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Article

Innovative Pathways: Leveraging AI Adoption and Team Dynamics for Multinational Corporation Success

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Abstract

This study examines the impact of AI adoption orientation on innovation performance in multinational corporations (MNCs), emphasizing team innovativeness as an intervening mechanism and technology orientation as a moderating factor. Using data from 410 respondents collected via a snowball sampling strategy and analyzed through partial least squares structural equation modeling (PLS-SEM), the findings reveal that artificial intelligence (AI) adoption orientation positively influences team innovativeness and innovation performance. Team innovativeness partially mediates this relationship, while technology orientation moderates the link between AI adoption and team innovativeness, underscoring the role of technological preparedness in enhancing innovation. The study contributes to theoretical understanding by integrating team dynamics and technology preparedness in AI-driven innovation. It provides practical insights for managers, policymakers, and organizational leaders on fostering an innovative culture and investing in technology skills to drive MNC competitiveness.

Keywords: AI models; team innovativeness; technology orientation; innovation performance; MNCs



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1. Introduction

Multinational corporations (MNCs) have seen immense growth opportunities in the last 3 decades. MNCs benefited from a multipolar world with comparatively unrestricted finance, trade, and idea generation by building enterprises that catered to global supply and demand, serving an increasingly globalized client base (K. Sharma, 2023). AI is used to explain its role in multinational enterprises (MNEs). Amazon utilizes AI for estimating demand, automating systems in its warehouses, and suggesting personalized ideas to enhance the company's operations and customer relationships. Likewise, powerful analytics powered by AI help Unilever manage and improve its supply processes, as well as analyze the views and opinions of consumers worldwide. Siemens also demonstrates how AI and the Internet of Things can be leveraged to help predict issues and enhance smart manufacturing. As a result of adopting AI, MNEs can reduce costs, streamline processes, and maintain a competitive edge over their rivals in various industries.

A noteworthy correlation is the simultaneous growth of China's economy and the attraction of MNCs to its market over the last decade. China's real GDP grew by approximately 10% annually between 1990 and 2019, accounting for over 25% of global GDP growth (Niu & Jiang, 2021). Likewise, the average family income increased from nearly

USD 750 to USD 13,000 (Lola et al., 2023). MNCs were drawn to China because of its dynamism and established operations there to aid in its expansion. MNCs employed 16 million individuals and accounted for more than half of China's export earnings. Additionally, they helped introduce best practices in China, improving efficiency in sectors like chemicals and cosmetics (Lola et al., 2023). However, due to significant environmental factors (e.g., COVID-19, carbon emissions, and other sustainable development goals) and technological shifts, such as machine learning (ML), artificial intelligence (AI), and other transformative changes, MNCs must adopt more innovative and adaptive strategies to sustain business, not just in China but globally. In recent years, many MNCs have been relocating their operations from China to other countries. Rising labor costs, trade tensions, and the need for supply chain diversification primarily drive this trend (Lola et al., 2023). The types of MNCs participating in this shift include Greenfield investments, which establish new operations in host countries; Brownfield investments, where existing facilities are acquired or leased; and various partnerships, including joint ventures and mergers and acquisitions. These strategic moves aim to enhance operational efficiency, mitigate risks, and expand market reach in the global business landscape (Lola et al., 2023).

In this wake, achieving and sustaining innovation performance is a turning point for the existence of MNCs (Belderbos et al., 2023). Innovation performance denotes the effectiveness and efficiency of a firm's developing and devising process and product innovations to reach strategic objectives and gain a competitive advantage (Iqbal et al., 2021). Due to the fast-paced technological transformations, attaining innovation performance remains a consistent challenge for MNCs, which becomes more crucial because of environmental differences. However, one commonality is rising in almost all contextual settings: the adoption of AI. MNCs globally use AI to automate repetitive jobs, streamline workflows, and produce insights from massive datasets to achieve innovative performance (Bahoo et al., 2023). Through tailored recommendations, quick prototyping, and predictive analytics, AI enables MNCs to enhance their product innovation. AI-driven automation also streamlines supply chain management (SCM), shortens the time it takes to launch new goods, and increases operational effectiveness (Jaiswal et al., 2022). AI also facilitates continual improvement by evaluating client input, identifying new trends, and modifying plans as necessary (Jaiswal et al., 2022). Ultimately, AI enables MNCs to stay competitive, innovate more quickly, and meet evolving customer needs in a rapidly changing global market.

However, implementing successful AI models is inevitable without recognizing team innovativeness in the MNCs' context. By promoting a culture of experimentation, collaboration, and adaptation, team innovativeness within MNCs is crucial in enhancing the orientation towards using AI to achieve innovation goals (F. J.-L. Chen et al., 2013). Teams with high levels of innovation are more willing to adopt new technologies, such as AI and ML implementations, viewing them as tools to enhance their creative processes and produce innovative results (Jin & Sun, 2010). These teams aim to explore AI options, test their features, and integrate them into their existing processes. Furthermore, team inventiveness promotes information discussion and skill development, empowering participants to utilize AI technologies as a complete predictor of creativity (W. Chen & Kamal, 2016). Ultimately, MNCs' innovation goals are accelerated by the link between team inventiveness and the adoption of AI. The complex connection between the orientation towards adopting AI models and team innovativeness is likely to be influenced by the technology orientation of companies. Organizational technology orientation has a substantial impact on the complex relationship between team innovativeness and the acceptance of AI models (Gatignon & Xuereb, 1997). Businesses that pay great attention to technology prioritize investing in and adopting state-of-the-art technologies (Benlian et al., 2015). This methodology fosters

an environment that promotes innovation, enhancing teams' readiness and capacity to implement AI solutions. It also shapes policies, resources, and organizational structures, all of which are expected to either facilitate or hinder team innovation and the adoption of AI (Upadhyay et al., 2022). The technology orientation of a company thus acts as a catalyst, increasing or decreasing the influence of AI adoption on team innovativeness and, eventually, innovation performance.

Building on past studies, this research addresses some gaps in the literature on the innovation performance of MNCs. Past research has demonstrated the impact of AI adoption on various organizational outcomes, highlighting its significant role in automating repetitive tasks, aligning workflows, and generating insights from large datasets (Bahoo et al., 2023). Also, extant research has shown the critical role of team innovativeness in leading innovation performance, as teams with higher levels of creativity and adaptability are more prone to develop and implement creative ideas (F. J.-L. Chen et al., 2013; Jin & Sun, 2010; Huang et al., 2022; Rayets et al., 2023). Nevertheless, such evidence has usually examined AI adoption and team innovativeness without focusing on the interplay between the factors suggested in this study, which has a primary goal of closing the gap between team inventiveness and the adoption of AI, with the aim to assess how team innovativeness mediates the connection between AI adoption and innovation performance in MNCs, and offer a thorough understanding of the innovation process. Prior research has frequently examined AI adoption or team innovativeness autonomously (F. J.-L. Chen et al., 2013; S. Sharma et al., 2022; Bahoo et al., 2023). This study also aims to investigate how technological orientation affects this organization. Limited research has assessed the moderating influence of technology orientation on the link between AI adoption and team innovativeness despite some understanding of the relevance of technology orientation in adopting innovation (Benlian et al., 2015; Upadhyay et al., 2022; Vrontis et al., 2022). Hence, this study aims to advance the understanding of the contextual factors impacting innovation outcomes by placing forth and testing the hypothesis that technology orientation improves the favorable advances of AI adoption on team innovativeness (Gatignon & Xuereb, 1997; Jaradat et al., 2025). Ultimately, this research addresses a gap in the literature by situating the study within the context of the Chinese market. Despite China's substantial role in the global economy, studies on innovation performance in the context of MNCs in China are still limited (Liu & Li, 2022; Lola et al., 2023). Considering China's economic, cultural, and regulatory policies, it is crucial to understand how these contextual elements influence the innovation systems of MNCs operating in this region. By focusing on China, this study enhances the understanding of the possibilities and limitations that MNCs face in the region, as well as how innovation systems within MNCs are shaped by changing global dynamics. Hence, this study intends to address the subsequent research questions:

1. Does the orientation to adopt AI models influence innovation performance?
2. Does team innovativeness positively mediate the relationship between the orientation to adopt AI models and innovation performance?
3. Does technology adoption positively moderate the relationship between the orientation to adopt AI models and team innovativeness?

This research offers both theoretical and practical insights into understanding how MNCs function in innovation. First, by employing the Technology Acceptance Model (TAM), innovation outcomes can be improved through the provision of a formal framework for understanding the adoption of AI technology. Second, this study examines the direct and indirect association between orientation towards adopting AI models and innovation performance, aiming to predict its relevance for MNCs. Third, theoretical contributions include clarifying the relationship between orientation and adopting AI models to enhance the understanding of innovation dynamics in multinational corporations by measuring the

mediating role of team innovativeness and moderating the effect of technology orientation. Fourth, this study framework extends its relevance to multinational contexts by addressing how cultural, institutional, and organizational differences shape AI adoption and innovation performance. For instance, the mediating role of team innovativeness may vary across cultures due to differences in risk tolerance, collaboration norms, or hierarchical structures. Similarly, the technology orientation moderating effect could be influenced by country-level factors such as digital infrastructure, regulatory environments, or workforce readiness. By integrating these dimensions, the research highlights the adaptability of TAM in diverse settings, providing MNCs with a nuanced lens to tailor AI strategies to local contexts while maintaining global innovation synergies. This cross-cultural perspective not only enriches the theoretical contribution but also provides actionable insights for MNCs operating in heterogeneous markets.

This remaining part of this paper is structured as follows: Section 2 offers hypothetical underpinnings and hypothesis prepositions, Section 3 explains the research methods adopted in this assessment, Section 4 describes the findings of robust statistical tests and analysis, and Section 5 details a discussion of the research findings, critical theoretical and practical implications, limits, and future explorative guidelines of the study. Lastly, Section 6 offers the conclusion of the study.

2. Theoretical Underpinnings and Hypothesis Development

A company's innovation process, particularly its digital business transformation, is complex and driven by interactions among multiple factors (Awa, 2019; Wu et al., 2022). Through these intricate relationships, various internal and external factors—including business and innovation strategies, resource capacities, firm size, technological levels, market demand, environmental issues, networking, and policy considerations—can impact a firm's innovation performance (Liao et al., 2023). Product and process innovation are two areas where businesses must excel in technological innovation (Chuang, 2005; Goni & Van Looy, 2022). Process innovation refers to the modification of existing procedures, while product innovation involves the creation of novel items to meet evolving market demands (Chuang, 2005; Marion & Fixson, 2021). The existing literature argues that organizations that innovate through their products and processes can create value, become more competitive, and achieve better innovation performance (Shahnaei & Long, 2015; Zeb et al., 2021; Muhamad et al., 2023). MNCs can enhance their product offerings, optimize workflows, and develop innovative business models by fostering a creative culture, thereby strengthening their market position. Recent research has highlighted the importance of innovation to MNCs. For instance, Belderbos et al. (2023) highlight how innovation helps MNCs navigate uncertainty and seize new opportunities. Burciu et al. (2023) emphasize how innovation enables MNCs to remain resilient against disruptive forces and thrive in adverse conditions. The literature also underscores the advantageous effects of innovation on the sustainability and financial performance of MNCs, highlighting a critical need for them to prioritize innovation due to its numerous benefits, ranging from organizational resilience to market relevance (Xie et al., 2022; Belderbos et al., 2023; Burciu et al., 2023).

2.1. Technology Acceptance Model and Conceptual Framework

To further explain the association between the innovation performance of MNCs, it is essential to understand the position of the Technology Acceptance Model (TAM). TAM's primary aim is to explore the processes for establishing technology adoption to predict technological behavior and advance a theoretical justification for its practical use. TAM's practical aim is to educate practitioners on possible actions they could take before implementing methods. Numerous strategies have been considered to meet the theory's aims

(Davis, 1985; Al-Emran & Granić, 2021; Al-Nuaimi & Al-Emran, 2021). At both managerial and individual levels, acceptance of information technology can offer short- and long-term benefits, including increased performance, cost and time savings, and opportunities (Marikyan & Papagiannidis, 2023). TAM has significant potential implications for the innovation performance of MNCs. TAM provides a systematic framework that primarily focuses on perceived utility and perceived ease of use to understand users' adoption of innovative technologies. MNCs can leverage TAM to enhance innovation performance by systematically identifying and addressing the factors influencing employees' adoption of new products and processes (Gacheri, 2018; Brandmeier & Rupp, 2024). First, multinational MNCs can emphasize the tangible advantages of innovations, including increased production, efficiency, or competitive advantage, by highlighting the perceived utility of these innovations (W. Chen & Kamal, 2016; Zhao et al., 2024). Secondly, MNCs can reduce resistance and encourage smoother employee adoption by ensuring that innovations are considered easy to use, which raises the intention to use and leads to actual use (Amusan & Ajibola, 2017; Mehboob & Jawad, 2023). MNCs can accelerate the implementation of product and process innovations by fostering an innovative culture and aligning innovations with employees' perceptions of utility and ease of use. MNCs can enhance their innovation performance across various operational domains by optimizing innovation adoption using TAM, a strategic tool.

Next, it is essential to identify the critical factors that affect innovation performance. The extant literature offers indicators of innovation performance, as it discusses how MNCs can improve their innovation performance by creating a conceptual framework that integrates the TAM with constructs, including technology orientation, team innovativeness, and orientation to adopt AI models (Dobre, 2022; Pai & Chandra, 2022; Rehman et al., 2024). The primary predictor is the orientation towards adopting AI models, encompassing generativity, affordance, and openness (Marcinkevicius & Vilkas, 2023; Upadhyay et al., 2023; Ramaul et al., 2024). This construct represents MNCs' readiness and willingness to utilize AI technologies, which are increasingly acknowledged as essential catalysts for innovation (Nambisan et al., 2019; Upadhyay et al., 2023; Ramaul et al., 2024). According to TAM, acceptance of AI models is influenced by how beneficial and simple people believe them to be (Davis, 1985; Upadhyay et al., 2023; Ramaul et al., 2024). As a result, this approach directly impacts innovation performance, as AI-enabled solutions can spur breakthroughs in both processes and products. Likewise, the crucial role of internal dynamics in invention is acknowledged by including team innovativeness as a mediation variable. The ability of teams within multinational corporations to develop and execute new ideas is referred to as team innovativeness (Jin & Sun, 2010; Berraies & Chouiref, 2023). Scholars argue that team innovativeness may mediate the relationship between innovation performance and orientation to adopt AI models, and it may also directly influence innovation performance (Tien-Shang Lee, 2008; Upadhyay et al., 2023). Teams with more significant degrees of innovation are better able to utilize AI technology to their advantage, thereby improving innovation outcomes (F. J.-L. Chen et al., 2013; Brem et al., 2021; Rammer et al., 2022).

Moreover, the association between team innovativeness and the orientation to adopt AI models is shaped by technology orientation (Gatignon & Xuereb, 1997; Upadhyay et al., 2023; Jaradat et al., 2025). MNCs that are more focused on technology are more inclined to invest in and use AI technologies (Belderbos et al., 2023). The significant impacts of using AI models on team inventiveness are amplified by attitude, which improves innovation performance (Belderbos et al., 2023; Upadhyay et al., 2023; Jaradat et al., 2025). The proposed model is further strengthened by incorporating established theoretical frameworks such as the Technology-Organization-Environment (TOE) framework and Socio-Technical

Systems Theory (STS). The TOE framework posits that technological adoption is influenced by technological capabilities, organizational readiness, and environmental pressures, aligning with the study's emphasis on team innovativeness as a key organizational factor in AI adoption. Meanwhile, STS theory highlights the interdependence between social (e.g., team dynamics) and technical (e.g., AI systems) elements, suggesting that successful AI integration requires harmonizing human and technological factors (Kudina & van de Poel, 2024). Recent research highlights that AI adoption often fails when teams lack the cognitive flexibility and collaborative culture necessary to adapt to new technologies (Yang et al., 2024). Thus, these theories provide a robust foundation for explaining why team innovativeness is critical in AI adoption. The proposed conceptual framework for this study, as depicted in Figure 1, offers a comprehensive knowledge of how MNCs can recover their innovation performance in the digital age by linking theoretical insights from the Technology Acceptance Model (TAM), Technology-Organization-Environment (TOE) framework, and Socio-Technical Systems Theory (STS) with current trends in AI use, team dynamics, and organizational contexts.

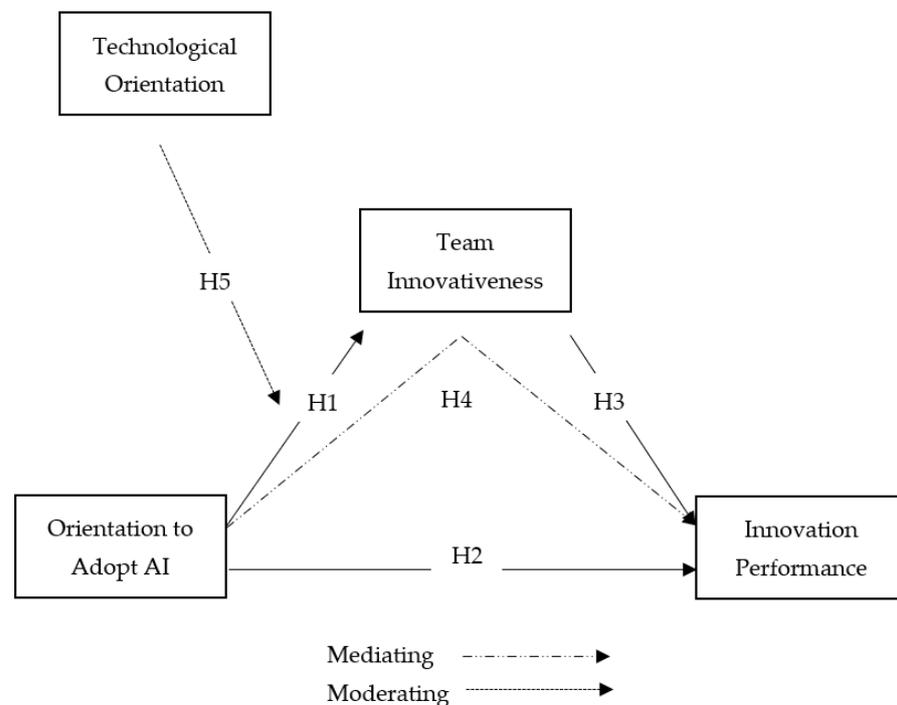


Figure 1. Conceptual model.

To enhance theoretical consistency, it is important to explicitly connect the TAM's core constructs to the study's variables. In the context of this research, the perceived usefulness of AI tools can be viewed as the degree to which employees believe that adopting AI will improve their performance, aligning directly with the construct of AI adoption orientation, particularly dimensions such as generativity and affordance, which reflect the perceived benefits and possibilities enabled by AI. Likewise, perceived ease of use corresponds with the openness dimension, which reflects how intuitively and seamlessly AI systems can be integrated into workflows. These perceptions are critical because they shape employees' motivation to engage with AI tools, which in turn influences their willingness to innovate, hence impacting team innovativeness. By explicitly framing AI orientation through the TAM lens, this study underscores how individual and team-level perceptions translate into organizational innovation performance via mediating and moderating dynamics.

2.2. Hypothesis Development

2.2.1. Orientation to Adopt AI Models

Orientation to adopt AI models refers to a firm or individual's inclination, strategy, and readiness to adopt and integrate AI technology into their business operations. Technological orientation encompasses a broader approach, including the overall attitude, investment, and strategic focus toward adopting and utilizing various technologies, not limited to AI. A three-dimensional concept of orientation to adopt AI models, encompassing openness, generativity, and affordance, is crucial for businesses to effectively integrate digital technologies (Nambisan, 2017; Dąbrowska et al., 2022; Chin et al., 2023). Where openness to digital technology influences involvement and levels of functional value (Broekhuizen et al., 2021), affordance offers likely activities and potential in a particular context for adopting digital technologies (Marcinkevicius & Vilkas, 2023). Generativity offers an integration amongst a wide array of unlinked or less-integrated possibilities to make changes (Lyytinen et al., 2017). These three factors are critical for MNCs to adopt AI models:

Openness illustrates how technology may help and enable actors' participation, interaction, and operationalization of processes and specific results. It suggests what participants contribute to creating results and how they contribute to building them. According to Lamarre et al. (2023) and Pascucci et al. (2023), digital technology connected to goods and services provides a variety of methods for achieving commercial value through digital components (hardware or software), applications, or content that link people, machines, and information. Furthermore, technological ecosystems and digitally enabled platforms enhance and encourage governance (Tiwana, 2013; Wareham et al., 2014; Zahra et al., 2023), cooperation, shared decision-making, and co-creation of profits (Wareham et al., 2014; Chin et al., 2023). As a result, businesses can develop by utilizing connection, collaboration, and collective intelligence methods due to technology's openness and suitability (Wareham et al., 2014; Chowdhury et al., 2022). Several scholars argue that technological openness fosters innovation in platform and business ecosystems (Maxwell, 2006; Bereznoy et al., 2021; Priyono & Hidayat, 2024). Furthermore, value creation is facilitated by accessible standards and interfaces in technology (Nenonen et al., 2019; Priyono & Hidayat, 2024). AI's adaptable and open standards and application programming interfaces enable businesses to collaborate and co-create business values, resulting in the development of new and innovative products and services (Upadhyay et al., 2022). These scholars all recognize the potential of AI's level and degree of openness to assist, facilitate, and propel business operations and digital transformation.

Affordance illustrates the possible uses and actions that an object might have for the client in a particular situation. In other words, affordance results from the relations between the user and the item in a condition where the client sees feasible actions that may be taken to accomplish a goal (Marcinkevicius & Vilkas, 2023). Furthermore, it focuses on the potential actions rather than the conditions or actions that result from actualizing an activity (Strong et al., 2014; Chowdhury et al., 2022). System and technological affordances significantly impact entrepreneurial and organizational endeavors. Organizations become immersed in creating and launching novel and innovative products and services when they perceive a high degree of affordance from a specific technology (Chatterjee et al., 2020; Dincelli & Yayla, 2022; Smagulova & Goncalves, 2023). When adopting technology, affordability becomes crucial (Faraj & Azad, 2012; Al-Emran & Griffy-Brown, 2023). Comparable digital artifacts, platforms, or infrastructure do not yield equivalent results. On the other hand, in the proper context, they can create, capture, and provide value (Nambisan et al., 2019; Mulvey & Goncalves, 2022; Al-Emran & Griffy-Brown, 2023).

Generativity, or the generativity of digital technology, highlights its potential to bring about changes through the participation of multiple, dispersed, and uncoordinated entities

and actors (Lyytinen et al., 2017; Thomas & Tee, 2022). By utilizing technology generativity, organizations operationalize their creative endeavors (Thomas & Tee, 2022). Technological generativity encompasses digital platforms, ecosystems, infrastructures, and artifacts that contribute to digital transformation and value generation (Lyytinen et al., 2017; Mulvey & Goncalves, 2022). Application programming interface generativity in AI promotes heterogeneous inventions spanning various fields and passions. Businesses eager to develop and use AI-driven, assisted, and supported goods and services must consider the operational and strategic ramifications (Upadhyay et al., 2022). The acceptance of AI models in MNCs is impacted by generativity, affordance, and openness. Global teams collaborate and share knowledge when there is openness. Cost-effectiveness ensures practical and accessible AI resources, promoting the exploration of innovative solutions. Teams can experiment and innovate with AI technology when there is a sense of generosity. When taken as a whole, these elements support experimentation, varied viewpoints, and resource accessibility, all of which enhance MNCs' ability to innovate. Based on such premises, this study offers the following hypothesis:

According to TAM, individuals are more likely to adopt a technology when they perceive it as valuable and easy to use. These perceptions are embedded in traits such as openness to AI, its usability, and generative capabilities. Teams that perceive AI as intuitive and capable of enhancing work outcomes are more inclined to experiment with it, integrate it into their workflows, and engage collaboratively in creative applications. This leads to increased team-level exploration, learning, and ideation—hallmarks of team innovativeness. Therefore, it is hypothesized that:

H1: *Orientation to adopt AI models has a positive effect on team innovativeness.*

H2: *Orientation to adopt AI models has a positive effect on innovation performance.*

2.2.2. Team Innovativeness

The successful implementation of creative ideas to introduce new products, processes, or services within an organization is referred to as innovation performance (Harvey et al., 2023). It is a vital contributor to the competitive position of the organizations. Team innovativeness is defined as the collective capacity of a team to create, promote, and implement new ideas and ways of working; it is a key antecedent of innovation performance (West & Sacramento, 2023; Majchrzak et al., 2022). Prior research has been conducted on teams of high innovativeness, proclaiming they are more adaptive to the environment, more creative, and adept at problem solving, all of which is directly related to increased innovation outcomes (Anderson et al., 2014).

Multiple theoretical lenses explain the relationship between team innovativeness and innovation performance. In an Input-Process-Output (IPO) framework (Mathieu, 2025), team innovativeness is one of the critical inputs to team processes (such as collaboration and knowledge sharing) and innovation performance. Teams that are high in innovativeness are more likely to behave in an exploratory manner, challenge existing assumptions, and maximize the diversity of perspectives in their interactions to experience breakthroughs in innovation (Somech & Drach-Zahavy, 2000).

Moreover, social cognitive theory suggests that a team that is more innovative nurtures shared beliefs of the team's ability to innovate; this further motivates and promotes persistence in complex tasks. Therefore, if team members perceive their group as being innovative, the odds are higher that they will engage in risk-taking and experimentation that are vital when trying to innovate (Luan et al., 2024). This is supported by empirical studies showing that innovative teams exhibit a higher level of psychological safety and intrin-

sic motivation, which mediate the relationship between innovativeness and performance (Edmondson & Lei, 2024).

This relationship has been recently confirmed by other meta-analytic evidence. González-Romá et al. (2024), in a study, showed a very strong positive relation between team innovativeness and innovation performance in all industries, especially those knowledge-intensive ones. Research by Wang et al. (2024) also indicates that teams with higher innovation capabilities are better positioned to leverage digital tools and AI algorithmic insights to achieve better innovation outcomes in dynamic environments (Bogers et al., 2024). Thus, we hypothesize:

H3: *Team innovativeness has a positive effect on innovation performance.*

Recent research suggests that simply using AI does not lead to innovation; instead, what matters most are leadership trust, digital awareness, and teamwork that comes from everyone (Mariani et al., 2023). There is also not enough research on how AI affects a team's level of innovation. Even though AI supports efficiency, it only helps boost innovation when teams put its suggestions into creative solutions (Davenport & Ronanki, 2018; McAfee et al., 2023).

AI has advanced significantly, leading businesses to rely more heavily on its capabilities to aid their progress. It has been found that utilizing AI in an organization is significant, but the influence it has on innovative output may depend on how effectively the team implements and utilizes the technology to address issues (Kumar et al., 2023). The ability of teams to generate, enhance, and utilize new ideas is a significant factor that ties these two concepts together. It has been found that organizations with highly innovative teams tend to utilize AI tools more effectively, tailor them to their specific needs, and achieve greater innovation outcomes (Gong et al., 2023; Jorzik et al., 2024).

Evidence for the mediating role of team innovativeness in the relationship between innovation performance and the orientation to adopt AI models can be found in varying contexts in the prior literature. For example, technological capability mediated the relationship between customer orientation and inter-functional collaboration regarding product innovation (Aydin, 2021). Similarly, some evidence has been found regarding the direct effects of team innovativeness on innovation performance (F. J.-L. Chen et al., 2013; Tien-Shang Lee, 2008). However, limited evidence exists regarding the mediating mechanism of team innovativeness in the association between the orientation towards adopting AI models and innovation performance. By fostering a culture of creativity, collaboration, and experimentation within teams, we suggest that team innovativeness mediates the relationship between the orientation to adopt AI models and innovation performance. The TAM further suggests that the benefits of perceived usefulness and ease of use are not only direct but can also shape downstream behaviors via internal processes. In this context, the orientation toward adopting AI fosters positive perceptions among teams, which in turn cultivates a culture of experimentation and creativity, making team innovativeness a mediating mechanism that links AI adoption to improved innovation performance.

H4: *Team innovativeness positively mediates the relationship between orientation to adopt AI models and innovation performance.*

2.2.3. Technology Orientation

An organization's ability to identify and adjust to new technologies is referred to as its "technology orientation." According to Gatignon and Xuereb (1997), technology-oriented businesses have a strong propensity to be eager to try out novel technologies and create additional products. A recent study that aligns with Gatignon and Xuereb's (1997)

findings is [Nassani et al. \(2023\)](#), which investigates the impact of technology orientation on innovation performance within the electronic industry, highlighting that firms with a strong technology orientation are more inclined to adopt novel technologies and develop new products. The study also identifies digital innovation as a key mediator in this relationship, suggesting that technology-oriented firms leverage digital advancements to enhance innovation outcomes. The existing literature supports the idea that a technology orientation positively modifies the association between team innovativeness and orientation towards adopting AI models. Studies ([Benlian et al., 2015](#)) show that a technology-oriented approach encourages innovation in platform and business ecosystems, resulting in a favorable environment for creative thinking. Furthermore, it emphasizes how technology's open standards and interfaces promote value creation, arguing that a technology-focused strategy enhances the adoption of AI ([Hasija & Esper, 2022](#)). Additionally, [Upadhyay et al. \(2022\)](#) argue that AI's flexible and open standards foster co-creation and cooperation, two essential aspects of team innovation. Because it promotes the adoption and utilization of AI technologies in ways that optimize their potential to foster creativity and innovation within teams, a strong technology orientation within MNCs is likely to amplify the positive effects of adopting AI models on team innovativeness. Technology orientation can strengthen or weaken the influence of perceived usefulness and ease of use by shaping organizational infrastructure, training, and openness to technological change. Thus, when technology orientation is high, it reinforces the positive impact of AI orientation on team innovativeness by making teams more capable and willing to adopt AI-driven innovations. Therefore, this study proposes that:

H5: *Technology orientation has a positive influence on the relationship between adopting AI models and team innovativeness.*

3. Research Methods

3.1. Data Collection and Sampling

Following the implementation of the “open-door” policy in 1978, aimed at drawing foreign direct investment (FDI) to support China's modernization, the country has experienced a substantial influx of overseas investment. This influx has significantly contributed to China's economic expansion and social transformation in subsequent decades through the creation of employment opportunities, the introduction of innovative technologies and management practices, the stimulation of legal and institutional reforms, heightened market competition, and the improved efficiency and global competitiveness of domestic industries ([Zheng, 2021](#)). By 2017, more than 136,997 global firms had been established in China ([NBSC, 2018](#)), with approximately USD 134.97 billion in foreign capital invested in China by foreign companies as of 2018. A significant share of this FDI came from Germany (79.3%) and the United Kingdom (150.4%) ([MCPRC, 2023](#)), and from such investments, around 60,533 were new venture foreign firms. Global companies play a noteworthy function in the Chinese economy ([Froese et al., 2019](#); [Jenkins, 2022](#)).

Targeting the workforce of MNCs in China, a snowball sampling approach was used to distribute an online survey (see Appendix A) link via social media apps such as WeChat, Weibo, TikTok, RedNote, QQ, Bilibili, and other prominent channels. The key reason for using the online mode was its efficiency in rapidly and cost-effectively reaching a broad and geographically dispersed sample. Also, it allowed participants to respond at ease, which can enhance response rates and data quality despite the drawbacks online data collection can present, such as sample bias, low response rates, and data security and authenticity ([Wright, 2005](#); [Goncalves & Cornelius Smith, 2018](#); [Salmons, 2022](#)) issues. To mitigate these challenges, a snowball sampling approach was adopted, leveraging a network of primary

respondents who then assisted in scaling to a more diverse and representative sample. Two soft reminders were sent at 1-week intervals to manage potentially low response rates. To ensure data security, authenticity, confidentiality, and non-repudiation, exclusive computer-generated numeric codes were assigned to responses. Data collection was conducted in two rounds with a time lag to minimize common method bias.

The survey included demographic questions and questions related to the study constructs using a five-point Likert scale due to its simplicity and ability to reduce respondents' fatigue, improving response rates and data quality (Dawes, 2008; Tanujaya et al., 2022). The Likert scale also facilitates comparability by enhancing response consistency and potential correlations with prior studies.

The data were collected in two rounds from September 2023 to December 2023, with a 2-month time lag to prevent common method bias (Podsakoff et al., 2003; Kock et al., 2021). The first round included demographic questions and innovation performance. Two soft reminders were sent, with 1 week in each reminder, and 474 responses were collected. The second round of data collection included questions related to orientation to adopt AI models, team innovativeness, and technology orientation. Computer-generated numeric codes were assigned to responses from the first round to match them with those from the second round of respondents. A reduced number of 441 responses were considered in this second round due to incomplete responses or non-responses from the first round, which, after excluding the outliers, totaled 410 usable responses for further analysis.

3.2. Ethical Approval and Research Authorization

Ethical approval for the research was obtained from the Evidence-based Research Center for Educational Assessment (ERCEA), the institutional review board (IRB) at Jiangsu University. The study was reviewed and authorized under approval number iJSDX2025041700. This authorization permitted the conduct of semi-structured interviews with entrepreneurs in China, ensuring that all research activities complied with ethical standards related to participant consent, data confidentiality, and the responsible handling of personal information.

3.3. Measurement Model

Data assessment measurement scales from the extant literature were adopted in this study. Orientation to adopt AI models was measured using three dimensions, including openness, affordance, and generativity, and three items for each scale adopted from previous studies for openness (Rothwell et al., 1974; Upadhyay et al., 2023), affordance (Faraj & Azad, 2012; Upadhyay et al., 2023), and generativity (Turner & Fauconnier, 1999; Upadhyay et al., 2023). In the study by Upadhyay et al. (2023), openness, affordance, and generativity were examined as formative dimensions, as each dimension forms orientation to adopt AI models. Team innovativeness was measured using four refined items adapted from Bamgbade et al. (2022) and Upadhyay et al. (2023) and adjusted to focus specifically on the team-level outcomes of innovation. For example, the item "Our team creates new ideas. . .critical to our team's innovation success" ensures conceptual alignment with the team context, avoiding ambiguous references to firm-level success. These refinements enhance hierarchical consistency in construct measurement.

3.4. Data Analysis Methods

The data analysis was conducted using SmartPLS 4.0 due to its easy-to-use structural equation modeling features. The analysis was divided into three steps: measurement model, structured model, and hypothesis testing. The data analysis method used was partial least squares structural equation modeling (PLS-SEM). PLS-SEM was chosen for this study for several specific reasons: (1) The study involved a complex model with multiple latent constructs and indicators, making PLS-SEM suitable due to its ability to

handle such complexity efficiently (J. Hair et al., 2017; Russo & Stol, 2021). (2) Due to the exploratory nature of the research and the aim to predict the impact of orientation to adopt AI models on innovation performance, PLS-SEM's strength in prediction and explanation of variance was a critical factor. (3) The study's sample size was relatively small (410 respondents), and PLS-SEM is known for its robustness in dealing with smaller sample sizes compared to covariance-based. (4) PLS-SEM is less stringent about data distribution assumptions, making it more appropriate for this study (J. F. Hair et al., 2019; Vaithilingam et al., 2024). The exploratory nature of this study, aimed at understanding new constructs and relationships, justified the use of PLS-SEM, which is particularly well-suited for exploratory research focused on theory building rather than theory testing (J. F. Hair et al., 2019; Vaithilingam et al., 2024). Therefore, PLS-SEM was employed as the data analysis method due to its capability to effectively manage complexity, address sample size constraints, and handle non-normal data distribution, which is specific to this research.

4. Research Findings

4.1. Respondents' Profile

The participants' demographic data provide significant insights into the sample's composition and illuminate the respondents' characteristics. The findings indicate that approximately 34% of respondents were female, and 65% were male. In terms of age categories, the highest percentage of responders (36%) fell within the 31–35 age range. This suggests that most participants are in their early-to-mid-30s, indicating a certain level of experiential and professional maturity. Additionally, 68% of respondents held jobs in middle management. Furthermore, 70% of them have a bachelor's or master's degree, comprising the majority of respondents' educational backgrounds. This suggests a well-educated group, likely possessing a solid theoretical foundation and more advanced analytical abilities. Additionally, most companies in the sample are medium-sized (48.8%), with technology firms being the most represented industry (29.3%). Small teams (1–5 members) are the most common (43.9%). Lastly, the distribution of respondents' experience levels across the different groups was relatively even. However, a sizable fraction (38%) has 6–10 years of experience, indicating that mid-career professionals are heavily represented in the sample. The demographic summary of the participants suggests a sample primarily composed of mid-level managers with moderate-to-substantial job experience and a strong educational background, as detailed in Table 1.

Table 1. Demographic information of respondents.

Factors	Range	Number	Frequency (%)
Gender	Male	267	65%
	Female	141	34%
Age	20–25	57	14%
	26–30	138	34%
	31–35	147	36%
	35–40	29	7%
	Above 40	39	10%

Table 1. *Cont.*

Factors	Range	Number	Frequency (%)
Team Leaders	Supervisors	31	8%
	Managers	277	68%
	CEO's	102	25%
Education Level	High school certificate	4	1%
	Bachelor's degree	129	31%
	Master's degree	160	39%
	Ph.D. degree	28	7%
	Other professional education	89	22%
Experience	1 year or less	15	4%
	1–5 years	83	20%
	6–10 years	157	38%
	11–15 years	140	34%
	More than 15 years	15	4%
Company Size	Small (1–50 employees)	150	36.6%
	Medium (51–500 employees)	200	48.8%
	Large (501 + employees)	60	14.6%
Industry Affiliation	Technology	120	29.3%
	Manufacturing	90	22.0%
	Healthcare	70	17.1%
	Finance	60	14.6%
	Retail	40	9.8%
	Other (Specify)	30	7.3%
Team Size	1–5 Members	180	43.9%
	6–10 Members	150	36.6%
	11–20 Members	60	14.6%
	21+ Members	20	4.9%
Total		410	100%

4.2. Common Method Bias

The previous literature suggests examining common method bias (CMB) to check likely measurement errors (Podsakoff et al., 2003; Podsakoff et al., 2024). Since this study employed a time-lag approach in survey data collection, the data may be inflated, which can be addressed through CMB tests. First, Harman's single-factor tests were performed, and the findings showed that the single-factor total variance was 41.5%, which indicates the absence of CMB (Ahrholdt et al., 2019). Secondly, the variance inflation factor (VIF) was assessed as a measure of full collinearity, in line with the past literature (J. F. Hair et al., 2019). The findings of VIF were less than 3, indicating that no multicollinearity issues were detected in the data, as shown in Table 2.

Table 2. Validity and reliability analysis.

Constructs	Items	Loadings	CA	CR	AVE	VIF
Innovation Performance (IP)	IP1, IP2, IP3, IP4	0.889, 0.882, 0.848, 0.863	0.893	0.926	0.757	
Team Innovativeness (TI)	TI1, TI2, TI3, TI4	0.842, 0.843, 0.900, 0.932	0.902	0.932	0.774	1.238
Orientation to Adopt AI (OAAI) Models	OAAI1, OAAI2, OAAI3	0.710, 0.822, 0.813	0.920	0.934	0.612	1.208
	OAAI14, OAAI5, OAAI6	0.831, 0.692, 0.776				
	OAAI7, OAAI8, OAAI9	0.841, 0.812, 0.727				
Technology Orientation (TO)	TO1, TO2, TO3, TO4	0.908, 0.886, 0.918, 0.926	0.931	0.951	0.828	1.367

Note: CA = Cronbach Alpha, CR = Composite Reliability, AVE = Average Variance Extracted, VIF = Variance Inflation Factor.

4.3. Measurement Model

Before assessing the structured equation model, a measurement model was developed to determine the items' loadings and reliability of the scales using Cronbach's alpha (CA), composite reliability (CR), average variance extracted (AVE), and discriminant validity checks. Findings show the results of CA and CR for innovation performance (0.893; 0.926), orientation to adopt AI models (0.920; 0.934), team innovativeness (0.902; 0.932), and technology orientation (0.931; 0.951), as depicted in Table 2 and Figure 2. According to past studies, the CA and CR must be equal to or greater than 0.70, as per the threshold (J. F. Hair et al., 2011; Purwanto & Sudargini, 2021). Also, convergent validity was assessed by having a value of AVE, which is recommended to be higher than 0.50 (Henseler et al., 2015; Cheung et al., 2024). The study's findings show that AVE was reasonably achieved for all variables (ranging from 0.674 to 0.819).

One item in the AI orientation scale displayed a loading of 0.692, slightly below the conventional threshold of 0.70. However, this value remains within the acceptable range as recommended by J. F. Hair et al. (2019), particularly when other psychometric indicators—composite reliability (CR = 0.934) and average variance extracted (AVE = 0.612)—exceeded recommended thresholds. Additionally, the item was conceptually aligned with the construct, and its retention improved the overall content coverage and dimensional representation of AI orientation. Therefore, it was retained for theoretical and statistical coherence.

The discriminant validity was also analyzed using two tests, the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT) (Fornell & Larcker, 1981; Henseler et al., 2015; Dirgiatmo, 2023). Table 3 shows that the Fornell-Larcker value is higher than the correlation, and the HTMT values are less than 0.90, as suggested by past studies. Thus, the discriminant validity benchmarks were met.

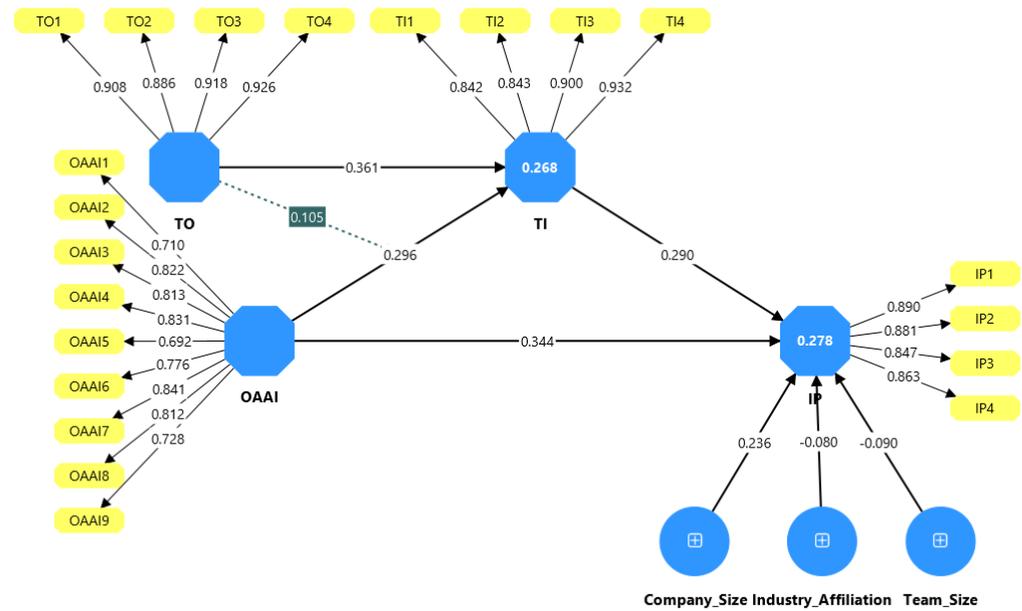


Figure 2. Measurement model displaying item loadings for AI orientation, team innovativeness, technology orientation, and innovation performance. TO: Technology Orientation; OAAI: Orientation to Adopt AI; TI: Team Innovativeness; IP: Innovation Performance.

Table 3. Discriminant validity.

Fornell-Larcker Criterion				
Constructs	OAAI	IP	TI	TO
OAAI	0.782			
PI	0.449	0.870		
TI	0.415	0.418	0.880	
TO	0.428	0.418	0.434	0.910
Heterotrait-Monotrait (HTMT) Ratio				
Constructs	OAAI	IP	TI	TO
OAAI				
PI	0.494			
TI	0.443	0.462		
TO	0.457	0.458	0.471	
TO × OAAI	0.267	0.145	0.085	0.405

4.4. Structural Model

The structural model was assessed using the 5000-bootstrap structure in SmartPLS. The first coefficient of determination (R^2) was evaluated, and the findings showed that innovation performance was altered by 26.6% due to team innovativeness and orientation to adopt AI models, while a 27.8% alteration was found in team innovativeness resulting from orientation to adopt AI models, as depicted in Table 4. The R^2 values should be higher than 0.1 (Yaacob et al., 2021). Likewise, the values of predictive relevance (Q^2) should be greater than zero, and the values of Q^2 in this study should be greater than 0, showing significant predictive relevance (Falk & Miller, 1992; Yaacob et al., 2021), as depicted in Table 4. Standardized root mean square (SRMR) was adopted to test model fit. According to past studies, the value of SRMR must be less than 0.08 (Henseler et al., 2015; Shi et al.,

2022). The SRMR value in this study is 0.059, which falls within the acceptable range, as depicted in Table 4. Bentler and Bonett’s (1980) normed fit index (NFI) was among the first fit metrics presented in the SEM literature. It assesses the recommended model’s χ^2 value and compares it against a significant reference point. Values of the NFI greater than 0.80 often show a good fit (Lohmöller, 2013; Sathyanarayana & Mohanasundaram, 2024). The NFI value for this study is 0.846, which indicates an acceptable fit, as shown in Table 4. Also, effect size (f^2) was assessed, and the values were considered substantial effects (0.125 for innovation performance and 0.097 for team innovativeness). According to Cohen (2013), the threshold values show substantial effects (0.02, 0.15, and 0.35, indicating small, medium, and substantial effects, respectively).

Table 4. Saturated model.

Constructs	R ²	Q ²	F ²	SRMR	NFI
Innovation Performance	0.278	0.224	0.125	0.059	0.846
Team Innovativeness	0.268	0.244	0.097		

Note: R² = Coefficient of Determination, Q² = Predictive Relevance, SRMR = Standardized Root Mean Square Residual, NFI = Normed Fit Index, F² = Effect size.

4.5. Hypothesis Testing

The structural model analysis assessed the proposed hypothesis using a 5000 bootstrap method using Smart-PLS software (Leguina, 2015; J. F. Hair et al., 2016). The findings in Table 5 and Figure 3 indicate that orientation to adopt AI models has a positive and significant impact on team innovativeness ($\beta = 0.296, t = 5.540, p < 0.001$) and innovation performance ($\beta = 0.344, t = 5.703, p < 0.001$). Thus, H1 and H2 were accepted. This outcome aligns with the existing literature, which shows that AI adoption plays a significant role in enhancing team dynamics and overall innovation performance (Shahnaei & Long, 2015; Nambisan, 2017; Belhadi et al., 2024). Moreover, team innovativeness had a positive and significant influence on innovation performance ($\beta = 0.290, t = 4.866, p = 0.000$), supporting the acceptance of H3. The results indicate that all three direct relationships were significant for forward innovation performance.

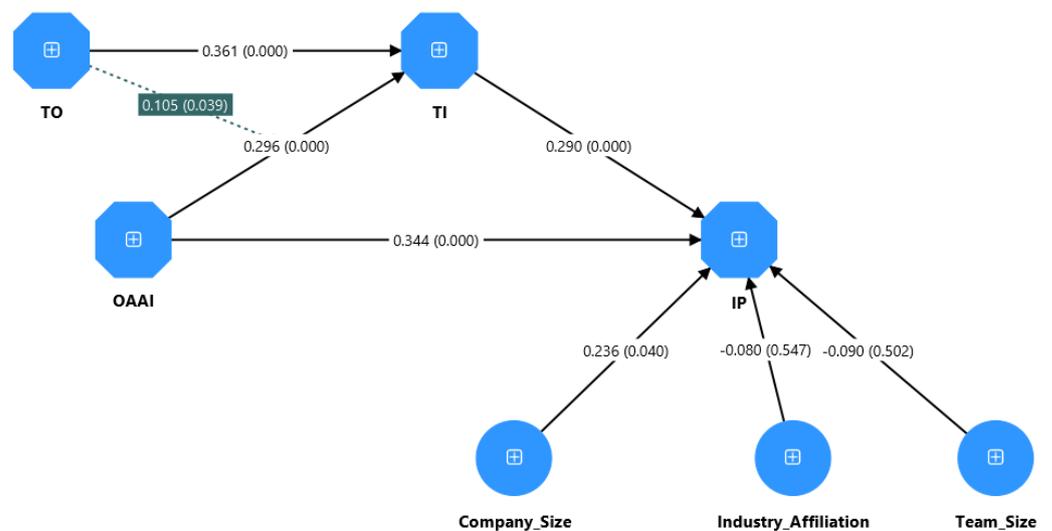


Figure 3. SEM analysis showing the path relationship between the proposed hypotheses.

Table 5. Testing of hypotheses results.

	Control Variables	Original Sample (O)	T statistics	p Values	Confidence Interval (2.5%; 97.5%)
	Company Size -> IP	0.236	2.049	0.040	0.006, 0.458
	Industry Affiliation -> IP	-0.080	0.602	0.547	-0.335, 0.180
	Team Size -> IP	-0.090	0.671	0.502	-0.351, 0.174
Hypothesis Relationship	Direct Effects				
H1	OAAI -> TI	0.296	5.540	0.000	0.189, 0.396
H2	OAAI -> IP	0.344	5.703	0.000	0.224, 0.460
H3	TI -> IP	0.290	4.866	0.000	0.172, 0.404
	Mediating Effect				
H4	OAAI -> TI -> IP	0.086	3.235	0.001	0.041, 0.143
	Moderating Effect				
H5	TO × OAAI -> TI	0.105	2.063	0.039	0.006, 0.205

Furthermore, we examined the mediating role of team innovativeness in the relationship between orientation towards adopting AI models and innovation performance. Nitzl et al. (2016) suggested that indirect effects can be considered significant when the confidence intervals for the lower and upper bounds of the indirect pathways do not include zero. As indicated in Table 5, the indirect effect meets this criterion, confirming its significance ($\beta = 0.086$, $t = 3.235$, $p = 0.001$). Consequently, team innovativeness has an indirect impact on the orientation to adopt AI models by fostering perceptions of innovation performance. According to TAM, the positive mediating influence of team innovativeness can be attributed to the perceived usefulness and ease of use of AI methods. When teams perceive AI tools as valuable and convenient to use, they are more likely to integrate them into their innovation processes, thereby improving their overall performance (Marikyan & Papagiannidis, 2023). Lastly, we also examined the moderating role of technology orientation on the relationship between orientation to adopt AI models and team innovativeness, which was positive and significant ($\beta = 0.105$, $t = 2.063$, $p = 0.039$). Figure 4 illustrates that the simple slope plot reveals the relationship between the independent, moderator, and dependent variables. The dotted lines specify that technology orientation moderated the slope for the connection between orientation to adopt AI models and team innovativeness. This is reflected by the fact that the link becomes more robust when technology orientation for team innovativeness is high. This aligns with TAM, which refers to the fact that a strong technology orientation enhances the perceived usefulness and ease of AI use, making it easier for teams to adapt to innovative tools. Firms with technology orientation are better prepared to implement AI usefully, leading to increased team innovativeness and innovation performance (Upadhyay et al., 2022). Thus, H4 and H5 were also accepted.

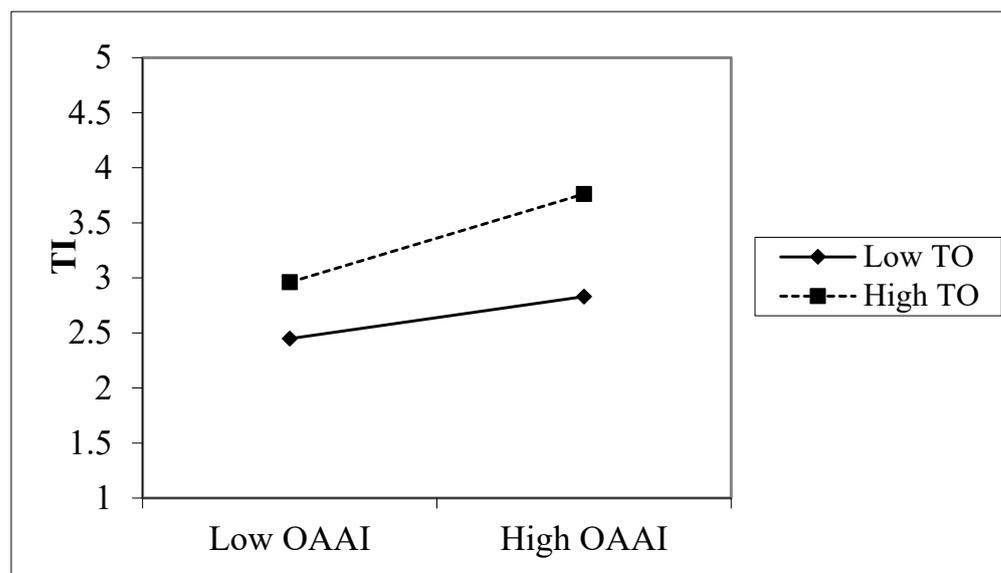


Figure 4. Moderating effect of Technology Orientation (TO) on the relationship between Orientation to Adopt AI Models (OAAI) and Team Innovativeness (TI), showing how higher TO strengthens the positive relationship between OAAI and TI within MNCs, thereby supporting the moderated mediation hypothesis of the study.

5. Discussion

This study aimed to investigate the relationship between MNCs operating in China and team innovativeness, technological orientation, innovation performance, and orientation towards adopting AI models. The focus of the research questions was to decide how these constructs affect the results of innovation in MNCs. The study's key findings demonstrated substantial associations between team innovativeness, innovation performance, and orientation towards adopting AI models. First, findings show that an inclination to adopt AI models has a significant impact on team innovativeness and performance. This finding is consistent with the study's theoretical framework, highlighting the importance of MNCs adopting innovative technologies to drive innovation (Shahnaei & Long, 2015; Nambisan, 2017). Furthermore, it was found that team innovativeness significantly predicted innovation performance, emphasizing the critical role that team dynamics and creativity play (Jin & Sun, 2010; F. J.-L. Chen et al., 2013; Chatzi et al., 2023).

Additionally, the study demonstrated that team innovativeness partially mediates the relationship between innovation performance and orientation towards adopting AI models. According to this research, adopting AI technology can substantially influence innovation results when teams are encouraged to cultivate an innovative culture. These results align with earlier studies (Bamgbade et al., 2022; Marcinkevicius & Vilkas, 2023) that emphasized the value of internal talents and team dynamics in fostering business creativity. Additionally, the study identified a robust moderating influence of technology orientation on the relationship between team innovativeness and the adoption of AI models. Matching organizational strategy and readiness with technology adoption is crucial to maximize innovation results (Gatignon & Xuereb, 1997; Benlian et al., 2015; Uren & Edwards, 2023). According to TAM, addressing these issues involves enhancing the perceived usefulness and ease of use of AI tools. By confirming that AI systems are user-friendly and functional, firms can minimize resistance to adoption and stimulate the effective integration of such technologies into their operations. This includes offering detailed training and assistance to guide employees in understanding and using AI techniques usefully, thus developing a more innovative culture. Additionally, integrating AI options with organizational objectives and capabilities can help create a conducive work environment for innovation. By

leveraging TAM, MNCs can steadily address challenges to AI adoption and improve their innovation performance. In short, the study questions were successfully addressed, and the main conclusions were substantially corroborated by current research, providing insightful information on the forces that drive innovation in MNCs operating in China.

5.1. Theoretical Implications

This study's findings contribute to the theoretical understanding of the relationships between team innovativeness, technology orientation, innovation performance, and the adoption of AI models. The study incorporates multilevel actors' participation, affordability, and the capacity to produce new digital artifacts and services into the literature on AI adoption by operationalizing the orientation to adopt AI models through dimensions such as openness, affordance, and generativity. These features reinforce the theoretical foundation for AI acceptance, which aligns with earlier research (Rothwell et al., 1974; Turner & Fauconnier, 1999; Faraj & Azad, 2012; Upadhyay et al., 2023). The research also clarifies how team inventiveness influences innovation performance. Building on earlier studies (Bamgbade et al., 2022) that emphasized the importance of developing novel concepts, procedures, and products for organizational performance, this study highlights MNCs' proactive adoption of cutting-edge technology and their ability to utilize it to meet changing consumer demands. This demonstrates the importance of teams being inventive to support organizational responsiveness and flexibility in shifting market conditions.

Furthermore, the results regarding technology orientation offer significant insights into the tactical application of cutting-edge technologies to enhance organizational efficiency. The study enhances knowledge on technology adoption and utilization in organizational settings by examining aspects such as the application of innovative technology, initiative in offering creative solutions, and the ability to create and market innovative products (Bamgbade et al., 2022). The study also closes theoretical gaps by demonstrating how team innovativeness mediates the relationship between innovation performance and orientation towards adopting AI models. According to this research, MNCs that cultivate an innovative culture benefit more from AI adoption in terms of innovation results, which is consistent with the technology acceptance model of the company (Jansen et al., 2006; Eitle, 2024).

Furthermore, the study presents empirical findings indicating that technology orientation moderates the relationship between team innovativeness and orientation towards adopting AI models. Firms with a strong technology orientation are more adept at leveraging AI to enhance team innovativeness, which, in turn, improves innovation performance. This moderation influence suggests that a higher technology orientation enables teams to utilize AI methods more effectively, fostering an environment where innovative solutions can thrive. The past literature has demonstrated that a robust technology orientation fosters platform and business ecosystem innovation, creating a suitable context for team development (Gatignon & Xuereb, 1997; Benlian et al., 2015; Battisti et al., 2022). The integration of technology and readiness with AI adoption is crucial for enhancing innovation outcomes, underscoring the importance of organizational competence and readiness in leveraging AI for innovation (Upadhyay et al., 2022). By combining various aspects of AI adoption, team innovativeness, technology orientation, and innovation performance within the framework of MNCs in China, the study advances theoretical knowledge overall. The results provide managers seeking to enhance innovation skills within their companies with valuable insights and a theoretical understanding of the complex relationships between these variables.

5.2. Practical Implications

This study provides practical insights across three dimensions: managerial guidance for MNCs, policy recommendations for innovation ecosystems, and the strategic role of governments in fostering AI-driven innovation.

Managerial Guidance for MNCs

MNCs operating in dynamic markets, such as China, can benefit from strategically aligning AI adoption with internal innovation goals. To achieve this, managers should invest in developing AI-related skills and capabilities across their teams, while fostering a culture of openness, experimentation, and knowledge sharing. Emphasizing dimensions such as generativity and affordance in AI tools enables teams to prototype, test, and scale innovations effectively. Furthermore, high levels of technology orientation should be nurtured through continuous training, digital infrastructure, and strategic alignment to enhance the team's capacity for innovation.

Policy Recommendations for Innovation Ecosystems

Policymakers can promote sustainable innovation by fostering favorable environments for AI investment, research, and development. Initiatives such as public-private partnerships, innovation hubs, and digital upskilling programs can incentivize both domestic and multinational firms to engage in co-creative and inclusive innovation practices. Encouraging inter-organizational collaboration and technological diffusion will also help expand the impact of MNC-led innovation across the broader economy.

Strategic Role of Governments in AI-Driven Innovation

Governments play a vital role in embedding AI innovation into national development strategies. Investments in digital infrastructure, AI governance, and data protection frameworks are crucial to ensure the ethical and effective adoption of AI. By supporting cross-sector AI initiatives, funding applied AI research, and enabling access to AI resources for SMEs, governments can enhance national competitiveness and technological resilience. Prioritizing digital inclusion and AI literacy ensures that the benefits of innovation are distributed equitably.

Collectively, these practical recommendations can empower firms, policymakers, and governments to harness AI's transformative potential in achieving sustained innovation and economic development.

5.3. Limitations and Future Research

This study examined the association between orientation towards adopting AI models, team innovativeness, technology orientation, and innovation performance in MNCs. However, the study that was undertaken also had some limitations. First, the use of self-administered online surveys, which may restrict the generalizability of the findings, is one of the study's limitations. Subsequent investigations may employ mixed-methods techniques, including case studies and interviews, to gain a deeper understanding of the processes driving AI innovation and adoption in multinational corporations. Second, the study's exclusive focus on MNCs in China limited the applicability of the findings to other cultural contexts. Further investigation into the cultural variations in AI adoption and innovation processes may be necessary to gain a deeper understanding of the topic. Moreover, the research employed a cross-sectional design, which hinders the ability to draw conclusions about causality and analyze the dynamic interactions between variables over time. Longitudinal studies may be employed in future research to investigate the evolution of AI innovation and adoption over time, as well as their long-term impact on organizational performance. Furthermore, the study used perceptual assessments of

variables susceptible to social desirability effects and standard method bias. Objective measurements, such as financial performance metrics or innovation output, could be used in future studies to provide more substantial evidence of the links studied.

To capture the diversity of AI adoption and innovation processes in future research, researchers should also broaden the study's scope to encompass a broader range of industries and geographical areas. Future studies may further investigate the moderating impacts of environmental elements on the links between AI adoption, innovation, and performance outcomes, such as organizational culture and the regulatory environment. Ultimately, longitudinal studies can provide valuable insights into the temporal dynamics of AI adoption and innovation processes, enabling researchers to identify key turning points and intervention points for enhancing organizational performance.

Finally, in refining the team innovativeness scale, attention was provided to eliminating ambiguities between team- and firm-level outcomes. Future research may continue validating these team-specific items across industries to ensure robust measurement consistency.

6. Conclusions

This study examined the impact of AI adoption orientation on innovation performance in multinational corporations (MNCs), focusing on the mediating role of team innovativeness and the moderating effect of technology orientation. The findings demonstrate that AI orientation positively impacts both team innovativeness and innovation performance, with technology orientation amplifying these relationships.

The study contributes theoretically by integrating TAM, TOE, and STS frameworks to explain AI-driven innovation outcomes, and it offers empirical evidence on the importance of team dynamics and technological readiness in the context of MNCs operating in China.

Future research should consider longitudinal designs, multi-industry sampling, and cross-cultural comparisons to further explore the evolving dynamics of AI integration and innovation performance across diverse organizational environments.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Evidence-based Research Center for Educational Assessment (ERCEA), the institutional review board (IRB) at Jiangsu University (Project identification code: iJSDX2025041700) on 17 April 2025.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Construct	Items	Sources	
Orientation to Adopt AI	OAAI-O1: "AI allows multilevel actors' participation, contribution, process and outcomes"	(Rothwell et al., 1974; Upadhyay et al., 2023)	
	OAAI-O2: "Actors' participation, contribution, process and outcomes are supported by AI"		
	OAAI-O3: "AI provides various ways to collaborate, participate, use process to generate outcomes"	(Faraj & Azad, 2012; Upadhyay et al., 2023)	
	OAAI-A1: "AI is affordable in a use context"		
	OAAI-A2: "I require AI in a use context"		
	OAAI-A3: "In a use context, AI is affordable"		
	OAAI-G1: "AI helps to create new digital artefacts, products and services"		(Turner & Fauconnier, 1999; Upadhyay et al., 2023)
	OAAI-G2: "AI provide APIs and libraries to build new digital artefacts, products and services"		
OAAI-G3: "I can develop new digital artefacts, products and services using AI APIs and Libraries"			
Team Innovativeness	TI1: "Our team creates new ideas, processes, products, and systems that are critical to our team's innovation success."	(Bamgbade et al., 2022; Upadhyay et al., 2023)	
	TI2: "Our team tends to be an early adopter of the innovative technologies."		
	TI3: "Our team actively seeks opportunities to apply innovative ideas and solutions."		
	TI4: "Our team proactively uses innovative technologies to address changing project or task needs."		
Technology Orientation	TO1: "Our firm uses innovative technologies in providing solutions"	(Bamgbade et al., 2022)	
	TO2: "Our firm uses state of the art of technology for products development"		
	TO3: "Our firm is very proactive in providing innovative solutions to respond to clients' needs"		
	TO4: "Our firm has the will and the capacity to build and market innovative solutions"		
Innovation Performance	IP1: "Highly responsive attitude towards environmental changes"	(Jansen et al., 2006; Tian et al., 2021)	
	IP2: "Actively innovates for products and services"		
	IP3: "Develops manufacturing process to improve quality and lower costs"		
	IP4: "Focuses on developing marketing process to improve products services"		

References

- Ahrholdt, D. C., Gudergan, S. P., & Ringle, C. M. (2019). Enhancing loyalty: When improving consumer satisfaction and delight matters. *Journal of Business Research*, 94, 18–27. [CrossRef]
- Al-Emran, M., & Granić, A. (2021). Is it still valid or outdated? A bibliometric analysis of the technology acceptance model and its applications from 2010 to 2020. In *Recent advances in technology acceptance models and theories* (pp. 1–12). Springer.
- Al-Emran, M., & Griffy-Brown, C. (2023). The role of technology adoption in sustainable development: Overview, opportunities, challenges, and future research agendas. *Technology in Society*, 73, 102240.
- Al-Nuaimi, M. N., & Al-Emran, M. (2021). Learning management systems and technology acceptance models: A systematic review. *Education and Information Technologies*, 26(5), 5499–5533. [CrossRef]
- Amusan, L., & Ajibola, K. (2017). Employees' attitudes towards innovation in workplace: An examination of the impacts of new technology on multinational corporations (MNCs). *African Journal of Public Affairs*, 9(7), 1–12.
- Anderson, N., Potočnik, K., & Zhou, J. (2014). Innovation and creativity in organizations: A state-of-the-science review, prospective commentary, and guiding framework. *Journal of Management*, 40(5), 1297–1333. [CrossRef]
- Awa, H. O. (2019). Some antecedent factors that shape actors' adoption of enterprise systems. *Enterprise Information Systems*, 13(5), 576–600. [CrossRef]

- Aydin, H. (2021). Market orientation and product innovation: The mediating role of technological capability. *European Journal of Innovation Management*, 24(4), 1233–1267. [CrossRef]
- Bahoo, S., Cucculelli, M., & Qamar, D. (2023). Artificial intelligence and corporate innovation: A review and research agenda. *Technological Forecasting and Social Change*, 188, 122264. [CrossRef]
- Bamgbade, J., Nawari, M., Kamaruddeen, A., Adeleke, A., & Salimon, M. G. (2022). Building sustainability in the construction industry through firm capabilities, technology and business innovativeness: Empirical evidence from Malaysia. *International Journal of Construction Management*, 22(3), 473–488. [CrossRef]
- Battisti, S., Agarwal, N., & Brem, A. (2022). Creating new tech entrepreneurs with digital platforms: Meta-organizations for shared value in data-driven retail ecosystems. *Technological Forecasting and Social Change*, 175, 121392.
- Belderbos, R., Leten, B., & Suzuki, S. (2023). International R&D and MNCs' innovation performance: An integrated approach. *Journal of International Management*, 29(6), 101083. [CrossRef]
- Belhadi, A., Mani, V., Kamble, S. S., Khan, S. A. R., & Verma, S. (2024). Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: An empirical investigation. *Annals of Operations Research*, 333(2), 627–652. [CrossRef]
- Benlian, A., Hilkert, D., & Hess, T. (2015). How open is this platform? The meaning and measurement of platform openness from the complementors' perspective. *Journal of Information Technology*, 30, 209–228. [CrossRef]
- Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, 88(3), 588–606. [CrossRef]
- Bereznoy, A., Meissner, D., & Scuotto, V. (2021). The intertwining of knowledge sharing and creation in the digital platform based ecosystem. A conceptual study on the lens of the open innovation approach. *Journal of Knowledge Management*, 25(8), 2022–2042. [CrossRef]
- Berraies, S., & Chouiref, A. (2023). Exploring the effect of team climate on knowledge management in teams through team work engagement: Evidence from knowledge-intensive firms. *Journal of Knowledge Management*, 27(3), 842–869. [CrossRef]
- Bogers, M., Zobel, A. K., & Afuah, A. (2024). The role of team innovativeness in digital transformation. *Technovation*, 125, 102–118.
- Brandmeier, R. A., & Rupp, F. (2024). *Structured innovation*. Springer. [CrossRef]
- Brem, A., Giones, F., & Werle, M. (2021). The AI digital revolution in innovation: A conceptual framework of artificial intelligence technologies for the management of innovation. *IEEE Transactions on Engineering Management*, 70(2), 770–776. [CrossRef]
- Broekhuizen, T. L., Emrich, O., Gijzenberg, M. J., Broekhuis, M., Donkers, B., & Sloot, L. M. (2021). Digital platform openness: Drivers, dimensions and outcomes. *Journal of Business Research*, 122, 902–914. [CrossRef]
- Burciu, A., Kicsi, R., Buta, S., State, M., Burlac, I., Chifan, D. A., & Ipsalat, B. (2023). The Study of the Relationship among GCI, GII, Disruptive Technology, and Social Innovations in MNCs: How Do We Evaluate Financial Innovations Made by Firms? A Preliminary Inquiry. *FinTech*, 2(3), 572–613. [CrossRef]
- Chatterjee, S., Moody, G., Lowry, P. B., Chakraborty, S., & Hardin, A. (2020). Information technology and organizational innovation: Harmonious information technology affordance and courage-based actualization. *The Journal of Strategic Information Systems*, 29(1), 101596. [CrossRef]
- Chatzi, S., Nikolaou, I., & Anderson, N. (2023). Team personality composition and team innovation implementation: The mediating role of team climate for innovation. *Applied Psychology*, 72(2), 769–796. [CrossRef]
- Chen, F. J.-L., Campbell-Bush, E. M., Wu, Z., & Wu, X. (2013). Teams as innovative systems: Multilevel motivational antecedents of innovation in R&D teams. *Journal of Applied Psychology*, 98(6), 1018. [CrossRef]
- Chen, W., & Kamal, F. (2016). The impact of information and communication technology adoption on multinational firm boundary decisions. *Journal of International Business Studies*, 47(1), 563–576. [CrossRef]
- Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, 41(2), 745–783. [CrossRef]
- Chin, T., Jin, J., Wang, S., Caputo, F., & Rowley, C. (2023). Cross-cultural legitimacy for orchestrating ecosystem-based business models in China: A Yin-Yang dialectical systems view. *Asia Pacific Business Review*, 1–24. [CrossRef]
- Chowdhury, S., Budhwar, P., Dey, P. K., Joel-Edgar, S., & Abadie, A. (2022). AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework. *Journal of Business Research*, 144, 31–49. [CrossRef]
- Chuang, L.-M. (2005). An empirical study of the construction of measuring model for organizational innovation in Taiwanese high-tech enterprises. *Journal of American Academy of Business*, 6(1), 299–304.
- Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*. Routledge.
- Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108–116.
- Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. Massachusetts Institute of Technology.

- Dawes, J. (2008). Do data characteristics change according to the number of scale points used? An experiment using 5-point, 7-point and 10-point scales. *International Journal of Market Research*, 50(1), 61–104. [[CrossRef](#)]
- Dąbrowska, J., Almpnopoulou, A., Brem, A., Chesbrough, H., Cucino, V., Di Minin, A., Giones, F., Hakala, H., Marullo, C., Mention, A.-L., Mortara, L., Nørskov, S., Nylund, P. A., Oddo, C. M., Radziwon, A., & Ritala, P. (2022). Digital transformation, for better or worse: A critical multi-level research agenda. *R&D Management*, 52(5), 930–954.
- Dincelli, E., & Yayla, A. (2022). Immersive virtual reality in the age of the Metaverse: A hybrid-narrative review based on the technology affordance perspective. *The Journal of Strategic Information Systems*, 31(2), 101717. [[CrossRef](#)]
- Dirgiatmo, Y. (2023). Testing the discriminant validity and heterotrait–monotrait ratio of correlation (HTMT): A case in Indonesian SMEs. In *Macroeconomic Risk and growth in the southeast Asian countries: Insight from Indonesia* (pp. 157–170). Emerald Publishing Limited.
- Dobre, M. (2022). *An evaluation of technological, organizational and environmental determinants of emerging technologies adoption driving SMEs' competitive advantage* [Doctoral dissertation, University of Bradford].
- Edmondson, A. C., & Lei, Z. (2024). Psychological safety and team innovation. *Academy of Management Review*, 49(1), 78–95.
- Eitle, R. (2024). *Cultivating AI: The role of corporate culture in AI integration an empirical study on cultural dimensions and their impact on the adoption and acceptance of AI in consulting companies* [Master's thesis, Universidade Catolica Portuguesa (Portugal)].
- Falk, R. F., & Miller, N. B. (1992). *A primer for soft modeling*. University of Akron Press.
- Faraj, S., & Azad, B. (2012). The materiality of technology: An affordance perspective. *Materiality and Organizing: Social Interaction in a Technological World*, 237(1), 237–258.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. [[CrossRef](#)]
- Froese, F. J., Sutherland, D., Lee, J. Y., Liu, Y., & Pan, Y. (2019). Challenges for foreign companies in China: Implications for research and practice. *Asian Business & Management*, 18, 249–262. [[CrossRef](#)]
- Gacheri, N. M. (2018). *The effects of organizational culture on the adoption of technology: A study of multinational corporations in Nairobi*. Strathmore University.
- Gatignon, H., & Xuereb, J.-M. (1997). Strategic orientation of the firm and new product performance. *Journal of Marketing Research*, 34(1), 77–90. [[CrossRef](#)]
- Goncalves, M., & Cornelius Smith, E. (2018). Social media as a data gathering tool for international business qualitative research: Opportunities and challenges. *Journal of Transnational Management*, 23(2–3), 66–97. [[CrossRef](#)]
- Gong, Y., Wang, M., & Huang, J. (2023). AI adoption and team creativity: The mediating role of Cognitive flexibility. *Journal of Business Research*, 158, 113–125.
- Goni, J. I. C., & Van Looy, A. (2022). Process innovation capability in less-structured business processes: A systematic literature review. *Business Process Management Journal*, 28(3), 557–584. [[CrossRef](#)]
- González-Romá, V., Hernández, A., & Ramos, J. (2024). Team innovativeness and performance: A meta-analysis. *Journal of Business Research*, 172, 114–129.
- Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems*, 117(3), 442–458. [[CrossRef](#)]
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, 19(2), 139–152. [[CrossRef](#)]
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. [[CrossRef](#)]
- Hair, J. F., Jr., Sarstedt, M., Matthews, L. M., & Ringle, C. M. (2016). Identifying and treating unobserved heterogeneity with FIMIX-PLS: Part I—method. *European Business Review*, 28(1), 63–76.
- Harvey, J. F., Cromwell, J. R., Johnson, K. J., & Edmondson, A. C. (2023). The dynamics of team learning: Harmony and rhythm in teamwork arrangements for innovation. *Administrative Science Quarterly*, 68(3), 601–647. [[CrossRef](#)]
- Hasija, A., & Esper, T. L. (2022). In artificial intelligence (AI) we trust: A qualitative investigation of AI technology acceptance. *Journal of Business Logistics*, 43(3), 388–412. [[CrossRef](#)]
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43, 115–135.
- Huang, Z., Sindakis, S., Aggarwal, S., & Thomas, L. (2022). The role of leadership in collective creativity and innovation: Examining academic research and development environments. *Frontiers in psychology*, 13, 1060412. [[CrossRef](#)]
- Iqbal, S., Moleiro, J., Nuno Mata, M., Naz, S., Akhtar, S., & Abreu, A. (2021). Linking entrepreneurial orientation with innovation performance in SMEs; the role of organizational commitment and transformational leadership using smart PLS-SEM. *Sustainability*, 13(8), 4361. [[CrossRef](#)]

- Jaiswal, A., Arun, C. J., & Varma, A. (2022). Rebooting employees: Upskilling for artificial intelligence in multinational corporations. *The International Journal of Human Resource Management*, 33(6), 1179–1208. [CrossRef]
- Jansen, J. J., Van-Den Bosch, F. A., & Volberda, H. W. (2006). Exploratory innovation, exploitative innovation, and performance: Effects of organizational antecedents and environmental moderators. *Management Science*, 52(11), 1661–1674. [CrossRef]
- Jaradat, Z., AL-Hawamleh, A. M., & Altarawneh, M. (2025). Investigating the impact of technological orientation and innovation orientation on the sustainability and development the industrial sector. *Competitiveness Review: An International Business Journal*, 35(2), 409–433. [CrossRef]
- Jenkins, R. (2022). *How China is reshaping the global economy: Development impacts in Africa and Latin America*. Oxford University Press.
- Jin, L., & Sun, H. (2010). The effect of researchers' interdisciplinary characteristics on team innovation performance: Evidence from university R&D teams in China. *The International Journal of Human Resource Management*, 21(13), 2488–2502. [CrossRef]
- Jorzik, P., Klein, S. P., Kanbach, D. K., & Kraus, S. (2024). AI-driven business model innovation: A systematic review and research agenda. *Journal of Business Research*, 182, 114764. [CrossRef]
- Kock, F., Berbekova, A., & Assaf, A. G. (2021). Understanding and managing the threat of common method bias: Detection, prevention and control. *Tourism management*, 86, 104330.
- Kudina, O., & van de Poel, I. (2024). A sociotechnical system perspective on AI. *Minds and Machines*, 34(3), 21. [CrossRef]
- Kumar, S., Lim, W. M., Sivarajah, U., & Kaur, J. (2023). Artificial intelligence and blockchain integration in business: Trends from a bibliometric-content analysis. *Information Systems Frontiers*, 25, 871–896.
- Lamarre, E., Chheda, S., Riba, M., Genest, V., & Nizam, A. (2023). *The value of digital transformation*. Available online: <https://hbr.org/2023/07/the-value-of-digital-transformation> (accessed on 6 January 2025).
- Leguina, A. (2015). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Taylor & Francis.
- Liao, Z., Liu, Y., & Lu, Z. (2023). Market-oriented environmental policies, environmental innovation, and firms' performance: A grounded theory study and framework. *Journal of Environmental Planning and Management*, 66(8), 1794–1811. [CrossRef]
- Liu, T., & Li, X. (2022). How do MNCs conduct local technological innovation in a host country? An examination from subsidiaries' perspective. *Journal of International Management*, 28(3), 100951.
- Lohmöller, J.-B. (2013). *Latent variable path modeling with partial least squares*. Springer Science & Business Media.
- Lola, W., Joe, N., Jeongmin, S., Kweilin, E., Nick, L., Franck, L. D., & Peixi, W. (2023). *The China imperative for multinational companies*. Available online: <https://www.mckinsey.com/mgi/our-research/the-china-imperative-for-multinational-companies> (accessed on 2 December 2024).
- Luan, X., Wang, X., & Li, N. (2024). Open innovation, digital transformation, the mediating effect of technological maturity and diversity. *Technology Analysis & Strategic Management*, 1–16. [CrossRef]
- Lyytinen, K., Sørensen, C., & Tilson, D. (2017). Generativity in digital infrastructures: A research note. In *The Routledge companion to management information systems* (pp. 253–275). Routledge.
- Majchrzak, Y. N., Peers, M. J. L., Studd, E. K., Menzies, A. K., Walker, P. D., Shiratsuru, S., McCaw, L. K., Boonstra, R., Humphries, M., Jung, T. S., Kenney, A. J., Krebs, C. J., Murray, D. L., & Boutin, S. (2022). Balancing food acquisition and predation risk drives demographic changes in snowshoe hare population cycles. *Ecology Letters*, 25(4), 981–991. [CrossRef]
- Marcinkevicius, G., & Vilkas, M. (2023). The affordances of digital technologies for business processes integration. *Journal of Systems and Information Technology*, 25(1), 74–90. [CrossRef]
- Mariani, M. M., Machado, I., Magrelli, V., & Dwivedi, Y. K. (2023). Artificial intelligence in innovation research: A systematic review, conceptual framework, and future research directions. *Technovation*, 122, 102623. [CrossRef]
- Marikyan, D., & Papagiannidis, S. (2023). *Technology acceptance model. TheoryHub book: Technology acceptance model*. ISBN 9781739604400. Available online: <https://open.ncl.ac.uk/> (accessed on 12 December 2024).
- Marion, T. J., & Fixson, S. K. (2021). The transformation of the innovation process: How digital tools are changing work, collaboration, and organizations in new product development. *Journal of Product Innovation Management*, 38(1), 192–215. [CrossRef]
- Mathieu, J. E. (2025). Reflections on the field of workgroup research and my personal journey. *Small Group Research*, 56(3), 451–468. [CrossRef]
- Maxwell, E. (2006). Open standards, open source, and open innovation: Harnessing the benefits of openness. *Innovations: Technology, Governance, Globalization*, 1(3), 119–176. [CrossRef]
- McAfee, A., Rock, D., & Brynjolfsson, E. (2023). How to capitalize on generative AI. *Harvard Business Review*, 101(6), 42–48.
- MCPRC. (2023). *Ministry of Commerce People's Republic of China (MOFCOM). 2019. MOFCOM department of foreign investment administration comments on China's absorption of foreign investment in January–December 2018*. Available online: https://english.mofcom.gov.cn/News/SpokesmansRemarks/art/2019/art_9724421b58c34857bd3ddae11c7777de.html (accessed on 20 December 2024).
- Mehboob, F., & Jawad, A. (2023). Technology adoption in small and medium enterprises: An integrated framework for success. *Management Science Research Archives*, 1(02), 70–80.

- Muhamad, L. F., Bakti, R., Febriyantoro, M. T., Kraugusteeliana, K., & Ausat, A. M. A. (2023). Do innovative work behavior and organizational commitment create business performance: A literature review. *Community Development Journal: Jurnal Pengabdian Masyarakat*, 4(1), 713–717.
- Mulvey, C., & Goncalves, M. (2022). An entrepreneur-driven technological innovation system for sustainable and inclusive international business: A case analysis of Lusophone-African MNEs. *Journal for International Business and Entrepreneurship Development*, 14(4), 404–433. [CrossRef]
- Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship Theory and Practice*, 41(6), 1029–1055. [CrossRef]
- Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy*, 48(8), 103773. [CrossRef]
- Nassani, A. A., Yousaf, Z., Grigorescu, A., & Popa, A. (2023). Green and Environmental marketing strategies and ethical consumption: Evidence from the tourism sector. *Sustainability*, 15(16), 12199. [CrossRef]
- NBSC. (2018). *National Bureau of Statistics of China. 1–8 number of business entities by region and status of registration 2017*. Retrieved from *China statistical yearbook 2018*. Available online: <https://www.stats.gov.cn/sj/ndsj/2018/indexeh.htm> (accessed on 2 February 2025).
- Nenonen, S., Storbacka, K., & Windahl, C. (2019). Capabilities for market-shaping: Triggering and facilitating increased value creation. *Journal of the Academy of Marketing Science*, 47, 617–639. [CrossRef]
- Nitzl, C., Roldan, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modelling, Helping researchers discuss more sophisticated models. *Industrial Management and Data Systems*, 116(9), 1849–1864. [CrossRef]
- Niu, F., & Jiang, Y. (2021). Economic sustainability of China's growth from the perspective of its resource and environmental supply system: National scale modeling and policy analysis. *Journal of Geographical Sciences*, 31(8), 1171–1186. [CrossRef]
- Pai, V., & Chandra, S. (2022). Exploring factors influencing organizational adoption of artificial intelligence (AI) in corporate social responsibility (CSR) initiatives. *Pacific Asia Journal of the Association for Information Systems*, 14(5), 4. [CrossRef]
- Pascucci, F., Savelli, E., & Gistri, G. (2023). How digital technologies reshape marketing: Evidence from a qualitative investigation. *Italian Journal of Marketing*, 2023(1), 27–58. [CrossRef]
- Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879. [CrossRef]
- Podsakoff, P. M., Podsakoff, N. P., Williams, L. J., Huang, C., & Yang, J. (2024). Common method bias: It's bad, it's complex, it's widespread, and it's not easy to fix. *Annual Review of Organizational Psychology and Organizational Behavior*, 11(1), 17–61. [CrossRef]
- Priyono, A., & Hidayat, A. (2024). Fostering innovation through learning from digital business ecosystem: A dynamic capability perspective. *Journal of Open Innovation: Technology, Market, and Complexity*, 10(1), 100196. [CrossRef]
- Purwanto, A., & Sudargini, Y. (2021). Partial least squares structural equation modeling (PLS-SEM) analysis for social and management research: A literature review. *Journal of Industrial Engineering & Management Research*, 2(4), 114–123.
- Ramaul, L., Ritala, P., & Ruokonen, M. (2024). Creational and conversational AI affordances: How the new breed of chatbots is revolutionizing knowledge industries. *Business Horizons*, 67(5), 615–627. [CrossRef]
- Rammer, C., Fernández, G. P., & Czarnitzki, D. (2022). Artificial intelligence and industrial innovation: Evidence from German firm-level data. *Research Policy*, 51(7), 104555. [CrossRef]
- Rayets, M., Tkachuk, V., Buryk, M., Kubitskyi, S., & Zhaldak, H. (2023). The role of leadership in stimulating innovation and the creative potential of the team. *Indian Journals*, 1603–1612. [CrossRef]
- Rehman, H. M., Adnan, N., & Moffett, S. (2024). Innovation bloom: Nurturing sustainability in urban manufacturing transformation amidst Industry 4.0 and aging workforce dynamics. *Annals of Operations Research*. Advanced online publication. [CrossRef]
- Rothwell, R., Freeman, C., Horlsey, A., Jervis, V., Robertson, A., & Townsend, J. (1974). SAPPHO updated-project SAPPHO phase II. *Research Policy*, 3(3), 258–291. [CrossRef]
- Russo, D., & Stol, K. J. (2021). PLS-SEM for software engineering research: An introduction and survey. *ACM Computing Surveys (CSUR)*, 54(4), 1–38.
- Salmons, J. (2022). Using social media in data collection: Designing studies with the qualitative e-research framework. *The SAGE Handbook of Social Media Research Methods*, 2, 112–126.
- Sathyanarayana, S., & Mohanasundaram, T. (2024). Fit indices in structural equation modeling and confirmatory factor analysis: Reporting guidelines. *Asian Journal of Economics, Business and Accounting*, 24(7), 561–577.
- Shahnaei, S., & Long, C. S. (2015). The review of improving innovation performance through human resource practices in organization performance. *Asian Social Science*, 11(9), 52–56. [CrossRef]
- Sharma, K. (2023). *Transformative change in global business after new world order* [Doctor's thesis, Selinus University Business School].
- Sharma, S., Islam, N., Singh, G., & Dhir, A. (2022). Why do retail customers adopt artificial intelligence (AI) based autonomous decision-making systems? *IEEE Transactions on Engineering Management*, 71, 1846–1861. [CrossRef]

- Shi, D., DiStefano, C., Maydeu-Olivares, A., & Lee, T. (2022). Evaluating SEM model fit with small degrees of freedom. *Multivariate Behavioral Research*, 57(2–3), 179–207. [\[CrossRef\]](#)
- Smagulova, G., & Goncalves, M. (2023). Technological innovation systems (TIS) as a tool for sustainable development of EdTech startups in developing countries: A case of the Republic of Kazakhstan. *Journal of Transnational Management*, 28(1–2), 74–100. [\[CrossRef\]](#)
- Somech, A., & Drach-Zahavy, A. (2000). Understanding extra-role behavior in schools: The relationships between job satisfaction, sense of efficacy, and teachers' extra-role behavior. *Teaching and Teacher Education*, 16(5–6), 649–659. [\[CrossRef\]](#)
- Strong, D. M., Volkoff, O., Johnson, S. A., Pelletier, L. R., Tulu, B., Bar-On, I., & Garber, L. (2014). A theory of organization-EHR affordance actualization. *Journal of the Association for Information Systems*, 15(2), 2. [\[CrossRef\]](#)
- Tanujaya, B., Prahmana, R. C. I., & Mumu, J. (2022). Likert scale in social sciences research: Problems and difficulties. *FWU Journal of Social Sciences*, 16(4), 89–101.
- Thomas, L. D., & Tee, R. (2022). Generativity: A systematic review and conceptual framework. *International Journal of Management Reviews*, 24(2), 255–278. [\[CrossRef\]](#)
- Tian, H., Iqbal, S., Anwar, F., Akhtar, S., Khan, M. A. S., & Wang, W. (2021). Network embeddedness and innovation performance: A mediation moderation analysis using PLS-SEM. *Business Process Management Journal*, 27(5), 1590–1609. [\[CrossRef\]](#)
- Tien-Shang Lee, L. (2008). The effects of team reflexivity and innovativeness on new product development performance. *Industrial Management & Data Systems*, 108(4), 548–569. [\[CrossRef\]](#)
- Tiwana, A. (2013). *Platform ecosystems: Aligning architecture, governance, and strategy*. Newnes.
- Turner, M., & Fauconnier, G. (1999). A mechanism of creativity. *Poetics Today*, 20(3), 397–418.
- Upadhyay, N., Upadhyay, S., Al-Debei, M. M., Baabdullah, A. M., & Dwivedi, Y. K. (2023). The influence of digital entrepreneurship and entrepreneurial orientation on intention of family businesses to adopt artificial intelligence: Examining the mediating role of business innovativeness. *International Journal of Entrepreneurial Behavior & Research*, 29(1), 80–115. [\[CrossRef\]](#)
- Upadhyay, N., Upadhyay, S., & Dwivedi, Y. K. (2022). Theorizing artificial intelligence acceptance and digital entrepreneurship model. *International Journal of Entrepreneurial Behavior & Research*, 28(5), 1138–1166. [\[CrossRef\]](#)
- Uren, V., & Edwards, J. S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, 68, 102588. [\[CrossRef\]](#)
- Vaithilingam, S., Ong, C. S., Moisescu, O. I., & Nair, M. S. (2024). Robustness checks in PLS-SEM: A review of recent practices and recommendations for future applications in business research. *Journal of Business Research*, 173, 114465. [\[CrossRef\]](#)
- Vrontis, D., Chaudhuri, R., & Chatterjee, S. (2022). Adoption of digital technologies by SMEs for sustainability and value creation: Moderating role of entrepreneurial orientation. *Sustainability*, 14(13), 7949. [\[CrossRef\]](#)
- Wang, K. J., Chen, Y. H., Lee, Y. C., & Lin, Z. Y. (2024). How is innovation empowered by design thinking for new product development? a case study in Taiwan. *Asian Journal of Technology Innovation*, 32(2), 437–455. [\[CrossRef\]](#)
- Wareham, J., Fox, P. B., & Cano Giner, J. L. (2014). Technology ecosystem governance. *Organization Science*, 25(4), 1195–1215. [\[CrossRef\]](#)
- West, M. A., & Sacramento, C. A. (2023). Team innovativeness: A dynamic capabilities perspective. *Organization Science*, 34(2), 210–228.
- Wright, K. B. (2005). Researching Internet-based populations: Advantages and disadvantages of online survey research, online questionnaire authoring software packages, and web survey services. *Journal of Computer-Mediated Communication*, 10(3), JCMC1034. [\[CrossRef\]](#)
- Wu, L., Sun, L., Chang, Q., Zhang, D., & Qi, P. (2022). How do digitalization capabilities enable open innovation in manufacturing enterprises? A multiple case study based on resource integration perspective. *Technological Forecasting and Social Change*, 184, 122019. [\[CrossRef\]](#)
- Xie, X., Wu, Y., & Tejerob, C. B. G. (2022). How responsible innovation builds business network resilience to achieve sustainable performance during global outbreaks: An extended resource-based view. *IEEE Transactions on Engineering Management*, 71, 12194–12208. [\[CrossRef\]](#)
- Yaacob, N. A., Ab Latif, Z., Mutalib, A. A., & Ismail, Z. (2021). Farmers' intention in applying food waste as fertilizer: Reliability and validity using Smart-PLS. *Asian Journal of Vocational Education and Humanities*, 2(2), 27–34. [\[CrossRef\]](#)
- Yang, J. Q., Blount, Y., & Amrollahi, A. (2024). Artificial intelligence adoption in a professional service industry: A multiple case study. *Technological Forecasting and Social Change*, 201, 123251. [\[CrossRef\]](#)
- Zahra, S. A., Liu, W., & Si, S. (2023). How digital technology promotes entrepreneurship in ecosystems. *Technovation*, 119, 102457. [\[CrossRef\]](#)
- Zeb, A., Akbar, F., Hussain, K., Safi, A., Rabnawaz, M., & Zeb, F. (2021). The competing value framework model of organizational culture, innovation and performance. *Business Process Management Journal*, 27(2), 658–683. [\[CrossRef\]](#)

-
- Zhao, S., Peerally, J. A., De Fuentes, C., & Gonzalez-Perez, M. A. (2024). The determinants of multinational enterprises' sustainable innovations. *International Business Review*, 33(5), 102318. [[CrossRef](#)]
- Zheng, Y. (2021). China's new foreign investment law and its contribution towards the country's development goals. *The Journal of World Investment & Trade*, 22(3), 388–428.

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