that endogeneity due to unobserved confounding with a Gaussian dependence pattern is not a major concern in our model, and the estimated path coefficients can be interpreted with confidence.

5. Discussion

The rapid advancement of NATs continues to disrupt the marketplace, while simultaneously offering unprecedented opportunities for businesses. Despite the growing body of valuable research on the impacts of NATs, such as AI technologies, there is still limited understanding of the intricacies involved in how businesses can effectively use AI to thrive in a technologically disrupted economy. Addressing this issue, our study provides insights into the role of AI-based stakeholder engagement in enhancing marketing agility and, subsequently, firm performance in technologically turbulent conditions. Our findings provide compelling evidence that AI-based stakeholder engagement significantly enhances a firm's marketing agility, which in turn positively impacts overall firm performance. Moreover, the strength of these relationships is amplified under conditions of high technological turbulence. We found conflicting evidence to support the moderating effect of technology turbulence on the relationship between AI-based stakeholder engagement and marketing agility. The lack of full statistical support may stem from variations in the strength of this interaction across different industries and contexts. For example, industries like IT, ICT and telecommunications inherently experience high levels of technology turbulence, whereas sectors such as agriculture may be less affected. Although the analysis of interactions curves confirms this moderating effect, future research should explore these nuances further to gain deeper insights into the moderating role of technology turbulence. This study offers several theoretical and practical contributions that extend the current understanding of the implications of AI's role in marketing dynamics.

5.1 Theoretical contributions

We offer two theoretical contributions to the AI powered marketing literature. First, although prior research has explored the benefits of AI technologies for businesses' marketing agility, such as the use of chatbots to enhance both internal and external agility (Wang *et al.*, 2022)

Table 7. Test of endogeneity (Gaussian copula method)

Test	Construct	Coefficient	*p*-value
Gaussian copula of model 1 (endogenous variable: AI-based stakeholder engagement)	Marketing agility	0.496	0.000
	AI-based stakeholder engagement	0.844	0.000
	[c]AI-based stakeholder engagement	−0.352	0.055
Gaussian copula of model 2 (endogenous variable: Marketing agility)	Marketing agility	0.593	0.000
	AI-based stakeholder engagement	0.401	0.000
	[c]Marketing agility	−0.075	0.362
Gaussian copula of model 3 (endogenous variables: Marketing agility and AI-based stakeholder engagement)	Marketing agility	0.593	0.000
	AI-based stakeholder engagement	0.844	0.000
	[c]Marketing agility	−0.075	0.362
	[c]AI-based stakeholder engagement	−0.352	0.055

Note(s): [c]indicates the copula term in the model
Source(s): Authors' own work

and the implication of AI portfolio capability for agility-driven performance (Masialeti *et al.*, 2024), less attention has been paid to how AI can be used as a mean to engage stakeholders in the business functions to improve firms' marketing agility. To address this gap, this study provides a more nuanced perspective on this issue. By doing so, we contribute to the realms of stakeholder engagement and marketing agility, while also highlighting the environmental conditions that enhance the role of AI in engaging stakeholders and improving firms' responsiveness to market changes. Our results suggest that firms operating in highly dynamic technological environments might derive greater benefits from AI-enabled engagement practices. Therefore, we add to the growing evidence on the importance of leveraging NATs in environments characterised by technological disruptions (e.g. Rodríguez-Espíndola *et al.*, 2020; Spanaki *et al.*, 2022; Hendriksen, 2023).

Second, our study corroborates that marketing agility significantly contributes to firm performance, with this relationship being positively moderated by technological turbulence. This finding resonates with prior research that emphasises the critical role of agility in achieving superior performance in rapidly changing markets (e.g. Tallon and Pinsonneault, 2011; Asseraf *et al.*, 2019; Zhou *et al.*, 2019). By showing the amplifying effect of technological turbulence, our research adds nuance to the understanding of how specific environmental factors, such as technological turbulence, influence the effectiveness of marketing agility practices. Consequently, we extend research on marketing agility by identifying the boundary conditions of its effectiveness in improving business performance.

5.2 Managerial implications

From a managerial perspective, our findings offer several important implications. Managers should consider investing in AI technologies not only to improve marketing agility but also to actively engage stakeholders. AI tools enable a deeper exploration of stakeholder needs and preferences, as well as the ability to harness their insights. These advantages position firms better recognise and respond to market demands and changes swiftly and effectively. This capability is especially critical in industries marked by continuous technological advancements, such as telecommunications and financial services, where agility can confer a significant competitive advantage (Liébana-Cabanillas and Blanco-Encomienda, 2024). Managers should prioritise integrating AI solutions that support comprehensive analysis of stakeholders' data and real-time feedback mechanisms for them, ensuring that stakeholder insights are effectively harnessed to drive agile marketing strategies. However, managers in traditionally less technology-intensive industries, such as agriculture and manufacturing, can also leverage AI to enhance stakeholder engagement and agility. In agriculture, AI-powered analytics can improve supply chain coordination, market responsiveness and customer engagement (Charles *et al.*, 2023). For example, AI-driven predictive models can help farmers and agribusinesses anticipate market demand fluctuations, optimise logistics and engage with key stakeholders – such as suppliers, distributors and policymakers – more effectively (Sharma *et al.*, 2020). AI-based stakeholder engagement tools, such as automated advisory systems for farmers or AI-enhanced traceability solutions, can also facilitate stakeholder engagement in the industry that leads to higher marketing agility. For example, an AI-based agriculture open network, launched in 2025 and powered by Gemini and the Beckn protocol, enables farmers in India to engage with a network of stakeholders in supply chain, financial institutions and advisory services providers (ETGovernment, 2025). While this study highlights the benefits of AI-based stakeholder engagement, managers must also account for ethical implications such as data privacy, algorithmic bias, transparency and AI fairness (John-Mathews *et al.*, 2022). Since AI enables engagement with a broader network of stakeholders across different regions, firms must navigate varying data protection

regulations (e.g. GDPR, CCPA) to ensure compliance and prevent unintended negative consequences.

Additionally, our findings underscore the critical importance of developing marketing agility in firms operating within highly dynamic technological environments. To capitalise on the benefits of such agility, managers should prioritise fostering a culture that values flexibility, proactiveness and continuous learning. This process involves implementing training programmes that keep employees abreast of the latest technological advancements and encouraging a mindset that embraces change and innovation very quickly. By creating an organisational environment where adaptability is ingrained in the company's ethos, managers can ensure their teams are better prepared to respond to rapid technological shifts. This proactive approach enables firms to not only react to changes but also to anticipate and leverage new technologies effectively, thereby gaining a competitive edge.

5.3 Limitations and future research directions

While this study provides valuable insights, it also opens several avenues for future research. First, although we found initial support for the moderating role of technology turbulence in the relationship between AI-based stakeholder engagement and marketing agility, our results marginally confirm this interaction. Therefore, future studies should replicate our model across diverse contexts and industries – particularly those with lower technology turbulence, such as public administration (Tan *et al.*, 2022) – to gain more nuanced insights into this relationship. Also, since our data was sourced from Australian companies, future studies could enhance the generalisability of our findings by replicating our model in other regions with different market characteristics or in emerging markets that may experience varying levels of technological disruption (Namal *et al.*, 2023). Second, since the field of AI-based stakeholder engagement is still emerging and our study is among the first empirical investigations in this area, we applied a broad conceptualisation of AI to ensure inclusivity and provide generalisable insights. This approach allowed us to establish core relationships in the most comprehensive way possible (Cheng *et al.*, 2016). However, to generate more granular insights, future research should examine the role of specific AI technologies, such as machine learning or natural language processing, in stakeholder engagement and marketing agility. This would provide a deeper understanding of which AI tools are most effective in different contexts. Third, while our cross-sectional findings are valuable, future research could provide a broader perspective by examining the long-term impact of AI-based stakeholder engagement on firm performance. This should also consider potential risks, such as data privacy concerns and ethical issues associated with AI. Understanding these long-term effects is important for managers and policymakers aiming to use AI responsibly and for social good (Tomašev *et al.*, 2020). Finally, future research should investigate the moderating effects of other environmental factors, such as market volatility or regulatory changes, on the relationships examined in this study, also considering how these moderators might interact. By exploring these variables, researchers can better understand how different environmental dynamics impact the effectiveness of AI in enhancing marketing agility and firm performance.

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