Doctoral Dissertation

An AI-Enabled Innovation Ecosystem Framework for Micro, Small, and Medium Enterprises in the Chinese Apparel Manufacturing Industry

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Abstract

Background

The fashion industry offers a compelling research scope with the evolution of artificial intelligence (AI) driving profound transformations in Industry 4.0 and 5.0 contexts. This is because of its mass production and its significant sustainability issues and challenges. This rapid advancement of AI in the traditional apparel manufacturing sector is accelerating innovation and transformation, as AI applications have been increasingly integrated into the industry in recent years. China's apparel industry is the world's largest apparel producer, which is predominantly composed of micro (fewer than 20 employees), small (21-300 employees), and medium-sized (301-1000 employees) enterprises (MSMEs). These MSMEs face challenges posed by AI-integrated technologies, particularly in adapting to digital transformation with limited resources and talents. At the same time, the Chinese government has introduced numerous policies to foster the application of AI in transforming traditional manufacturing in different areas of industry.

Rationale and Gaps

However, the favorable technological, industrial, and Chinese AI policy context has not attracted scholars' research interest in the Chinese apparel manufacturing sectors. While China has made outstanding achievements in applying AI in the apparel manufacturing sectors, the adoption of AI by traditional apparel manufacturers has progressed slowly. Therefore, it is necessary to investigate the factors that drive or hinder AI adoption. Among the 41 studies selected on technology adoption in manufacturing sectors from the Scopus database using preferred reporting items for systematic reviews and meta-analysis protocol, the study focused on a specific manufacturing sector with evidence from China is still relatively rare, with limited studies focus on specific manufacturing, and only one, focuses on MSMEs (Gap 1). Second, current studies have not examined the correlations between AI adoption and open innovation toward these emerging technologies applied to Chinese apparel manufacturing sectors through knowledge/resource-based views (Gap 2). Third, current research overlooks how apparel manufacturing companies collaborate with the government and universities to develop an innovation ecosystem considering the China's institution regulations and policy context (Gap 3).

Research Objectives

Therefore, this thesis's main research objective (***MRO)*** aims to develop a framework for propositions for micro, small, and medium-sized Chinese apparel manufacturing's innovation ecosystem. Accordingly, this thesis comprises two sub-research objectives (***SROs)***. ***SRO 1*** provides the initial exploratory correlations between AI adoption and open innovation from apparel manufacturing MSMEs managers' perspectives, identifying knowledge absorptive capacity (KACAP)'s significant impacts through an integrated and extended technology acceptance model (TAM) and technological, organizational, and environmental (TOE) framework; ***SRO 2*** aims to ground the required AI capabilities and barriers to adopting AI in Chinese apparel manufacturers, subsequently through coding the diverse perspectives from managers of the apparel industry, university staffs and leaders of apparel associations, thereby developing a novel triple-layer framework of AI-enabled innovation ecosystem, thus generating the conceptual propositions. This demonstrates a significant connection between ***SRO 1*** and ***SRO 2***, which achieves the ***MRO***.

Design/Methodology/Approach

Two studies fulfill the two ***SROs***. ***Study 1*** (to achieve ***SRO 1***) predominantly utilized a quantitative research approach, leveraging Partial Least Squares-Structural Equation Modeling (PLS-SEM) to empirically validate the antecedents of AI adoption and its consequential effects on knowledge absorptive capacity and open innovation capability. It collected 269 apparel MSMEs' top managers from June to August 2024. Through the rigorous statistical analysis of a substantial dataset, this study examined the causal relationships underpinning AI adoption and these critical innovation-related constructs, thereby furnishing robust empirical evidence that substantiates the proposed hypotheses. ***Study 2*** (to achieve ***SRO2***) adopted a qualitative research approach grounded in the principles of grounded theory to explore the intricate processes

through which organizations architect an AI-driven innovation ecosystem from two required AI capabilities and three barriers to adopting AI. Through semi-structured interviews with 15 participants and another five for data saturations conducted from June to October 2024, this study constructed an interpretive framework and propositions that explain the specific mechanisms and pathways through which AI catalyzes the development of innovation ecosystems within organizational settings.

Findings

The results of ***Study 1*** show that the TAM-TOE structural model explains 60.7% of the variance in AI adoption, 47.4% in KACAP, and 55.4% in open innovation, which suggests the good explanatory, and all these Q^2 values indicate a large predictive accuracy threshold. Drawing on the proposed model, the study has identified technological (e.g., perceived usefulness) and environmental factors (e.g., competitive pressure, market uncertainty, and government support and policy) that significantly impact AI adoption. Meanwhile, organizational factors (e.g., organizational readiness) directly impact KACAP, and environmental factors (competitive pressure, supplier involvement, and market uncertainty) directly impact open innovation. Subsequently, the AI construct having a significant influence on MSMEs' open innovation through KACAP. Based on the preliminary results of ***Study 1***, ***Study 2*** adopted a grounded theory approach to qualitatively analyze interviews with representatives from enterprises, universities, and apparel associations to obtain the required AI capabilities and barriers to adopting AI. Through systematic coding and comparison, the study selected a coding framework to align the 13 propositions with the theoretical framework, ultimately forming a novel AI-enabled Triple Layer Innovation Ecosystem Framework. This framework reflects the dynamic interplay between external knowledge absorption and the firm's internal innovation capacity, highlighting the collaborative roles of different stakeholders in driving AI adoption and open innovation, thereby achieving the ***MRO*** of the thesis.

Research Significance

Theoretically, the research developed a novel extended TAM-TOE framework that integrates AI adoption with open innovation and KACAP in the Chinese apparel manufacturing industry. This fills existing theoretical gaps by linking AI technology to organizational innovation processes and demonstrating the mediating influence of KACAP. Also, the proposed model provides a foundation for future research exploring the intersection of AI and innovation in similar industries. By categorizing key required AI capabilities in the Chinese apparel manufacturing sector and the factors hindering their AI adoption, this study also provides a theoretical lens in a novel theoretical triple-layer framework for innovation ecosystems to understand how open innovation within the apparel industry, universities, associations, and government entities collaborate to leverage AI technologies for mutual benefit.

Practically, the research provides insights for apparel manufacturers seeking to adopt AI technologies to foster open innovation. By identifying the key factors affecting AI adoption and highlighting the importance of KACAP, the study offers enterprises 13 propositions for integrating AI into their innovation processes. This will enhance their ability to produce small-batch, highly personalized products and increase their competitiveness in a rapidly evolving market. Furthermore, the framework developed offers guidance on how traditional businesses improve collaboration with universities, associations, and government agencies to co-create values in the AI-enabled innovation ecosystem. Simultaneously, the research outcomes provide the innovation path for university talent cultivation in the AI-driven innovation context.

Policy-related, the research informs policymakers by unveiling the mechanisms through which AI can promote collaboration between enterprises, academic institutions, and government bodies. Policymakers can use the findings to develop strategies that encourage the integration of AI into industry and innovation systems, contributing to the broader goal of sustainable economic development in the Chinese apparel manufacturing sector, concreting, and practical policy measures for apparel industrial transformation and upgrading.

Keywords: Artificial Intelligence adoption; Open innovation; Innovation ecosystems; Knowledge absorptive capacity; Chinese apparel manufacturing micro, small and medium-sized enterprises

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1. Introduction

This chapter describes the research context and theoretical background, supported by rationales. The research gap, therefore, is identified, and the main research objective (**MRO**) and two sub-research objectives (**SROs**) are outlined within the scope of the research, emphasizing its significance. The chapter concludes with the thesis structure and a summary. A flowchart of Chapter 1 is shown in **Figure 1.1.**

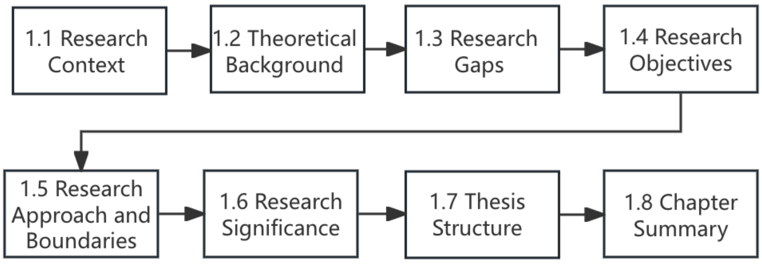

Figure 1.1 Flow Chart of Chapter 1

1.1. Research Context

1.1.1. Evolution of AI: From The 1940s to the 2020s

The evolution of artificial intelligence (AI) represents one of the most compelling narratives in the history of technology. Different perspectives on the criteria for classifying the phase of AI evolution have been debated. A technical report by the Joint Research Centre (JRC) (Delipetrev et al., 2020) presented AI's three key periods: AI foundations (1950s-1970s), symbolic AI (1970s-1990s), and machine learning and deep learning (1990s-2020s). Lu (2019) defined the AI period as the initial phase (1956-1980), the industrial phase (1980-2000), and the explosion phase (2000-present). Russell and Norvig (2016, pp.17-27) specified eight stages: "the inception of AI (1943–1956)", "early enthusiasm, great expectations (1952-1969), "a dose of reality (1966–1973), "Expert systems (1969-1986)", "the return of neural networks (1986-present)", "probabilistic reasoning and machine learning (1987-present)", "big data (2001-present)", and "deep learning (2011-present)".

Despite varying perspectives on the delineation of AI development stages, it is widely acknowledged that the inception of AI can be traced back to the 1956 Dartmouth Conference, during which AI was formally named, and missions were established (Delipetrev et al., 2020). This conference laid the foundational starting point for AI (Y. Lu, 2019). After the conference, McCarthy (1960) first proposed the "LISt processor" programming system, which became the primary language for AI research, particularly in symbolic processing and manipulation, inaugurating the era of symbolic AI. Thus, this period was also called the symbolic AI period. In fact, before AI existed, Alan Turing had been thinking about using machines to simulate the human brain through the Turing test, the first experiment proposed to measure machine intelligence in 1950 (Delipetrev et al., 2020). Newell and Simon (1956) began the logic theorist, an early AI program designed to prove mathematical theorems using symbolic logic and heuristic search methods. They subsequently developed a series of influential AI projects and ideas, including General Problem Solver, Soar, and their unified theories of cognition (Radanliev, 2024). This work demonstrated the feasibility of using computers to perform tasks requiring symbolic reasoning and problem-solving, laying the groundwork for future AI and cognitive science research. However, the development of AI encountered its first winter in the 1970s due to the "impossible-to-overcome technological barriers," resulting in a sharp decrease in AI-related activities in both industry and academia (Delipetrev et al., 2020, p. 8).

The second phase of AI development went to connectionist from 1990 to the present, which was also a data-driven AI period, with machine learning and deep learning emerging (Delipetrev et al., 2020; B. Zhang et al., 2023). Meanwhile, AI experienced its second winter at the end of the 1980s, although the AI industry gained significant economic growth from 1980 to 1988, with hundreds of companies investing in building expert systems. This was partly because the reasoning methods used by these systems collapsed when faced with uncertainty and partly because the systems could not learn from experience (Russell & Norvig, 2016). The second AI winter marks the end of the symbolic AI period (Delipetrev et al., 2020). This period was also classified by shallow machine learning models (1990s) and deep learning into two phases (2000s-present) (Y. Lu, 2019), and the development of machine learning led to the development of deep learning and the spring of the 2010s.

Thus, the third wave of AI might be marked by the introduction of deep learning from the 2010s to the present (Hinton et al., 2006; Shao et al., 2022), where AI has exceeded human performance (Russell & Norvig, 2016), such as generative adversarial networks for speech recognition, music, and visual processing (Goodfellow et al., 2014), deep reinforcement learning in game playing (Mnih et al., 2015), transformer algorithms in machine translation (Vaswani et al., 2017), etc. These performances present the prosperity of AI in the state-of-art period. Based on the previous narratives, the key milestones of AI development from the 1950s to the present might be quickly understood in the history of AI in **Figure 1.2.**

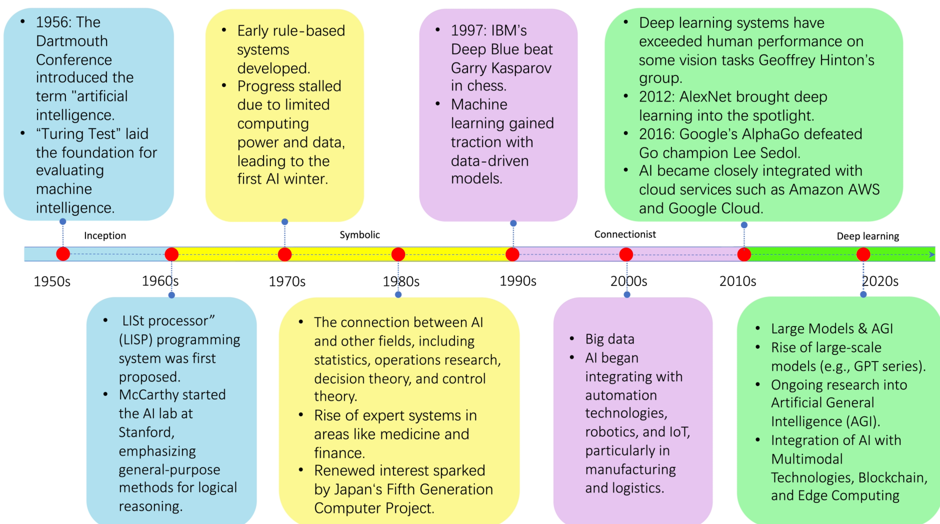

Figure 1.2 The Evolution of AI from the 1950s to the Present (Source: the Author)

The four AI phases progressed from its inception period to symbolic systems, to connectionist systems, and to current data-driven machine learning and deep learning, where intelligent systems integrate various cutting-edge technologies, such as artificial neural networks, blockchain, digital twins, the Internet of things, big data analytics, decision support systems, robotic process automation, etc. Each stage of advancement has significantly expanded AI capabilities and applications, driving profound transformations in Industry 4.0. The following section specifically introduces the applications of AI in Industry 4.0.

1.1.2. AI-integrated Technologies in the Fashion Industry 4.0 and 5.0.

The Industry 4.0 plan was first proposed by the German government in 2011, which is related to the fourth industrial revolution in the manufacturing paradigm to be competitive through the potential digital technologies (Bertola & Teunissen, 2018; R. C. Oliveira et al., 2022). The initial conceptualization of the Industry 4.0 paradigm emphasized "smart manufacturing," positioning the factory as the central focus and envisioning its transformation through digitalization (Bertola & Teunissen, 2018). The early paradigm is founded on integrating physical and digital realms, where advanced robotic automation is orchestrated by a suite of technologies (Bertola & Teunissen, 2018). These technologies are associated with AI-integrated technologies, such as cloud computing, Internet of Things, big data analytics, decision support systems, robotic process automation, blockchain, etc., as previously introduced in the recent phase of AI evolution. However, innovations and digital networks have accelerated the first wave of Industry 4.0, demonstrating that integrating machines, humans, resources, and stakeholders across supply chains, retail channels, and end customers can create a complex, interconnected ecosystem, enhancing decision-making processes by aligning them with market and user demands (Bertola & Teunissen, 2018). In addition, manufacturing environments are evolving to be more dynamic and interconnected while also becoming inherently more complex due to increased interdependencies, uncertainties, and the generation of vast amounts of data within these settings (Spahiu et al., 2021). Thus, Industry 4.0 requires a systemic approach encompassing the entire ecosystem around the factory, integrating all upstream and downstream processes. This comprehensive integration enhances manufacturing efficiency within Industry 4.0 and extends its transformative potential to economies and societies, underscoring its role as a critical element of national strength (Arenal et al., 2020).

The concept of Industry 5.0 was formally introduced by the European Commission (2021), which emphasizes a human-centric, sustainable, and resilient approach to industrial development. It builds on Industry 4.0 by focusing on technological and economic growth and on even broader societal goals, including environmental sustainability and worker well-being. This Industry 5.0 vision leans toward a human-centered human-machine symbiosis during manufacturing to achieve sustainable development and become a robust and resilient provider of future industrial ecosystems. Therefore, in the context of the AI era, Industry 5.0 also entails the incorporation of AI into human operations to enhance human capacity, highlighting the "harmony of machines, humans, values, tasks, and finally, knowledge and skills" (Leng et al., 2022, p. 283).

Fashion provides a compelling research background for Industry 4.0 and Industry 5.0 across several dimensions. First, evidence from The State of Fashion (2017) suggests that "if it were ranked alongside individual countries' gross domestic product, the global fashion industry would represent the seventh-largest economy in the world" (Akram et al., 2022; McKinsey & Company, 2017, P. 6). Despite the economic disruption in the fashion industry during the Covid-19 pandemic period, it simultaneously spurred the adoption of new technologies, propelling the industry towards innovative business models. For example, apparel manufacturers were required to invest in automated sewing, knitting, and post-production logistics to accommodate small-batch production in the post-pandemic (BOF & McKinsey, 2023). According to BOF& McKinsey (2024), generative AI that employs generative adversarial network as one of its implementation methods and frameworks to produce realistic data can add value across the fashion value chain. Second, it is one of the significant industries influenced by the constant change induced by Industry 4.0-enabled technologies (Nouinou et al., 2023). As per the previous reports by the State of Fashion 2017-2024 (BOF& McKinsey), the fashion industry is characterized by intricate supply chains involving multiple stages, such as raw material procurement, design, production, logistics, and retail. Therefore, Industry 4.0 technologies, including Internet of Things, Big Data Analytics, blockchain, and AI, can enhance supply chains' transparency and efficiency (Ebinger & Omondi, 2020) and solve sustainable issues, such as fabric waste and consumption, supplier selection, customer satisfaction, etc. (Dey et al., 2023; Ebinger & Omondi, 2020; M. Gupta & Jauhar, 2023; M. M. Khan et al., 2023; Zekhnini et al., 2023). Third, the fashion industry is one of the most sustainable problem manufacturing industries that generates a large environmental impact because of consuming substantial energy, water, and other natural resources (Khairul Akter et al., 2022), which is also the mission that Industry 5.0's highlights.

In fact, AI has been rapidly invading the fashion industry, with the most emerging forms already making their way into it in recent years (Banerjee et al., 2021). This invasion of AI into the fashion sector is accelerating, with the latest and most innovative AI applications already being integrated into the industry over the past few years. The scope of potential applications of AI in the fashion industry has been widely applied in GAN in fashion design (Ak et al., 2020; Luce, 2018; Q. Wu et al., 2021; H. Yan, Zhang, Liu, et al., 2023; H. Yan, Zhang, Shi, et al., 2023), robotic process automation in apparel manufacturing (Babu et al., 2022; Dal Forno et al., 2023; Herm et al., 2023), AI-based decision support systems in sustainable clothing supply chain management (SCM) (Belhadi et al., 2022; González Rodríguez et al., 2020; A. M. Pereira et al., 2022), etc. These evolving AI technologies are revolutionizing traditional fashion paradigms from design and manufacturing to retail and customer engagement, driving further innovation and transformation across the industry (Adekunle, 2024; David Iyanuoluwa Ajiga et al., 2024; Silvestri, 2020).

1.1.3. AI Applied in Chinese Traditional Apparel Manufacturing

1.1.3.1. China Government Promotes AI Applied into Manufacturing-Policy Context

AI plays a pivotal role in fostering technological innovation within low-tech industries and propelling the digital transformation of traditional manufacturing sectors, with the evidence previously mentioned by Liu et al. (2020). The traditional apparel manufacturing industry is characterized by its extensive scale yet low technological sophistication because it is described by others as low-skilled and labor-intensive (Goedhuys et al., 2014; Hansen & Winther, 2015; Piana & Tagliari Brustolin, 2023). Thus, the innovation process of apparel sectors stands to benefit significantly from strategically developed and applied AI initiatives. Moreover, innovation development always needs a national strategy to support technology innovation and growth from policies (Lundvall, 2007). Therefore, it is important to consider how policy context can play an active role in researching and developing AI in innovation for industries, which is in line with the previous section mentioned that AI has been an element of national strength driven by Industry 4.0 (Arenal et al., 2020). As one of the apparel manufacturing countries, China must devise comprehensive AI development and application strategies to enhance knowledge creation and promote technology spillover effects, elevating technological innovation's national level and scale (Liu et al., 2020). Based on the database of PKULAW (www. pkulaw.com, accessed on 13 July 2023), China has released 982 plans, laws, and policy documents to promote AI development in various areas. These policy documents and reports provide informative content on AI research's development and future directions.

Figure 1.3 depicts that China's national AI policies remain a growth trend from 2017 to 2022. The X-axis represents the policy issuance time, while the Y-axis represents the number of policies. There is a total of 39 policies in 2017. These policy developments signaled China's strategic commitment to positioning AI as a leading force in a new wave of technological transformations. This phase signifies a crucial step in setting the desired objectives. The policy entitled "Next Generation Artificial Intelligence Development Plan" (State Council, 2017) establishes the goal of China is becoming a global leader in AI by 2030. In 2018 and 2019, of which 125 policies were issued, focusing on stimulating demand for AI technologies. The policy approach during this stage was characterized as the "demand side" since AI development policy transitioned into a highly practical phase (C. Yang & Huang, 2022). The Ministry of Industry and Information Technology (MIIT) General Office released "Action Plan for Integrating Artificial Intelligence into the Real Economy" in 2018, aiming to drive digital transformation and enhance productivity. Pilot projects in these sectors showcased the value of AI in industrial upgrading. "China's AI Open Innovation Platform Initiative" issued by Ministry of Science and Technology (MOST) in 2019, promoted the development of open-source AI platforms and encouraged collaboration between Chinese enterprises, research institutions, and global partners to foster innovation through shared resources. From 2020 to 2021, 127 policies in this phase aimed to enhance AI-related resources and infrastructure supply. While there was a decrease in the number of policies issued in 2020 due to the COVID-19 pandemic, this disrupted environment accelerated China's government's release of the deployment of AI in healthcare, logistics, and other emergency response sectors. In 2021, there was a boost in increasing AI policies released. The MOST issued six supportive regional AI pilot zones, enhancing collaborations with universities to promote the integration of disciplines and expedite the training of graduate students in AI. This shift implies that AI policy instruments have transitioned to a "supply side" approach, which includes a focus on "cultivating talents" (Qu & Kim, 2022). The year 2022 is the new supply side, issuing 99 policies in this phase, likely including novel AI policy approaches. This year, the Ministry of Science and Technology (MOST) and six other stakeholders jointly issued the "Guiding Opinions on Accelerating Scene Innovation to Promote High-quality Economic Development with High-level Application of Artificial Intelligence". This signifies that the Chinese government is inclined to invest more in AI adoption for scene innovations, a part of the "supply side" approach. Furthermore, 18 competition notices were released for AI application innovations. These policies were expected to attract more AI talents and indirectly strengthen the path of industrial innovation for AI. **Appendix A (a)** and **Appendix A(b)** list China's national and regional AI policy authorities with the number of issued policies.

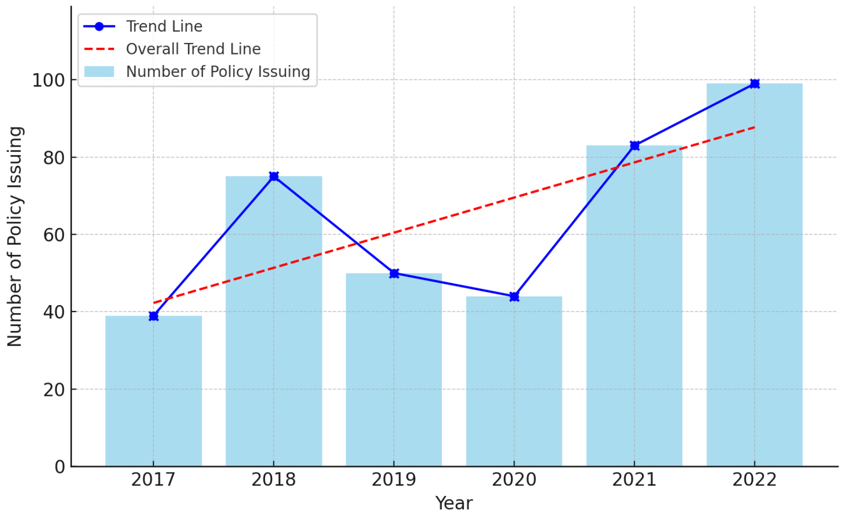

Figure 1.3 The Trends of China's AI Policy Issuing (Source: Qu et al., 2023)

There are few AI policies associated with apparel manufacturing industry during the period between 2017 and 2022; however, the Chinese government has introduced corresponding policies for intelligent manufacturing industrialization after 2022. For example, the MIIT Union Regulation (2023) No. 258 released the AI policy titled "Accelerating the Transformation and Upgrading of Traditional Manufacturing Industry Guidance", which highlights that the Chinese government tends to accelerate the comprehensive empowerment of digital technology and intelligent manufacturing. Based on this stimulation of deep fusions of intelligent technologies and the real economy, it is imperative to foster the initiation and pilot testing of intelligent upgrades, digital conversion, and network connectivity within SMEs to enhance the digital transformation of these entities. In particular, this policy document underscores that the textile and apparel manufacturing industry serves as a vital basis for supporting the development of the national economy and meeting the essential needs of the people's livelihoods. The latest policy was released on 22 January 2024; the executive meeting of The State Council studied and deployed related work to promote new industrialization enabled by AI. The meeting stressed that it is necessary to coordinate high-quality development and high-level security, take the deep integration of AI and manufacturing as the main line, take intelligent manufacturing as the main direction, and take scene application as the impetus, accelerate the intelligent upgrading of key industries, vigorously develop intelligent products, enable high-level industrial manufacturing systems, and accelerate the formation of new quality productivity. China endeavors to provide strong support for building a strong manufacturing country, a strong network country, and a digital China.

1.1.3.2. The State of Arts of AI-Integrated Technologies in Chinese Apparel Manufacturing

China's strategic AI initiatives, notably the 2017 "New Generation Artificial Intelligence Development Plan," aimed to position China as a global AI innovation hub by 2030, further propelled the digital transformation occurring within the AI adoption in the fashion industry. As China's government has released fruitful AI policies that leaned toward manufacturing, AI has been applied in many fields of apparel manufacturing in China, such as Unicom Digital Science Platform (UDCP), Style3D (www.linctex.com/), Huawei Cloud (https://www.huaweicloud.com/), FeiLiu Tech Smart Sew (www.heydaizi.com), Alibaba's Xiniu Manufacturing (https://www.xiniuim.com/) etc. These AI technologies and platforms have brought benefits to the traditional apparel manufacturing industry upgrading, but are disrupting traditional manufacturing in the fashion industry, reflecting in sustainable production (Matin et al., 2023; Ramos et al., 2023), technological innovation (Liu et al., 2020) and SCM (Qu & Kim, 2024a), and human-machine interactions (Kaasinen et al., 2022; J. Yang et al., 2022). For example, IoT sensors and AI algorithms enhance production speed, product lifecycle management, preventive maintenance, and recycling operations in the textile and apparel manufacturing industry, enabling efficient up-cycling and flaw reduction through advanced data tracking and predictive capabilities (Matin et al., 2023). Employing a back-propagation artificial neural network (ANN) to predict the anthropometric data essential for pattern-cutting in optimizing apparel production processes, offering a precise alternative to traditional methods (Y. Huang et al., 2024). AI-powered decision support systems are adopted to enhance supply chain resilience (SCR) by enabling better anticipation of disruptions, improving decision-making processes, and optimizing operational efficiency (Dey et al., 2023). AI adoption in SCs, which creates the most value in the manufacturing industry, is critical in improving SCM in dynamic environments (Helo & Hao, 2022).

1.1.3.3. Distinct Characteristics of the Apparel Manufacturing Sector

The apparel manufacturing sector exhibits unique characteristics that differentiate it from other industries. First, the sector is highly dynamic and trend-sensitive, driven by rapid fashion and consumer preference changes (Trieu, 2024). This industry demands a production system that can quickly adapt to changing trends and handle diverse, small-scale orders with high customization. Second, apparel represents a "buyer-driven value chain" (Staritz& Frederick, 2014, p.211), common in labor-intensive and consumer goods industries. This labor-intensive nature of apparel manufacturing relies heavily on manual skills, particularly in tasks like sewing and finishing. Also, such buyer-driven value chains are defined by globally dispersed production networks coordinated by lead firms controlling high-value-added activities, such as design, branding, and marketing, while outsourcing the manufacturing process to a network of suppliers (Gereffi& Memedovic, 2003). Third, the apparel manufacturing heavily relies on human labor. For example, many core processes in the apparel manufacturing industry, such as cutting, sewing and weaving, and quality inspection, are challenging to fully automate, particularly for diverse, small-batch, and customized orders. As a result, manual operations remain the primary production method. These low added value of individual apparel products, combined with intense market competition and price sensitivity, compels manufacturers to reduce labor costs to maintain profit margins. Furthermore, the apparel industry is driven by rapidly changing fashion trends, requiring highly flexible production systems to adapt to diverse and small-scale orders quickly; thus, manual labor is better suited for swiftly adjusting production processes to meet these demands. Apparel production involves handling flexible materials such as fabrics and trimmings, which also demand a high level of manual dexterity and skill from experienced workers. Finally, the apparel industry features a complex supply chain structure, where the buyer-driven nature of the value chain leads to outsourcing production tasks to countries with lower labor costs. As one of the world's largest apparel manufacturers, China exemplifies this structure and often determines the dynamics of global apparel sourcing, supported by a robust domestic supply of raw materials and an ample low-cost labor force (Lu & Karpova, 2011). Its dominant position is supported by its extensive production capacity, established industrial clusters, and comprehensive supplier networks that span various stages of the value chain, from textile sourcing to garment production (Qu &Kim, 2024a).

While China has made outstanding achievements in applying AI in the apparel manufacturing sectors, the industry's reliance on low-cost labor and fragmented supply chains shapes its specific challenges and opportunities for AI adoption. AI adoption by traditional apparel manufacturers has still proceeded slowly in China because the effectiveness of technological innovations is fundamentally reliant upon their acceptance and utilization by the designated user (apparel workers and managers) base (Park et al., 2009). As such, Chinese apparel manufacturing encounters the challenges that AI adopts in six aspects. First, the issues with the usage of AI tools may hinder employees' acceptance due to their low learning ability and educational level (Venkatesh, 2022). Second, adopting AI may raise concerns about unemployment among apparel production workers due to labor replacement by AI (Chiarini et al., 2023), and the labor-intensive nature of apparel manufacturing relies heavily on manual skills, which are less automated compared to other industries with more streamlined processes. The fashion industry is characterized by intensive labor with low production costs (Jin, 2004), and China has traditionally relied on its advantage of cheap labor; however, with AI technology, this low-cost labor advantage is being eroded. AI technology and automation equipment replace low-skilled jobs, which could lead to significant unemployment (Mabungela, 2023; Mukherjee, 2022; Wadley, 2021), especially in a country like China that depends heavily on labor-intensive production. Third, from organizational perspectives, limited digital skills and resources (knowledge), lack of funds, lack of the technical foundation and experience to transition and adapt to the application of AI technology quickly (Giri et al., 2019). this also causes a large number of low-skilled workers to need retraining to adapt to the new technological environment, which poses a significant challenge for China given its large population and limited education and training resources (Chiarini et al., 2023). Fourth, 92% apparel manufacturers are micro (fewer than 20 employees), small (21-300 employees) and medium (301-1000 employees)-sized enterprises (MSMEs) (China national textile and apparel council, as of 2022) defined by the China Ministry of Industry and Information Technology (2011) No. 300. These traditional apparel MSMEs have limited digital skills and resources (knowledge), lack of funds, the technical foundation and experience to transition and adapt to the application of AI technology quickly (Giri et al., 2019). Fifth, Chinese apparel industry has become the world's largest manufacturer and exporter since 1993, which occupies an important economic position in China's industrialization process (Ruan et al., 2022). However, many Chinese apparel manufacturing enterprises continue to rely on traditional production models and lack the technical foundation and experience required to transition to and adopt AI technology effectively (Giri et al., 2019). These enterprises face significant resistance to technological updates and industrial upgrading due to the complexity of their operations, which makes it challenging to coordinate activities and integrate advanced technologies like AI across the supply chain. Last, as other countries actively adopt AI technology, Chinese apparel manufacturing enterprises face greater international competitive pressure to adopt AI (Z. Guan et al., 2019). Thus, given the above, a thorough study of organizational AI adoption from both individual and organizational actors' perspectives, emphasizing Chinese apparel manufacturers, is crucial.

1.2. Theoretical Background

1.2.1. Technology Adoption in Manufacturing Sectors

Shedding light on the theoretical lens, the research on technology adoption mainly includes the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), the Technology Acceptance Model (TAM) (Davis, 1989), Technology-Organization-Environment (TOE) framework (Tornatzky et al., 1990), the Theory of Planned Behaviour (TPB) (Ajzen, 1991), Diffusion of Innovation (DOI) (Rogers, 1995), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and the extended TAM 2 (Venkatesh & Davis, 2000), and UTAUT 2 (Venkatesh et al., 2012). Except for the DOI and TOE frameworks, these theories and models have predominantly analyzed user adoption behavior from an individual perspective, concentrating on technology rather than organizational dimensions (Dobre, 2022). For example, the TAM is used to understand the individual factors influencing the behavioral intention to use technology, measured from two determinants in their adoption behavior: perceived usefulness (PU) and perceived ease of use (PEOU).

However, the TOE framework ({Citation}Tornatzky and Fleischer (1990) suggests the factors affecting the implementation of technological innovation in an organizational context (AL-khatib, 2023; Chittipaka et al., 2023; Kinkel et al., 2022; Zhong & Moon, 2023). It is often used with a resource-based view (RBV) (Barney, 1991) in several studies (Fernando et al., 2021; Maroufkhani, Tseng, et al., 2020; Maroufkhani, Wan Ismail, et al., 2020; Wang & Su, 2021) to examine the relationship between technology adoption and organizational performances where technology is seen as a resource or a capability in manufacturing firms and is considered an intangible resource (Barney, 2014; Maroufkhani, Tseng, et al., 2020). Also, several studies incorporate DOI theory that emphasizes technology diffusion and the process of diffusing technology adoption throughout the firm into the TOE framework to illuminate the diffusion of intra-firm innovation (Amini & Javid, 2023; Correia Simões et al., 2020; Maroufkhani, Tseng, et al., 2020; Oliveira et al., 2014). In manufacturing sectors, the studies in technology adoption lean toward TOE with TAM to understand the technology adoption factors in SMEs in developing countries (Chatterjee et al., 2021; Forootani et al., 2022; Gangwar et al., 2015; Legesse et al., 2024; Patil et al., 2023; Sharma et al., 2020; Tasnim et al., 2023) as a hybrid framework to comprehensively understand the mechanisms of AI acceptance from both individual and organizational focus. Another frequently used with the TOE framework is institutional theory (Berger & Luckmann, 1967). Information technology adoption is the most frequently applied area for institutional theory to as organizational factors impact information technology adoption behavior (Bag et al., 2021; Li et al., 2021). It is often used in TOE framework to underline the external environmental factors (Lutfi, 2020; Lutfi et al., 2022; Malik et al., 2021; Mujalli & Almgrashi, 2020; Oliveira & Martins, 2011).

Considering the organizational perspectives, AI-based innovation management requires substantial technical and organizational changes to cope with the associated challenges of firm size (Füller et al., 2022). A firm size refers to “the number of employees of the organization”(Rogers, 1995). Prior research has shown that firms of different sizes, types, and ages have different motivations and ways to engage with innovation (Belhadi et al., 2024). For example, SMEs adopting AI can create opportunities and improve manufacturing capacity and profits, meanwhile facing challenges in adopting, adapting, modifying, implementing, and developing new AI-based capabilities for innovation (Mariani et al., 2023). MSMEs with limited resources look upon AI as a tool for accelerating their growth (Kumar et al., 2024; Sharma et al., 2022). Furthermore, business scope in the manufacturing sector, such as the types of industries, range of products, geographic areas where the business operates, and target customer segments (Belhadi et al., 2024; Lee et al., 2015), could have different attitudes towards adopting AI for different innovation purposes (Mariani et al., 2023). Given this evidence, individual factors with firm-level driving AI adoption have been presented concerning AI adoption (Badghish & Soomro, 2024; Baroni et al., 2022; Cao et al., 2021; Chatterjee et al., 2021; Choung et al., 2023; Gangwar et al., 2015; Qin et al., 2020). This also provides the theoretical grounds for selecting apparel manufacturing regarding firm sizes and business scope as the thesis case. **Table 1.1** summarizes the existing technology adoption using TOE applied in the manufacturing sector studies from the Scopus database. The studies are selected based on a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol (Busalim et al., 2022; Moher et al., 2010) (see **Figure 1. 4**).

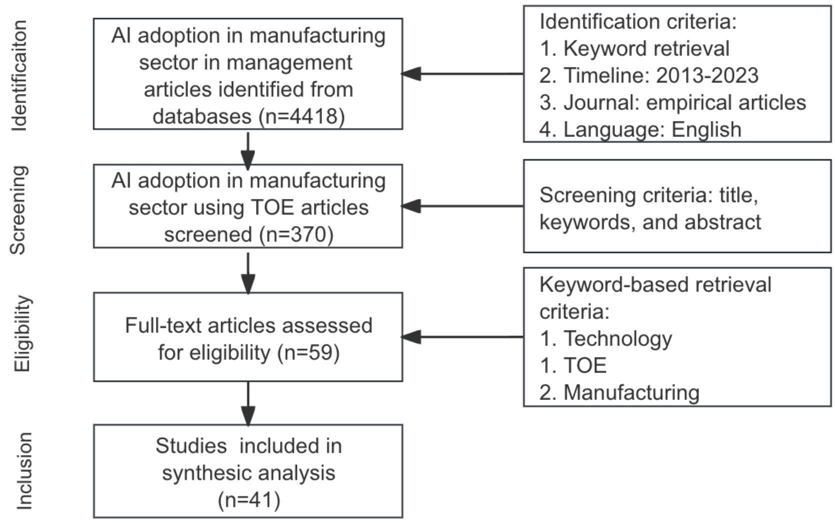

Figure 1.4 Data sampling process based on the PRISMA protocol.

Table 1.1 Selected technology adoption studies in manufacturing sector (Source: Scopus database, N=41)

Technology Adoption Model	Specific Manufacturing	Firm size	Firm Country	Source	Frequency
DOI-TOE	NA	SMEs	Malaysia	Amini & Javid, 2023)	3
DOI-TOE	NA	NA	Portugal	Oliveira et al., 2014	
DOI-TOE	NA	NA	NA	Correia Simões et al., 2020	
RBV-TOE	NA	SMEs	Iran	Maroufkhani et al., 2020	3
RBV-TOE	NA	NA	China	Wang and Su, 2021	
RBV-TOE	NA	SMEs	Malaysia	Fernando et al., 2020	
RBV-TOE-DOI	NA	SMEs	Iran	Maroufkhani, Tseng, et al., 2020	1
TAM-TOE	NA	NA	India	Gangwar et al., 2015	10
TAM-TOE	NA	NA	China	Cao et al., 2020	
TAM-TOE	NA	NA	India	Gangwar& Date, 2016	
TAM-TOE	NA	NA	India	Patil et al., 2023	
TAM-TOE	NA	SMEs	India	Chatterjee et al., 2021	
TAM-TOE	NA	NA	Ethiopian	Legesse et al., 2024	
TAM-TOE	Automobile component	LMs	India	Kamble et al., 2021	
TAM-TOE	NA	SMEs	Bangladesh	Tasnim et al., 2023	
TAM-TOE	NA	SMEs	Iran	Forootani et al., 2022	
TAM-TOE	NA	NA	India	Sharma et al., 2020	
TOE	NA	SMEs	India	Badghish & Soomro, 2024	24
TOE	NA	NA	China	Guan et al., 2023	
TOE	NA	NA	India	Pillai et al., 2022	
TOE	NA	NA	Middle East	Ronaghi, 2023	
TOE	NA	SMEs	Iran	Maroufkhani et al., 2023	

TOE	NA	NA	China	Xing et al., 2023
TOE	NA	NA	NA	Kinkel et al., 2022
TOE	NA	NA	German	Zhuankhan et al., 2023
TOE	NA	NA	China	Zhou& Zheng, 2023
TOE	NA	SMEs	Europe and the UK	Marrucci
TOE	Food	SMEs	China	Shen et al., 2023
TOE	NA	SMEs	Egypt	Aboelmaged, 2018
TOE	NA	NA	NA	Aboelmaged, 2014
TOE	NA	SMEs	Malaysia	Baig et al., 2023
TOE	NA	NA	Vietnamese	Hue, 2019
TOE	NA	NA	the UK	Kalaitzi& Tsolakis, 2022
TOE	NA	NA	Inida	Angwar, 2018
TOE	NA	NA	China	Yeh& Chen, 2018
TOE	NA	SMEs	India	Sivathanu, 2019
TOE	NA	SMEs	Malaysia	Ghani et al., 2022
TOE	NA	SMEs	Inida	Kumar, 2023
TOE	NA	SMEs	Nigeria	Usman et al., 2019
TOE	Food	NA	Thailand	Opasvitayarux et al., 2022

Legend: NA=Not Available; DOI=Diffusion of Innovation; RBV= Resource-Based View; TAM=Technology Acceptance Model; TOE=Technology-Organization-Environment; SMEs= Small and Medium-sized Enterprises

1.2.2. Open Innovation Ecosystem

The open innovation concept has emerged as the distributed innovation process, which is based on the efficient knowledge flows with the help of managed across the operational gates and is grounded in the significance of collaborative networks in the modern practices of innovation (Chesbrough et al., 2014; Vlaisavljevic et al., 2020). The present-day open innovation models have moved from the conventional company in-house Research & Development to the hybrid approach that unites both the internal and the external sources, so that the companies can take advantage of external ideas, technologies and expertise (Radziwon & Bogers, 2019). This change is in line with the innovation ecosystem model, which locates firms within constantly changing networks of interdependent actors who evolve collectively to meet the changing market requirements (Adner, 2006; Adner & Kapoor, 2010). In open innovation ecosystems, different stakeholders, e.g., suppliers, customers, competitors, and research institution, can be seen as key drivers of knowledge sharing and talents co-innovation (Adner & Kapoor, 2010). Also, due to the purposeful inflow and outflow of knowledge in the open innovation ecosystem, open innovation support this ecosystem model by allowing companies to integrate external resources and share unused knowledge with third parties (Chesbrough, 2003; Chesbrough & Bogers, 2014). In line with the resource-based view (RBV) and knowledge-based view (KBV) (Barney, 1991; 1995), open innovation explains how firms leverage external knowledge as a critical resource to enhance their competitive advantage. However, the open innovation ecosystem that makes collaboration and openness the main highlight also suggests that more research is needed to find the conditions that will allow open innovation to be sustained within an ecosystem context (Bogers et al., 2019).

Further, the Triple Helix (TH) model (Etzkowitz & Leydesdorff, 1995) which is about the near and affectionate interaction among universities, industry, and governments coincides with the open innovation ecosystems stressing the collaborations and the opening up in order to promote innovation (Vlaisavljevic et al., 2020). The TH model brings about a situation that is favorable to open innovation by being a conduit through which knowledge flows and technology transfer could be achieved (Leydesdorff, 2012), facilitating dynamic co-evolution, and helping the formation and commercialization of innovations (Bogers et al., 2017; Adner & Kapoor, 2010, cited in Vlaisavljevic et al., 2020).

1.3. Research Gaps

The previous sections depict the scenario of AI in the Chinese apparel manufacturing industry in the context of Industry 4.0 and 5.0, the status quo and challenges of AI adoption with a comprehensive industrial and theoretical background. While AI-integrated technologies significantly impact technology innovation in manufacturing, which disrupts the traditional apparel manufacturing sector, given that apparel manufacturing sectors are one of the most significant low-tech industries, existing gaps need to be identified on the research agenda.

First, the favorable technological, industrial, and Chinese AI policy context has not attracted scholars' research interest in technology adoption in Chinese apparel manufacturing sectors based on the theoretical model and theories as previously mentioned (***Gap 1***). Among the 41 studies selected on technology adoption in manufacturing sectors from the Scopus database using preferred reporting items for systematic reviews and meta-analysis (PRISMA) protocol, there are three aspects identifying the first research gap. 1) The study focused on specific manufacturing sector is still relatively rare, expect for two studies in the food industry (Opasvitayarux et al., 2022; Shen et al., 2003) and one in automobile component industry (Kamble et al., 2021). 2) Almost half of studies focuses on small and medium-sized manufacturing firms and only one focuses on large and medium-sized one (e.g., Kamble et al., 2021). 3) While China has provided extensive AI policies regarding AI-enabled traditional manufacturing industry upgrading since 2022, there is limited research on AI adoption in China's manufacturing sectors (e.g., Cao et al., 2020; Guan et al., 2023; Shen et al., 2023; Wang & Su, 2021; Xing et al., 2023; Yeh & Chen, 2018; Zhou & Zheng, 2023).

Second, the existing studies have not examined or investigated to what extent AI adoption drives open innovation in Chinese apparel manufacturing sectors from RBV and KBV perspectives (***Gap 2***). As the labor-intensive market experiences a shift from China to Southeast Asia, such as Indonesia, Vietnam, and Cambodia, apparel manufacturing has to face this pressure from the increasing labor costs and competition. These nations continue to develop their manufacturing capabilities and offer a viable alternative to Chinese production; the competitive landscape has thus shifted, requiring Chinese apparel manufacturers to adapt to enhance their open innovation to remain competitive. This adaptation involves relocating production with new customers and suppliers, collaborating with external partners to adopt new technologies, and extending the resources to universities (Enkel et al., 2009; Laursen & Salter, 2006; Lichtenthaler & Lichtenthaler, 2009). The adoption of AI in apparel manufacturing can be comprehensively understood through the lens of the RBV and KBV for several reasons. First, RBV posits that a firm's competitive advantage stems from its possession of unique, heterogeneous, and scarce resources that are difficult to imitate or substitute (D. Chen et al., 2022; Hossain et al., 2022; Mikalef & Gupta, 2021). Thus, AI technologies represent such valuable resources through data analysis, predictive modeling, and automation capabilities, facilitating innovation processes in manufacturing processes. Second, the successful integration and application of AI technologies exemplify a firm's dynamic capabilities, allowing for the continuous reconfiguration of resources to adapt to external changes (Chatterjee et al., 2021; Hossain et al., 2022; Schoemaker et al., 2018). This integration necessitates the effective amalgamation of AI with existing resources, such as production equipment, data systems, and workforce skills, to harness its potential fully. Thus, AI adoption and corporate open innovation need to consider RBV, emphasizing the cruciality of a firm's resources to influence its open innovation (M. A. Hossain et al., 2022). Third, KBV can be seen as an outgrowth or extension of the RBV as it focuses on knowledge as the most strategically important resource of any size of organization (Cooper et al., 2023; Kogut & Zander, 1992; Pereira & Bamel, 2021). Adopting AI involves significant knowledge absorption, enhancing the firm's technical expertise and innovation capacity. Furthermore, KBV is a critical mechanism for realizing, using, and maintaining AI resources, facilitating their subsequent adoption (Chowdhury et al., 2022). Combined with the previous RBV stressed, both the KBV and RBV emphasize the importance of possessing unique, difficult-to-imitate resources as the foundation of a firm's competitive advantage. While the RBV focuses broadly on various valuable resources, including tangible and intangible assets, the KBV focuses on knowledge as a critical intangible resource (Pereira & Bamel, 2021). These knowledge-based resources are a subset of the broader category of unique, heterogeneous, and scarce resources emphasized by RBV (D. Chen et al., 2022). Therefore, integrating these perspectives provides a comprehensive understanding that a firm's competitive advantage is derived from its unique knowledge base and overall resource heterogeneity and scarcity.

Furthermore, current research overlooks how apparel manufacturing companies collaborate with the government and universities to build an innovation ecosystem (***Gap 3***). AI accelerates traditional apparel manufacturing innovation processes, underscoring the necessity for organizations to integrate, build, and reconfigure both internal and external competencies to adapt to rapidly changing environments. Also, China's central government provides favorable economic and regulatory conditions on acting as an investor and as a provider of key data for companies experiencing advantageous conditions, with policies systematically disseminated down to autonomous regions and research institutions (Arenal et al., 2020). Following the policy guidelines, the main Chinese universities are launching educational programs and research opportunities in AI. Therefore, it is significant to identify "the main aspects related to the flows of skills, knowledge and funding and the interactions among them" (Arenal et al., 2020). As previously mentioned, the TH model (Etzkowitz & Leydesdorff, 1995) aligns with the open innovation ecosystem by emphasizing the role of close, collaborative networks among the three actors (i.e., companies, knowledge-generating institutes and government) in fostering innovation. However, despite the critical importance of collaboration among government, universities, and enterprises in constructing innovation ecosystems, there is currently a lack of research on the specific operational models and effectiveness of these cooperative mechanisms. In particular, there is a deficiency in systematic studies and practical case analyses on orchestrating resources from each party and clearly defining their respective roles and responsibilities. In addition, most studies on innovation ecosystems tend to be generalized, with few focusing on specific industries, requiring more specialized research is needed on industry-specific innovation models, technological requirements, and market dynamics.

1.4. Research Objectives and Questions

Based on the identified research gaps, this thesis's Major Research Objective (***MRO***) aims to develop a framework for propositions for micro, small and medium-sized Chinese apparel manufacturing's innovation ecosystem. Accordingly, this thesis comprises two ***SROs***.

SRO 1 aims to examine the antecedents of AI adoption, thus driving open innovation in Chinese apparel manufacturers, emphasizing the significant mediating role of knowledge absorptive capacity (KACAP) from the KBV perspective in innovation processes in Chinese apparel manufacturing. It also addresses two sub-research questions (***SRQs***):

SRQ1**:** What factors affect AI adoption, knowledge absorptive capacity (KACAP), and open innovation in Chinese apparel manufacturing?

SRQ2**:** What is the role of KACAP in the linkage between AI adoption and organizational open innovation?

According to the results of ***SRO 1***, ***SRO 2*** aims to ground the required AI capabilities and barriers to adopting AI in Chinese apparel manufacturers. The study addresses three ***SRQs***:

SRQ3: What are the emerging concepts of AI capabilities needed?

SRQ4: What are the emerging concepts of challenges that hinder AI adoption in China's manufacturing sector?

Based on the above SROs and respective SRQs, to achieve the MRO, the ***MRQ*** is: How can we develop an AI-enabled innovation ecosystem to explain how enterprises, universities, and governments enhance collaboration in China's manufacturing sectors?

In summary of the significant relationships between ***SRO1***, ***SRO2***, and the ***MRO***, ***SRO 1*** aims to identify the relationship between AI adoption and open innovation, providing a theoretical framework and preliminary empirical evidence. ***SRO 2*** further aims to explore the specific AI capabilities enterprises require and the barriers to AI adoption, offering mechanism for strengthening open innovation through the collaborations between enterprises universities, and governments. By integrating theoretical and practical perspectives, these two studies (to achieve ***SRO1*** and ***SRO2***) collectively achieve the ***MRO*** of developing an AI-driven innovation ecosystem framework for Chinese apparel MSMEs. **Figure 1.4** depicts attaining the ***MRO*** through the ***SRO 1*** and the ***SRO 2***.

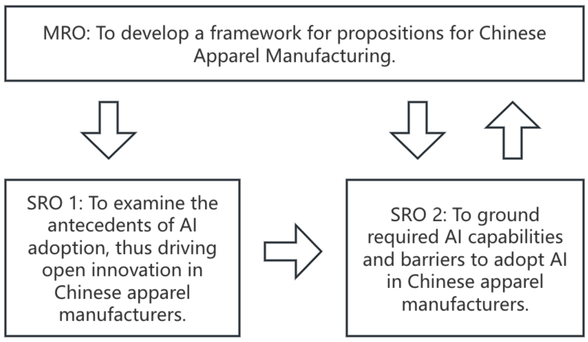

Figure 1.5 Relationship of the Main Research Objective (MRO) and Sub-Research Objectives (SROs)

1.5. Research Approach and Boundaries

As the research thesis consists of two studies with different SROs, two research approaches are constructed for the scope of the thesis (**Figure 1.5**). In ***Study 1,*** technology adoption is a well-established domain in the literature, utilizing various theories to explore AI adoption. The approach addressing ***SRO 1*** builds on the KBV theory applied to apparel manufacturing firms for open innovation and incorporates the TAM (Davis, 1989) and TOE framework (Tornatzky et al., 1990). This model tests associated hypotheses through quantitatively collected survey data. In ***Study 2***, based on the antecedents of AI adoption and open innovation consequences, the research conducts qualitative semi-structured interviews by grounding deep insights concerning particular AI capabilities in their practical work and the factors that hinder adopting AI. Thereafter, a framework and propositions are developed to address ***MRO,*** interpreting how collaborative actors leverage resources (AI) and institutions (AI policy support) in activities. Combining quantitative and qualitative methods enables this research to overcome the limitations of each approach when used alone, potentially leading to a more substantial research thesis (Clark et al., 2021). The research paradigms and the rationale behind selecting a mixed-quantitative and qualitative approach are provided in Chapter 3.

To complete the quest for these research objectives, this paragraph provides the research scope that describes the scope of this thesis, including its inclusions and exclusions. ***Study 1*** initially focuses on the antecedents of AI adoption, mediators, and the consequences to open innovation, enabling firms' open innovation ecosystem. Further, ***Study 2*** focuses on the organization as a reference unit, with manufacturing sectors evaluated in China having extensive AI policy interventions in implementing digital transformation. In addition, Chinese apparel manufacturing is specified as the focus of this research in that the most labor-intensive and significant sustainable issues emerged in garment production and manufacturing processes. Therefore, AI adoption can be applied to possess the capability of enabling an open innovation ecosystem with interactive attributes in governments, industries, and universities. ***Study 1*** limits to consequences, as they are only applicable to China. ***Study 2*** is limited to categorizing AI capabilities and the barriers to adopting AI in Chinese apparel manufacturing from the perspectives of governments, enterprises, and universities, as this grounded data further supplemented ***Study 1***'s results. This research's interest is in supporting AI adoption, which could enhance firms' open innovation through KBV perspectives, thereby developing a theoretical framework in Chinese apparel manufacturing's AI-enabled innovation ecosystem.

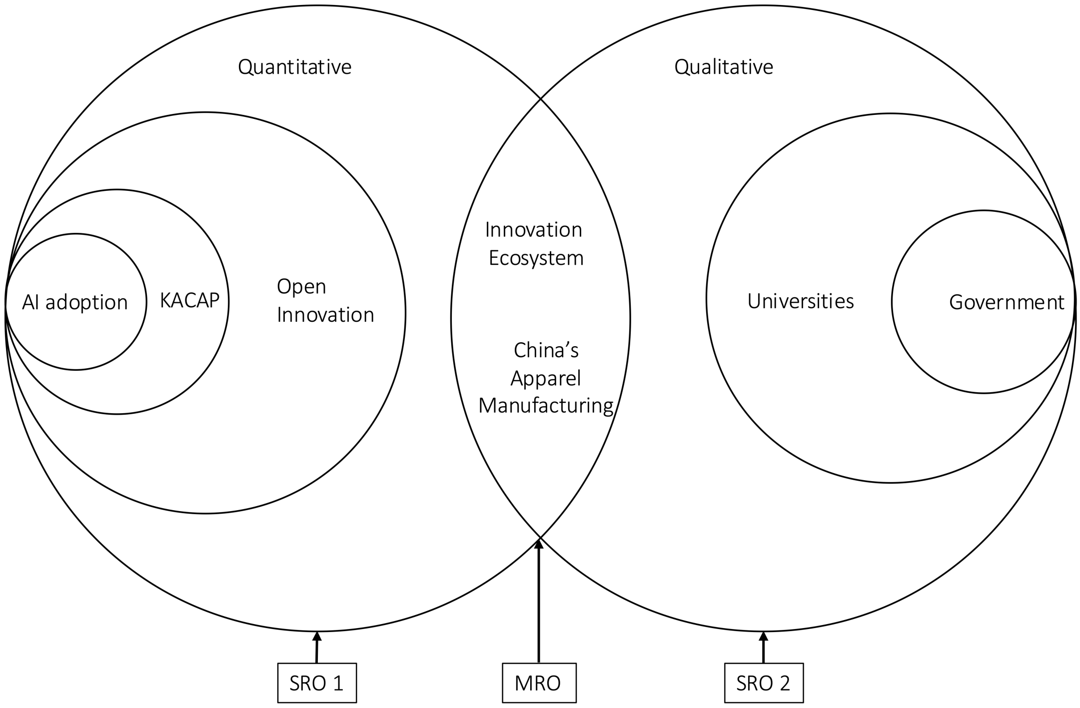

Figure 1.6 Research Approach and Boundary of the Two SROs

1.6. Research Significance

Based on the research objectives of two studies, this thesis contributes to building an AI-enabled innovation ecosystem for apparel manufacturing firms by orchestrating existing theories and generating theoretical frameworks, as mentioned before. Thus, the thesis provides theoretical, practical, and policy-related significance.

Theoretically, the research builds a novel theoretical framework that integrates AI adoption with open innovation and KBV perspectives in Chinese apparel manufacturing industry. By employing grounded theory, the study offers new perspectives on the role of AI in enhancing collaboration among industries, academia, and government bodies within an innovation ecosystem. This fills existing theoretical gaps by linking AI technology to organizational innovation processes. The framework developed provides a foundation for future research exploring the intersection of AI and innovation in similar industries.

Practically, the research provides insights for apparel manufacturers seeking to adopt AI technologies to foster open innovation. By identifying the key factors affecting AI adoption and highlighting the importance of KBV, the study offers enterprises a roadmap for integrating AI into their innovation processes. This will enhance their ability to produce small-batch, highly personalized products and increase their competitiveness in a rapidly evolving market. Furthermore, through a deep understanding what AI capabilities the Chinese manufacturing demands to enable apparel productions, and what the factors hinder Chinese MSMEs to adopt AI, the grounded framework developed offers guidance on how traditional businesses improve collaboration with universities, associations, and government agencies to co-create values in the AI-enabled innovation ecosystem. Simultaneously, the research outcomes contribute to providing the innovation path for talents cultivations.

Policy-related, the research informs policymakers by unveiling the mechanisms through which AI can promote collaboration between enterprises, academic institutions, and government bodies. Policymakers can use the findings to develop strategies that encourage the integration of AI into industry and innovation systems, contributing to the broader goal of sustainable economic development in Chinese apparel manufacturing sector, concreting, and practical policy measures for apparel industrial transformation and upgrading.

This thesis is set against AI innovation and Industry 4.0 and 5.0 in China. In this disruptive context, it examines how the traditional apparel manufacturing industry leverages AI for human-machine interactions and industry, university and government collaboration. By conducting a quantitative survey in ***Study 1***, this research deductively constructs a hypothetical reflective model using a PLS-SEM to identify the correlations between the antecedent impact of AI adoption, the mediation of KACAP, and the consequence of open innovations. These quantitative findings from ***Study 1*** serve as a critical empirical base for the subsequent ***Study 2***, which delves deeper into how KACAP enhances the construction of AI-driven innovation ecosystems. ***Study 2*** inductively extracted categories and concepts from diverse perspectives of apparel manufacturers, institutional professors, and apparel association leaders. Using grounded theory, this thesis developed a novel theoretical framework, integrating industry (firms, suppliers, and customers), universities (specialized instructors and students), and government (central government, local governments, and industry associations) interactions to synthesize the dynamic innovation ecosystem. This valuable guidance can inform policymakers, industry experts, and academic institutions or universities, fostering stakeholder orchestration with AI-driven value creation in the innovation process by the cooperative mechanisms' specific operational models and effectiveness.

1.7. Thesis Structure

Followed by ***Chapter 1***, this thesis is structured into six subsequent chapters, as detailed below.

Chapter 2 (Literature Review) reviews extensive literature, consisting of literature review for ***Study 1*** and ***Study 2***. It focuses on conducting a literature review to provide a theoretical lens for understanding AI's capabilities toward open innovation in addressing ***SRO 1***. The literature review for ***Study 1*** leads to the proposed conceptual model that explores the antecedents of AI adoption that drive apparel manufacturing firms' open innovation, as outlined in this chapter. This provides a guideline for developing the conceptual model, assessing the relationships between its latent variables, and establishing the rationale of the hypotheses for ***SRO 1***. The literature review for ***Study 2*** draws on the definitions of innovation ecosystem and its associated theoretical lenses, i.e., open innovation ecosystems and the TH model, to construct theories for addressing ***SRO 2***.

Chapter 3 (Methodology) presents a research onion (Saunders et al., 2016) that lays out research philosophies, design, approaches, strategies, time horizons, and data collection and analysis techniques for addressing the research questions. It also describes ethical considerations before data collection procedures.

Chapter 4 (Analysis and Results of ***Study 1*** identifies the correlations between AI adoption and open innovation, emphasizing the significant role of KACAP as a mediating linkage between AI adoption and open innovation. The measurement and the structural models are analyzed in detail. This chapter addresses ***SRO 1***.

Chapter 5 (Findings of ***Study 2***) conducts grounded theory, confirming the conceptual proposing propositions from stakeholders' perspectives by conducting coding processes to categorize the two specific required AI capabilities and three main dimenssions of barriers to adopting AI. This addresses ***SRO 2,*** and provides theoretical lenses for clarifying how to develop an AI-enabled innovation ecosystem through interactions among government, industry, universities, and associations while unveiling fundamental mechanisms and pathways in this process.

Chapter 6 (Discussions and Valuable Contributions) integrates the findings of ***Study 1*** and ***Study 2***, explaining and discussing the hypothesized model, thereby supporting establishing an AI-driven innovation ecosystem through grounded theoretical data analysis. More importantly, this chapter provides a theoretical lens to academia and practical implementation for Chinese apparel manufacturers. These are the novelties and originalities of the thesis for valuable contributions. The findings and the ***MRO*** are synthesized in the last.

Chapter 7 (Conclusion, Limitations and Future Research, and Highlights) summarizes the thesis's conclusion, the key findings, limitations and future research, and highlights.

1.8. Chapter Summary

Chapter 1 provides an overview of this thesis, including the research context that delivers a comprehensive background on the disruption in the Chinese apparel manufacturing sector. It highlights the research rationales, emphasizing the need for organizations to navigate the uncertain and competitive environment shaping traditional enterprises' transformation. The theoretical background identifies research gaps and establishes the research objectives. A concise explanation of the research approach is presented alongside the delineation of research boundaries defining the scope of this thesis. The chapter concludes by introducing the subsequent chapters. The next chapter will deliver the literature review related to the theoretical foundations of ***Study 1*** and ***Study 2***.

2. Literature Review

2.1. Introduction

This chapter first focuses on conducting a literature review to understand AI's capabilities toward open innovation and AI adoption in addressing ***SRO 1***. The literature review for ***Study 1*** leads to the proposed conceptual model that explores the antecedents of AI adoption that drive apparel manufacturing firms' open innovation, as outlined in this chapter. Based on AI capabilities and innovation background, relying on an organizational perspective, this chapter further presents the literature review on AI capabilities-enabled innovation ecosystems, further addressing ***SRO 2***, thereby developing a framework for practical implementations to achieve the ***MRO***. Therefore, as shown in **Figure 2.1**, this chapter is structured initially in section 2.2 (Literature review for ***Study 1***), which presents a theoretical foundation of AI adoption that drives open innovation with an extended TAM-TOE structural model. Then, this chapter reviews the literature on innovation ecosystems in section 2.3 (Literature review for ***Study 2***). Section 2.4 synthesizes the reviewed literature, followed by the chapter summary in section 2.5.

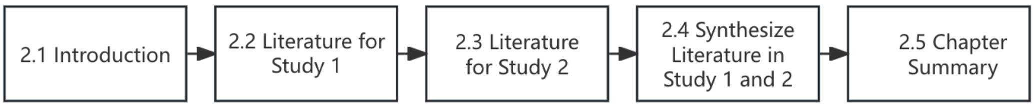

Figure 2.1 Flow Chart of Chapter 2

2.2. Literature Review and Conceptual Model for Study 1

2.2.1. AI Capabilities

The prior introduction has described how AI has evolved over several decades. However, there is still a lack of comprehensive understanding of the capabilities that AI enables, leading to a lack of definition to ground empirical studies on AI capability. It is widely recognized as being fundamentally derived from its enabling technological competencies (Chan et al., 2020; Kassa et al., 2023; Manis & Madhavaram, 2023; Sigov et al., 2022; Sjödin et al., 2023; Tariq, 2023; Teece, 2018; Wu et al., 2021). Among the literature, a sample understanding of the enabling roles of AI capability is that a technology-level capability executes tasks and resolves problems that typically require human intelligence (Wu et al., 2021). Wu et al. (2021) define four levels of AI capabilities: 1) Data collection and transmission capabilities that transfer the collected data within and between product modules, such as sensors and information communication technologies; 2) Bridging capabilities that connect end users through cloud technology; 3)Algorithms capabilities that use machine learning, deep learning, big data analytics, and artificial neural network to perform specific business tasks; 4) Applications capabilities that realize mature technological convergences between Internet of things and robots to provide innovative products. These AI techniques were depicted in the previous introduction section. Mikalef and Gupta (2021, p. 3), grounded on a series of prior definitions, initially define the meaning of AI capability and subsequently conceptualize AI capability as "the ability of a firm to select, orchestrate, and leverage its AI-specific resources”. This definition articulates AI capability from a resource-built perspective, incorporating three components: tangible resources (data, technology, and basic resources), human resources (technical skills and business skills), and intangible resources (inter-departmental coordination, organizational change capacity, and risk proclivity). Within this definition, resources are a prerequisite for using AI to achieve organizational performance (Mikalef & Gupta, 2021; Van Noordt & Tangi, 2023). Akter et al. (2023) systematically reviewed 33 papers on AI in the service innovation capability from market, infrastructure, and management capability parameters. The market capability focuses on the market demand, using AI to predict and satisfy customers and the industry’s requirements (Akter et al., 2023). This capability parameter is also defined as integrating AI to enhance network resource integration by leveraging organizational resources. Infrastructure capability emphasizes an organizational capability that enables AI-powered service delivery within a social-technical space and first mentions AI ecosystem capability encompassing high-speed computing, comprehensive data management, advanced cloud computing, innovative service platforms, and “dynamic capabilities such as sensing and innovation capabilities” to ensure technological and evolutionary fitness (Akter et al., 2023, p. 10). The understanding of management capability consists of AI ethics, orientation, and organizational learning, which provides organizations with propositions about effective governance, improvement, and innovation in knowledge development utilizing AI technologies (Akter et al., 2023). Another parameter of AI capability stems from human decision-making, which three levels possibly replace and complement the human brain (Haefner et al., 2021). **Table 2.1** categorizes the constructs and characteristics of AI’s capabilities from the previously mentioned studies (Akter et al., 2023; Haefner et al., 2021; Mikalef & Gupta, 2021; Sjödin et al., 2021; M. Wu et al., 2021) for the detailed understanding.

Accordingly, given the existing literature on AI capabilities, this thesis refers to AI capability as:

An organization’s innovative and practical ability to utilize, reorganize, and orchestrate internal and external resources driven by industry needs and technological advancements. Under the supervision of organizational governance and in compliance with ethical standards, this capability automates tasks and enables human decision-making through AI-integrated technologies to create business value.

Table 2.1 Construction of AI capabilities in application areas

AI capabilities	Understanding	Constructs	Characteristics	Author and year
Information processing capabilities.	The ability of AI systems to replace and complement human decision making.	Exploiting level (support not fully replacing humans)	Identify more information than develop ideas, overcome cognitive information processing constraints, and data processing.	(Haefner et al., 2021)
		Expanding level (in tandem with humans)	Recognize more problems, opportunities, and threats, and identify and evaluate ideas or support humans in developing more innovative ideas and solutions.	
		Exploring level (replace humans to a certain extent.	Explore new avenues in the innovation process, generate new ideas, and explore new ways of defining problems and way of addressing problems.	
Resource-built capabilities.	The ability of a firm to select, orchestrate, and leverage its AI-specific resources.	Tangible resources	Data, technology and basic resources.	(Mikalef & Gupta, 2021, p. 4)
		Human resources	Technical skills and business skills.	
		Intangible resources	Inter-departmental coordination, organizational change capacity, and risk propensity.	
Market capability.	The market-oriented capability that understands customers' demands and industry requirements integrates organizational resources by AI.	Customer orientation	Using AI processes to understand customers' demands, and transform them in marketing initiatives.	(Akter et al., 2023)
		Industry orientation	Using AI to understand the requirements of the industry.	
		Cross-functional integration	Using AI to integrate organizational resources in enhancing networking and integration.	
Infrastructure capability.	The organizational capability to enable AI-powered service delivery within a socio-technical space.	Data capability	Data-driven business environment to facilitate decision support systems and foster value creation.	(Akter et al., 2023)
		Model development capability	The comprehensive process of creating, training, and refining machine learning models to perform specific tasks or solve particular problems.	
		AI ecosystem capability	Encompasses high-speed computing, comprehensive data management, advanced cloud computing, innovative service platforms, and dynamic capabilities to ensure technological and evolutionary fitness.	

Table 2.1. Cont.

AI Capabilities	Understanding	Constructs	Characteristics	Author and year
Management capability.	The comprehensive ability of an organization to effectively govern and utilize AI technologies.	AI ethics	The psychological, social, environmental and political impacts of AI.	
		AI orientation	Market-orientated AI to satisfy customers' demands through ML and DL.	
		Organizational learning	Organizations build a robust knowledge base and gain insights, leading to continuous improvement and innovation in the process of knowledge development.	
The implementation and scalability.	The ability that leverages AI within the core processes of the business model.	Data pipeline	Monitoring the industrial environment by collecting data and insights from various sources and then organizing and presenting the gathered information in a systematic manner.	(Sjödin et al., 2021)
		Algorithm development	Predicting the future state or actions of the business through development of algorithms.	
		AI democratization capabilities	Making AI accessible to the entire organization and demonstrating its potential.	
Technology-level capabilities.	AI technologies possess the collective abilities and potential to perform tasks and solve problems that typically require human intelligence.	Data collection and transmission	The capability to leverage technologies that collect data from the physical world or transfer data within and between product modules, e.g., sensors and information communication technologies.	(M. Wu et al., 2021)
		Bridging	The ability to connect (disparate) end-users with AI products and services/products, e.g., cloud technology.	
		Algorithms	The ability to use AI techniques and algorithms to perform specific business tasks, e.g., ML, DL, BDA, ANNs, etc.	
		Applications	The capability to realize mature technological convergences between AI and/or other technologies to provide innovative products, e.g., IoT and robots.	

2.2.2. AI Adoption

2.2.2.1. Technology Acceptance Model

The original technology acceptance model (TAM) was introduced by Davis (1989), who adapted it from TRA, specifically meant to explain computer usage behavior (Davis et al., 1989). It has been confirmed as an essential theoretical framework for describing and predicting attitudes toward technology acceptance and behavioral intentions. In this model (**Figure 3.4**), the external factors are mediated by perceived usefulness and perceived ease of use to drive attitude, thereby driving intention, which leads to the actual use (Davis, 1989). Many quantitative studies employ the TAM as a primary theory. Some research has applied the TAM in AI-related applications. For example, Choung et al. (2023) extended the TAM with trust in AI to empirically examine the influence of trust on usage intention. The model explained the 52% variance for four factors loading onto the usage intention of AI voice assistants: perceived usefulness, perceived ease of use, trust perception, and attitude (Choung et al., 2023). Pillai et al. (2020) revealed that the perceived usefulness and perceived ease of use of AI-powered automated retail stores were affected by consumers' innovativeness and optimism. Also, they are along with other determinants such as perceived enjoyment, customization, and interactivity, are significant predictors of consumers' shopping intention.

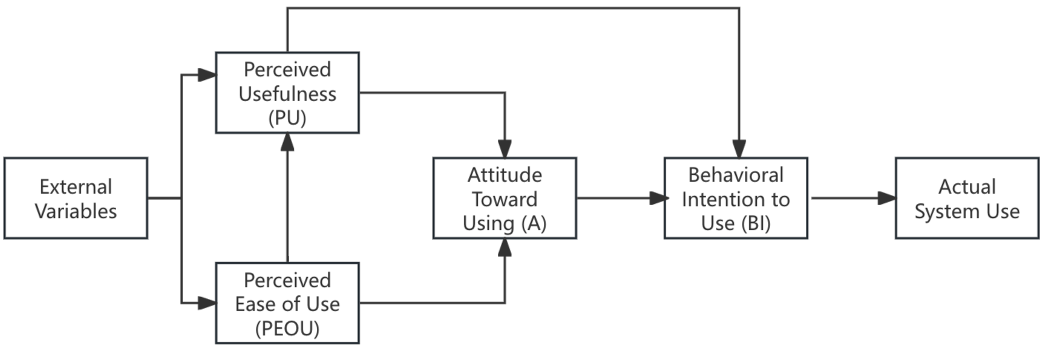

Figure 2.2 Technology Acceptance Model (TAM) (Source: Davis, 1989, p. 985).

TAM is also applied to adopting AI-integrated technologies research along with other theories. S.-F. Wang & Chen (2024) integrated the TAM and TPB behavioral measurement model, incorporating designers' characteristics, revealing that designer trust is the primary factor influencing their behavioral choices. Sohn and Kwon (2020) integrated TAM with TPB, UTAUT, and the Value-based Adoption Model (VAM) to investigate AI-based intelligent product adoption. The finding reveals that perceived usefulness and perceived ease of use significantly affected BI with an explained variance of 63%; TPB showed that attitude, perceived behavioral control, and subjective norms significantly affected BI and that TPB explained 66.8% of the variance, and both UTUAT and VAM explained that the model was higher than 70 % in BI affected by respective factors (Sohn & Kwon, 2020). Patil et al. (2023) employed TAM and TOE models to identify the adoption intention of IoT-based intelligent manufacturing systems. They identified technological (perceived ease of use) and environmental (competitive pressure) factors that influence micro, small, and medium enterprises (MSMEs) intentions to adopt intelligent manufacturing systems (SMS) enabled by the IoT. A 58% variance in IoT-based SMS adoption intention was explained (Patil et al., 2023). They complement the original TAM model when considering the organizational perspective of technology adoption rather than just the individual adopter perspective (Dobre, 2022). Chatterjee et al. (2021) integrated TAM and TOE to evaluate AI adoption, revealing that the model explains the 71% variance of AI adoption, with the main driver roles of perceived usefulness and perceived ease of use in the intention to adopt AI.

2.2.2.2. Technological, Organizational, and Environment (TOE) Framework

Diffusion of innovation (DOI) is a groundbreaking theory that has since become a cornerstone in innovation adoption research (Roger, 2014). This theory posits that the acceptance of an innovation is a gradual process in which the adoption rate is influenced by "the perceived relative advantage", "compatibility", "trialability", "observability", and "lower complexity" of the innovation, all contributing to its eventual acceptance (Dobre, 2022; Rogers, 2003). Inspired by DOI in technology adoption, Tornatzky and Fleischer (1990) identified relative advantage, compatibility, and complexity support Rogers' innovation adoption model. Compared to the DOI theory, the TOE framework offers a more decisive advantage in analyzing external environmental factors influencing the adoption of technology (AL-khatib, 2023). It is a theory that "supports the evaluation of innovation adoption from both the individual and organizational perspectives" on technology adoption at organizational resources and environments "within internal and external networks" (Dobre, 2022, p. 73), rather than the previous models' solely individual perspectives, such as users and consumers.

Figure 2.3 depicts the construction of the TOE framework. The three attributes of the TOE framework influencing adopting and implementing technological innovations are: (1) Technological context describes internal and external technologies available for possible adoption to a firm (Amini & Javid, 2023; T. Oliveira & Martins, 2011). (2) Organizational context involves the characteristics of such organizations, including formal and informal linking structures, communication processes among employees, competencies, firm size, and organizational slack (Näslund & Naslund, 1964; Stenberg & Nilsson, 2020). (3) Environmental context refers to external forces, such as industry characteristics and market structures, technology support infrastructure, competitors, and government regulations (Oliveira & Martins, 2011). The TOE framework encompasses a range of context-specific factors designed to aid in the comprehensive evaluation and understanding of technology adoption processes. We reviewed diverse studies on selecting factors in the ongoing study of AI-integrated technology adoption, utilizing the TOE framework, as detailed below.

Polisetty et al. (2023) employed the TOE framework at an organizational level to examine how AI enablers and AI readiness influence the competitive advantage with due acceptance of AI practices through gathering from 866 employees (managers) of SMEs. The antecedents behind AI adoption readiness and competitive advantage relations are TOE factors. They selected and extended the original factors identified by Tornatzky and Fleischer (1990) and redefined the selected predictors based on the

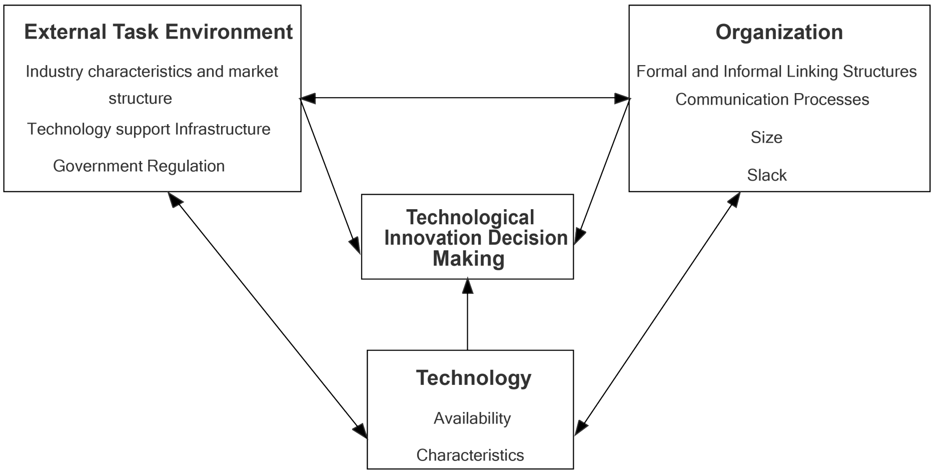

Figure 2.3 Technology, Organizational, and Environment (TOE) Framework (Source: Tornatzky & Fleischer, 1990, p. 153)

TOE framework, which are technological factors (AI compatibility, perceived benefits), organizational factors (role clarity and perceived trust), and environmental factors (data governance and data quality). They conducted a mixed approach, finding that AI compatibility, perceived trust, data governance, and data quality influence AI adoption readiness. This model explains 41% of the variance in AI adoption readiness and 51% in the effect of AI adoption readiness on competitive advantage. However, this study has not considered the industry sectors, geographic location, and firm size. In addition, the TOE focuses on both organizational and individual respects. The study of Polisetty et al. (2023) focuses on the organizational-level factors, but employee attitudes and perceptions about AI from individual-level factors have not been identified.

Badghish and Soomro (2024) used the TOE framework, identifying that relative advantage, compatibility, sustainable human capital, market and customer demand, and government support affect the adoption of AI by SMEs. Similar to Polisetty et al.(2023)'s model, they employed TOE as the antecedent of AI adoption toward sustainable business performance. They focus on the readiness of TOE, reflecting cost, relative advantage, complexity & compatibility as technological readiness, organizational support, sustainable human capital as organizational readiness, market and customer demand, and government support as external environmental readiness. Their conceptual model explains the 72.7% variance in AI adoption and 67.8% and 69.6% in economic and operational performance, respectively. Findings reveal that economic, infrastructure, and knowledge internal barriers are the main obstacles to deploying the "Four Smarts", while external barriers do not pose challenges in the deployment phase.

Aniceski et al. (2024) use the TOE framework to investigate the relationship between the implemented I4.0 technologies associated with the "Four Smarts" and the presence of internal and external barriers to distinct outcomes pursued by companies. This study has examined the barriers to industry 4.0 technology adoption, thus understanding how to achieve resilience and human-centric approaches and sustainable outcomes towards Industry 5.0. The technological dimension is related to the functionality, complexity, and compatibility with existing systems. In their work, the adoption of Industry 4.0 technologies is associated with smart products, manufacturing, supply chain, and working-led companies. Then, they defined internal barriers as an organizational dimension, where a lack of infrastructure and knowledge, economic aspects, and cultural factors associated with deploying Industry 4.0 technologies. Last, the external barriers are considered as an environmental dimension, from the aspects of technical norms, lack of partnerships and support, and lack of infrastructure and skills. The effects of all three dimensions were investigated on the benefits of Industry 4.0 technologies adopted from the environmental and social aspects, operational performance, and innovation capacity. The model has two large effect sizes of independent variables toward benefits.: 44% variance in smart products to technological dimensions and 54% variance in smart manufacturing for organizational dimension. However, this study has yet to investigate how to overcome the barriers of the smarts. Also, it lacks the investigation of human-centric systems towards possible barriers in the context of Industry 5.0.

AL-khatib (2023) uses the TOE framework to investigate Gen-AI adoption in Jordan's retailing industry. The research reveals that relative advantage, top management support, organizational readiness, and customer pressures influence Gen-AI adoption, while complexity negatively influences it. This research also demonstrates the positive impact of Gen-AI on both exploratory and exploitative innovation, which contributes to presenting new paths in this relationship.

Maroufkhani et al. (2023) investigated 171 Iranian SME manufacturing firms to determine the influence of TOE factors on Big Data Analytics (BDA) adoption. The model explained the 65.8% variance in BDA adoption, revealing that compatibility, competitiveness, and organizational readiness impact BDA adoption, and top management support mediates this. Environmental factors moderate the impacts of compatibility and organizational readiness on top management support. This study highlights the mediating role of top management support between the linkage of technological and organizational factors and BDA adoption and the moderating role of the environmental factors on the effects of technological and organizational factors on top management support. Maroufkhani and co-authors employed RBV and TOE to identify BDA adoption and SMEs' financial and market performance (Maroufkhani, Wan Ismail, et al., 2020a). Specifically, TOE defines the antecedents of BDA, and grounding in RBA theory, BDA mediates the TOE variables and firm performance. This model explains the 69.4% variance in BDA adoption, 68% in financial performance, and 58.2% in market performance. Drawing on the DOI and RBV theories, Maroufkhani, Tseng, et al.(2020) propose a conceptual model with a wide range of TOE factors that have influenced technology adoption. Complexity, uncertainty and insecurity, trialability, observability, top management support, organizational readiness, and external support have been confirmed to affect BDA adoption significantly. This model explains the 78.3% variance in BDA adoption.

2.2.2.3. Constructs of TOE and Integrated TAM-TOE in AI adoption Studies in Manufacturing Sectors

To provide the theoretical foundations for addressing ***Study 1***'s research questions, this part of the literature review critically evaluates 10 key peer-reviewed empirical journal articles from Scopus database on the predictors of AI adoption in manufacturing based on the TOE, and the integrated TAM and TOE, as shown in **Table 2.3 and Table 2.4**. Blockchain technology, robots, cloud computing, and

IoT are increasingly integrated with AI technologies (Kurni et al., 2022; Kuznetsov et al., 2024; Qu & Kim, 2024b), and thus, these studies have focused on empirical research around the factors that influence the adoption of AI-integrated technologies using the TOE framework, and the integrated TAM-TOE framework (Gangwar et al., 2015; Guan et al., 2023; Kamble et al., 2021; Legesse et al., 2024; Patil et al., 2023; Pillai et al., 2022; Tasnim et al., 2023). For example, influential research on AI adoption in Chatterjee et al. (2021) integrated TOE with TAM to explore the applicability of Industry 4.0 and how socioenvironmental and technological factors influence the adoption of AI-embedded technology by digital manufacturing and production organizations. They embedded perceived usefulness and perceived ease of use as the intermediating technological factors linking organizational and environmental antecedents and consequences of the intention to adopt AI. The mediating effect of perceived usefulness and perceived ease of use has been presented in many research that employs the TAM-TOE model, such as Gangwar et al. (2015), Kamble et al. (2021), Legesse et al. (2024), Patil et al. (2023), and Tasnim et al. (2023). Other antecedents of TOE are explained in detail as follows.

Organizational competency (OCM) is associated with employees' skills, knowledge, and capabilities, which explains that employees capable of using technology enhance the manufacturing organization's competency, thereby improving performance (Chatterjee et al., 2021). It is often similar to organizational readiness (ORE) defined from the perspective of organizational resources (i.e., technological and financial) for adopting new technologies (Iacovou et al., 1995a). In addition, previous content has stated that managing AI-based innovation necessitates substantial technical and organizational adjustments, particularly to address the challenges arising from the firm size (Füller et al., 2022). Therefore, the role of firm size is a key aspect of organizational readiness, which has been presented in the studies of Guan (2023) and Chatterjee et al. (2021). Chatterjee et al. (2021) amalgamate firm size with organizational readiness, whereas Guan (2023) and other authors defined it as a stand-alone concept (Kinkel et al., 2022). However, the studies confirm that firm size does not significantly impact dependent variables (Cao et al., 2021; Hsu & Lin, 2018; Iacovou et al., 1995).

Organizational complexity (OCX) is closely associated with the lens of TAM (Chatterjee, Rana, Dwivedi, et al., 2021). It is "the perceived degree of difficulty of understanding and using a system" (Sonnenwald et al., 2001, cited Chatterjee et al., 2021; Gangwar et al., 2015, p. 113). As the complexity appears in internal organizations, it is demonstrated to negatively influence perceived and usefulness and perceived ease of usefulness by many prior studies (Chatterjee, Rana, Dwivedi, et al., 2021; Gangwar et al., 2015; Kamble et al., 2021; Tasnim et al., 2023). Some authors defined the term complexity in a tangible object, such as new system (Gangwar et al., 2015) or product complexity (W. Guan et al., 2023; Kinkel et al., 2022). However, their alignment is consistent in the view that complexity negatively impacts individuals' intentions to use AI.

Table 2.2 Hypothetical predictors driving AI technologies adoption based on TAM-TOE in manufacturing from peer-reviewed journal articles.

Theory	**Source**	**Consequence**	**Antecedent**												
			Technological			**Organizational**						**Environmental**			
			PU	**PEOU**	RAD	OCM	**OCX**	**ORE**	T&E	OCO	TMSU	COA	**PSU**	**GSP**	**CP**
TAM-TOE	(Chatterjee, et al., 2021)	Intention to adopt AI	x	x		x	x	x		x		x	x		
	(Gangwar et al., 2015)	Cloud computing adoption intention	x	x	x	x	x		x	x	x	x			
	(Kamble et al., 2021)	Blockchain adoption	x	x	x		x	x	x	x	x		x		x
	(Legesse et al., 2024)	Intention to adopt blockchain	x	x	x						x			x	
	(Patil et al., 2023)	IoT adoption	x	x							x			x	x
	(Tasnim et al., 2023)	Intention to adopt blockchain	x	x	x		x	x	x		x				

Legend: TAM= Technology Acceptance Model; TOE=Technology-Organization-Environment; PU=perceived usefulness; PEOU=perceived ease of use; RAD=relative advantage; OCM=organizational competency; OCX=organizational complexity; ORE=organizational readiness; T&E=training and education; OCO=organizational compatibility; TMSU= top management support; COA=competitive advantage; PSU=partner support; GSP=government support and policy; CP=competitive pressure.

Table 2.3 Hypothetical predictors driving AI technologies adoption based on TOE in manufacturing from peer-reviewed journal articles.

Theory	**Source**	**Consequence**	**Antecedent**										
			Technological	**Organizational**			**Environmental**						
			RAD	**OCX**	**ORE**	OCO	**COA**	**PSU**	FS	GSP	PCX	**CP**	**MU**
TOE	(Badghish & Soomro, 2024)	AI adoption	x	x	x					x			
	(Kinkel et al., 2022)	AI adoption					x		x		x		
	(W. Guan et al., 2023)	Intention to adopt blockchain			x			x	x		x	x	x
	(Pillai et al., 2022)	Intention to adopt AI-powered robot			x	x							

Legend: TOE=Technology-Organization-Environment; RAD=relative advantage; OCX=organizational complexity; ORE=organizational readiness; OCO=organizational compatibility; COA=competitive advantage; PSU=partner support; FS=firm size; GSP=government support and policy; PCX= product complexity; CP=competitive pressure; MU= market uncertainty

Rogers (2014) and Géczy et al. (2012) define organizational compatibility (OCO) as the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of adopters and which is that of potential users. It is also an internal organizational issue and is associated with these characteristics of a manufacturing organization that are reconcilable with AI, which can be found in four studies (Chatterjee, Rana, Dwivedi, et al., 2021; Gangwar et al., 2015; Kamble et al., 2021; Pillai et al., 2022). However, the TAM-TOE model suggests that compatibility positively affects perceived usefulness but not perceived ease of use (Chatterjee, Rana, Dwivedi, et al., 2021), further indicating that the determinant of compatibility with old production systems impacts potential users' demands, thereby influencing AI adoption.

Top management support (TMSU) provides facilitating conditions that are the employees' perception stimulated by organizations, of which the necessary technical and organizational capacity and infrastructure for them to be able to adopt new technologies (Badghish & Soomro, 2024). Tasnim et al. (2023) find top management support significant for enhancing the perceived usefulness of this technology among employees, then drive the organizations to adopt new technology by taking risks for adopting blockchain technology and providing resources, consistent with the studies of Gangwar et al. (2015), Kamble et al.(2021) and Legesse et al. (2024). Therefore, employees' perceived usefulness and perceived ease of use mediate the impacts of top management support on technology adoption. According to this perspective, "technological adoption is generally carried out using a top-down approach" (Gangwar et al., 2015, p. 122). On a different approach, Patil et al. (2023), although they also conduct a hybrid TAM-TOE model, find that perceived usefulness and perceived ease of use positively influence technology adoption so that top management would support technology implementation.

This support by top management in internal organizations is also reflected by training and education (T&E) in several studies. For example, Tasnim et al. (2023) find that the fear of the complexity of technology can be reduced by anticipating proper training and education, and technical knowledge to the employees, further implying that blockchain adoption requires top management support. Badghish and Soomro (2024) emphasize the importance of sustainable human resource (SHR) policies in facilitating the changes that become pivotal for AI adoption. SHR practices encompass various sustainable activities aimed at mitigating the skill gap by implementing employee development initiatives, training programs, and reward systems that promote work-life balance and enhance employee well-being, all to facilitate the adoption of new digital technologies. Training and education antecedent representing the organizational factor was found to positively influence perceived usefulness and perceived ease of use by Kamble et al. (2021). The finding suggests that as employees gain more technical knowledge about deploying blockchain technology, organizations find utilizing blockchain in the supply chain easier and are more convinced of its usefulness (Kamble et al., 2021). This is consistent with the study of cloud computing adoption by Gangwar et al. (2015).

Competitive advantage (COA) is applied to AI adoption, allowing for better production and benefiting organizations (Rogers, 2014). It is associated with unique resources and capabilities and is ahead of competitors (Dobre, 2022). AI's competitive advantages were represented in its capabilities, as previously outlined. AI's enabling roles in innovation will help organizations gain competitive advantages. In the TAM-TOE framework, competitive advantages indirectly affect the intention to use AI through perceived usefulness and perceived ease of use (Chatterjee et al., 2021; Gangwar et al., 2015); therefore, employees perceive the usefulness of AI and the ease of use of AI could help organizations gain competitive advantages.

Yang (2015) highlights that the drive to gain competitive advantages is a key pressure for adopting innovative technology. This means firms experience substantial competitive pressure (CP), which incentivizes the adoption of innovative technologies to maintain a favorable position. Competitive pressure refers to the degree of pressure a firm has from competitors within the industry, which directly influences AI adoption in the manufacturing sector. These findings support the literature from other studies (W. Guan et al., 2023; Kamble et al., 2021). However, in a TAM-TOE model, competitive pressure indirectly influences AI adoption through perceived usefulness (Patil et al., 2023; Tasnim et al., 2023). This is partially in line with the results from employees' perspectives.

Relative advantage (RA), as applied to adopting AI-related technologies, such as blockchain, allows for "improved transparency, enhanced traceability, increased reliability, and potential gains in efficiency" (Kamble et al., 2024; Legesse et al., 2024, p. 9). Cloud computing leads to "greater efficiency of internal processes, increased employee productivity, improved customer service, reduced inventory costs, and improved coordination with trading partners" (Gangwar et al., 2015, p. 121). Similarly, adopting AI integrated with the existing technologies in manufacturing organizations has advantages over other technologies, such as enhancing product efficiency (Kumar et al., 2022), enabling sustainable supply chains (Dey et al., 2023; Kamble et al., 2022), supporting decision-making (Hao & Demir, 2023), reducing supply chain disruption (Kuźnar & Lorenc, 2023), etc. Therefore, understanding these advantages relative to existing systems strengthens relationships with customers and business partners and helps better management (Gangwar et al., 2015). Prior studies based on the TAM-TOE model have demonstrated that relative advantage directly impacts perceived usefulness and perceived ease of use, which are two mediating variables between relative advantage and AI adoption in manufacturing organizations (Gangwar et al., 2015; Kamble et al., 2021; Legesse et al., 2024; Patil et al., 2023). This means if employees believe the new systems bring advantages related to the existing production systems, they are more likely to perceive it as useful (enhancing work efficiency and performance) and easy to use (simple to operate and learn).

Partner support (PSU) and government support and policy (GSP) are external environmental factors that impact technology adoption in organizations. Partner support acts as an external agent to help an organization develop the knowledge repository of employees from knowledge-based view perspectives (Chatterjee, Rana, Dwivedi, et al., 2021). Government support and policy entails the provision of assistance or enabling conditions to organizations to facilitate the adoption or implementation of technology diffusion within the firm (Badghish & Soomro, 2024), which encompasses regulations, incentives, and measures for promoting AI for innovation in industries (Qu et al., 2023). As the theoretical background mentioned, it is related to INT that is often employed as an environmental factor in the TOE framework (Lutfi, 2020; Lutfi et al., 2022; Malik et al., 2021; Mujalli & Almgrashi, 2020; Oliveira & Martins, 2011). Due to the limited resources, SMEs need additional resources and government support, such as monetary incentives or government subsidies and making credit available from commercial banks, facilitating SMEs for implementing technological innovations (Badghish & Soomro, 2024). This is consistent with the study of Legesse et al. (2024) and Patil et al. (2023).

Market uncertainty (MU) refers to the constantly changing state of a highly unpredictable and complex environment, including unstable customer demands and becoming more sophisticated (W. Guan et al., 2023). In this dynamic and challenging business environment characterized by high market uncertainty, the impact of business strategy on manufacturing performance may decline (Handoyo et al., 2023). This environmental uncertainty reflects "the degree to which it is difficult to predict the nature of an environment and the consequences of environmental changes" (Lu et al., 2021 cited Hashem & Aboelmaged, 2023, p. 4577). Scholars assert that companies operating under high environmental uncertainty are motivated to adopt innovative corporate-level practices, enabling them to respond swiftly to ecological changes, such as the Internet of Things (Arnold and Voigt, 2019). SCM is a significant task in manufacturing as it involves planning, sourcing, making, delivering, and returning processes. Recent studies on logistics have highlighted that market uncertainty drives manufacturing organizations to adopt AI-related technologies to build resilience supply chains (Al-Banna et al., 2023; Arranz et al., 2023; Belhadi et al., 2022; Dey et al., 2023)

2.2.2.4. Selection of Hypothetical Constructs based on TAM-TOE

In examining AI adoption within Chinese apparel manufacturing industry, this study incorporates perceived usefulness, perceived ease of use, organizational complexity, organizational readiness, competitive pressure, supplier involvement, market uncertainty and government support and polices as essential constructs within the TAM-TOE framework. The integration of TAM with TOE provides a robust theoretical foundation for analyzing the interplay of technological, organizational, and environmental factors driving AI adoption in this sector. Perceived usefulness and perceived ease of use, core tenets of TAM, have demonstrated mediating roles in technology acceptance, representing the extent to which AI is perceived as advantageous and manageable by users. In the context of Chinese apparel manufacturing, perceived usefulness and perceived ease of use are particularly relevant, as they align with the industry's need for efficient and intuitive technologies that enhance productivity.

Organizational complexity and organizational readiness are integral to the TOE framework, capturing internal dimensions that shape AI adoption within manufacturing firms. As previously explained, organizational complexity refers to the structural and operational challenges that may inhibit the straightforward implementation of AI, while organizational readiness reflects the availability of resources and infrastructure necessary for successful adoption. These organizational factors are critical in Chinese apparel sector, where rapid technological advances necessitate firms to carefully assess their internal capacities for integrating AI.

The environmental dimension of the TAM-TOE model is addressed through constructs such as competitive pressure, supplier involvement, market uncertainty, and government support. Competitive pressure and supplier involvement underscore the role of external stakeholders and market forces that propel organizations towards adopting AI to maintain competitiveness (Jöhnk, 2021; T. Oliveira &

Martins, 2011). Supplier involvement (SIV) is associated with partnership support as several studies employed (Chatterjee et al., 2021; Kamble et al., 2021; W. Guan et al., 2023). Market uncertainty, characterized by fluctuating demand and supply chain disruptions, further drives firms to seek adaptable, AI-enabled solutions. Government support and policies are particularly salient in the Chinese context, as policy directives and incentives play a pivotal role in facilitating technology diffusion within industries.

By integrating these constructs, this model allows for a nuanced examination of the factors influencing AI adoption in Chinese apparel manufacturing sector, balancing internal organizational attributes with external pressures and regulatory influences that collectively impact the adoption landscape.

2.2.3. Extending TAM-TOE to Open Innovation Consequences

2.2.3.1. AI's Enabling Roles in Innovation

The initial section of the Chapter provides the umbrella of AI capability that provokes an understanding of its nature. This understanding facilitates AI's enabling roles in innovation processes to create maximum value and gain profits (Teece, 2018). Innovation has been fundamental to human striving throughout history, and since the Industrial Revolution, there have been clear periods of intensive activity (Millar, 2012). Innovation is defined as the result of a cumulative process in which existing knowledge is combined in new ways into something novel and useful (Sternberg and O'Hara, 1999, p.251 cited Bahoo et al., 2023; Arthur, 2007; Basalla, 1988, cited Grashof & Kopka, 2023). The notion of innovation also encompasses technological changes(Schumpeter, 1911, 1934 cited Carayannis, 2013), strategic paradigms (Sundbo, 1991), the exploitation of "idea generation" to "produce new products, processes, services and business practices" (Pittaway et al., 2004, p. 144; Sarooghi et al., 2015), and creative-innovation link (Sarooghi et al., 2015). However, these innovation concepts have yet to notice that emerging technologies drive scholars to revisit innovation and classify the types of innovation. The unaddressed gaps are unsurprising, given that the research field was not yet mature at the time. In the digitalized world, innovation is a transformative change ranging from incremental to radical in firms (Bahoo et al., 2023), and AI drives this radical transformation (Grashof & Kopka, 2023). The application of AI is expected to enable new opportunities for innovation management and reshape innovation practice in organizations (Füller et al., 2022), and therefore, increasing cases demonstrate that AI has been adopted in different innovation activities (Davenport & Ronanki, 2018). For example, Mariani et al. (2023, p. 18) have identified the outcomes of AI adoption for three major categories of innovation that are "economic outcomes (performance, effectiveness, efficiency), competitive and organizational outcomes (competitive advantage, organizational capabilities), and innovation outcomes (development of patents; development of new technology; product, process and business model innovation)". Furthermore, they expand the types of innovation consequences to the scopes of "product innovation, process innovation, business model innovation, incremental innovation, radical innovation, digital innovation, social innovation, sustainable innovation, open innovation, service innovation, disruptive innovation, market innovation, and organizational innovation" to identify AI's enabling antecedents (Mariani et al., 2023, p. 11). They elaborate on how AI capability enables innovation activities, especially in proposing a future research direction on AI-enabled sustainable development goals of the innovation consequence. This demonstrates that AI is driving innovation in all aspects, both macro and micro. Therefore, following the antecedents and consequences of AI's enabling roles, 12 groups of AI antecedents and innovation consequences in six types of innovations are categorized from the selected 12 studies, as this thesis focused in **Table 2.4**. These 12 studies were selected based on their relevance to AI-enabled innovation, the diversity of innovation types they represent, and their empirical evidence supporting AI's impact on organizational innovation. Priority was given to studies with rigorous methodologies and those published in high-impact journals from the Scopus database, ensuring a comprehensive and reliable basis.

Table 2.4 AI's Enabling Roles in Innovation

AI capability	Types of innovation	Through… (Antecedents)	For… (Consequences)	Author and year
Infrastructure capability.	Technological innovation	"accelerating knowledge-creating and technology spillover, improving the capability of learning and absorption, increasing R&D and talent investment…"	promoting technological innovation.	(Liu et al., 2020)
The technology-level capabilities.		enhancing machine autonomy, optimizing control transfer, increasing acceptance and trust, clarifying the roles of human employees, and developing measures to improve human-computer interaction (HCI)	improving operational efficiency and decision-making quality and promoting social sustainability.	(Klumpp & Zijm, 2019)
Information processing	Corporate innovation	"supporting creativity and out-of-box thinking…"	the idea generation stage of corporate innovation.	(Bahoo et al., 2023)
The implementation and scalability.		"effective search for new opportunities and solutions…"	idea development in corporate radical innovation.	(Eggers and Kaplan, 2009, cited Bahoo et al., 2023)
		"evaluating and implementing the best opportunity or solution to the problem…"	idea evaluation and implementation of corporate innovation.	(Bahoo et al., 2023)
Resource-built capabilities	Radical innovation	"the application-related AI knowledge the technique-related AI knowledge…"	the increase of radical innovation. the decrease of radical innovation.	(Grashof & Kopka, 2023)

Table 2.4. Cont.

AI capability	Types of innovation	Through… (Antecedents)	For… (Consequences)	Author and year
Information processing capabilities.	Open innovation	"providing ample opportunities for enabling effective knowledge sharing among organizations…"	fostering the initiation, development, and realization stages of open innovation.	(Broekhuizen et al., 2023)
The implementation and scalability.		"automating the identification and evaluation of external ideas and technologies…"	enhancing the efficiency of the inbound open innovation process.	(Bahoo et al., 2023; Sahoo et al., 2024)
Resource-built capabilities		"examining an organization's internal resources and capabilities…"	identifying potential areas of collaboration with external partners, allowing organizations to develop more targeted and effective outbound open innovation strategies.	(Cui et al., 2022; Sahoo et al., 2024)
		big data analysis and text mining techniques of AI	identifying potential partners for open innovation.	(Yoon & Song, 2014)
The implementation and scalability.		"access to new ideas, knowledge, and expertise…"	competitive advantages in the marketplace thereby culminating in higher business performance.	(Sahoo et al., 2024)
Information processing capabilities.	Knowledge innovation	"intelligence from data collection to feedback, monitoring, evaluation, analysis, prediction, and decision-making…"	promoting the transformation of knowledge acquisition and innovation, knowledge sharing, and knowledge creation from tacit knowledge to explicit knowledge.	(Bai & Li, 2020)
The technology-level capabilities.	Product innovation (tangible: good; intangible: service)	"using autonomous conversational interfaces…"	improving customer service.	(Correani et al., 2020; Gama & Magistretti, 2023)

2.2.3.2. AI Enables Open Innovation

The Definitions of Open Innovation

Chesbrough (2003, p43) first defined the definitions of open innovation as "... valuable ideas can come from inside or outside the company and can go to market from inside or outside the company as well", and later supplements to ". . . the use of purposive inflows and outflows of knowledge to accelerate internal innovation and expand the markets for external use of innovation, respectively" (Chesbrough et al., 2006, cited Gassmann et al., 2010, p. 213). These definitions highlight the significance of knowledge sources and better explain that open innovation provides a framework for utilizing external and internal knowledge, technology, and resources to accelerate internal innovation and expand markets for external innovation. The evidence of Kuzior (2023) supports this perspective. Kuzior (2023) finds that absorptive capacity has a significant, inverted U-shaped impact on new product development and that the interplay between external knowledge sources and a firm's absorptive capacity initially hinders, but ultimately enhances, innovation after surpassing a high level. In addition, Kuzior (2023) emphasizes that while a strong absorptive capacity can lead to organizational inertia, thereby reducing innovation, it is crucial to identify and understand the distinct effects of various external knowledge sources on innovation, as these effects vary with the level of internal knowledge.

Gassmann and Enkel (2004, p. 2) define open innovation as "the company needs to open up its solid boundaries to let valuable knowledge flow in from the outside to create opportunities for co-operative innovation processes with partners, customers and/or suppliers". This definition highlights an understanding of an innovation ecosystem where the emphasis is on collaboration with partners, customers, and suppliers, as well as the interdependent relationships within the innovation ecosystem (Granstrand & Holgersson, 2020). By opening up its boundaries, a company can share knowledge and collaborate with external partners, customers, and suppliers, forming a mutually beneficial innovation network. All participants contribute to the innovation process within this ecosystem by leveraging their unique expertise and resources, further accelerating technological advancements and market innovation.

Enkel et al. (2009) further emphasize the necessity of understanding how and where open innovation can add value in knowledge-intensive processes, using three firm's process perspectives: 1) the outside-in process, 2) the inside-out process, and 3) the coupled process. The outside-in process increases a company's innovativeness (Laursen and Salter, 2006; Lettl et al., 2006; Piller and Walcher, 2006, cited Enkel et al., 2009), revealing that the significance of enriching a firm's knowledge base by integrating external resources such as customers, suppliers, and competitors to enhance the company's innovative capabilities (Enkel et al., 2009). The inside-out process emphasizes that companies generate profits by externalizing their knowledge and innovations through market commercialization, licensing, and technology transfer, particularly highlighting the use of these strategies by large multinationals and the growing awareness of corporate venturing and cross-industry innovation (Enkel et al., 2009). The third coupled process highlights the importance of co-creation in the open innovation literature, which "strongly focuses on peer production through communities, consumers, lead users, universities or research organizations, and partners from other industries" (Enkel et al., 2009, p. 313).

Motivated by the paradigm of open innovation in industrial applications, Obradović et al. (2021) synthesized 239 articles within manufacturing research and assessed open innovation research streams, highlighting the necessity for further explorations of open innovation perspectives. Their findings suggest that manufacturing firms need to consider sustainable activities, especially in addressing the environmental and social issues throughout the supply chain. The study of Obradović et al. (2021) particularly states Industry 4.0 technologies adoption and open innovation regarding knowledge exchange and technology transfer among partners.

Lichtenthaler (2008, pp. 148–149) defined an open innovation approach as "systematically relying on a firm's dynamic capabilities of internally and externally carrying out the major technology management tasks, i.e., technology acquisition and technology exploitation, along the innovation process". Thus, open innovation processes involve a wide range of internal and external technology sources and a wide range of internal and external technology commercialization channels" (Lichtenthaler, 2008, pp. 148–149). Thus, in a technologically advanced environment, firms need to reach out to sources of scientific knowledge to access highly novel insights and enhance their innovation performance (Gassmann et al., 2010).

Hung and Chiang (2010) highlight that open innovation enhances as a factor of radical innovation (Gassmann et al., 2010). As previously outlined, AI's enabling roles in radical innovation are reflected in the application toward the increase of radical innovation, and the technique-related AI knowledge leads to the decrease of radical innovation, which is from an RBV perspective (Grashof & Kopka, 2023). Thus, numerous studies have systematically explored the correlations between open innovation and AI capability, revealing significant effects between AI and open innovation in organizations.

The latest research by Enkel et al. (2020) revisits the exploration of open innovation in the digital era. "The digital era provides new enabling factors for generating, sharing, retrieving, and storing data, information, or knowledge that could dramatically impact how organizations manage their boundaries" (Enkel et al., 2020, p. 162). The previous section has provided evidence of emerging technologies, such as AI's enabling roles in innovation, which aligns with Enkel et al.'s (2020) concern. As a result, organizations need to develop new strategies for managing the entire ecosystem, where they work alongside complementary partners to jointly innovate and create achievable solutions through their collaboration (Chesbrough et al., 2014; Enkel et al., 2020). Under this research motivation, the study of Enkel and his co-authors informs a research agenda on establishing a co-innovating ecosystem, and it proposes the "importance of alliances, innovation ecosystems, and the triple helix (TH) in the digital age" (Enkel et al., 2020, p. 162). However, this proposition critiques the previously mentioned outside-in process, where firms focus on collecting ideas from customers and suppliers. In contrast, the inside-out portion of open innovation remains unused (Enkel et al., 2009). Hence, companies will attract new partners from within and outside the industry who possess valuable knowledge and capabilities, forming long-term collaborations across various stages of the innovation process by leveraging a portfolio of activities, including the outside-in integration of external knowledge and co-creation with partners, to drive innovation (West & Bogers, 2014, cited Enkel et al., 2020).

The above contributions to open innovation provide the paradigm by presenting future research directions from individual challenges (micro) to applications of open innovation at an industry or national level) (macro) (Obradović et al., 2021). Overall, these scholars demonstrated that it is important to study drivers and roles in open innovation in a manufacturing context, thus reiterating the necessity of our study. Therefore, the following section expands previous AI's enabling roles in open innovation to specific literature in the manufacturing sector.

The Roles of AI Capabilities in Open Innovation

AI capabilities-enabled open innovation is an important way for manufacturing enterprises to gain competitive advantages in the digital economy (L. Wu et al., 2022), thus driving scholars to revisit open innovation from a traditionalist enterprise to a visionary enterprise (Enkel et al., 2020). Digital transformations in manufacturing systems confer advantages for enhancing competitiveness and ensuring the survival of companies by reducing operating costs, improving quality, and fostering innovation, falling within the overarching umbrella of Industry 4.0 (Goecks et al., 2024). An AI-powered digital transformation (Gołąb-Andrzejak, 2023; Z. Huang et al., 2021), its enabling roles have been identified in open innovation, particularly in the aspects of "providing ample opportunities for enabling effective knowledge sharing among organizations," thus fostering the initiation, development, and realization stages of open innovation (Broekhuizen et al., 2023), "automating the identification and evaluation of external ideas and technologies thus enhancing the efficiency of the inbound open innovation process (Bahoo et al., 2023; Sahoo et al., 2024), "examining an organization's internal resources and capabilities to identify potential areas of collaboration with external partners, allowing organizations" to develop more targeted and effective outbound open innovation strategies (Cui et al., 2022; Sahoo et al., 2024), "access to new ideas, knowledge, and expertise" to gain competitive advantages in the marketplace thus culminating in higher business performance (Sahoo et al., 2024). **Table 2.5** shows the enabling roles of four AI' capabilities in open innovation from antecedents and consequences.

Table 2.5 AI's enabling roles in open innovation

AI capability	**Through… (Antecedents)**	**For… (Consequences)**	**Source**
Information processing capabilities. (Haefner et al., 2021)	"providing ample opportunities for enabling effective knowledge sharing among organizations…"	fostering the initiation, development, and realization stages of open innovation.	(Broekhuizen et al., 2023)
	Data analysis and insight generation; support for collaboration and innovation	Provides data-driven insights for decision-making, enhances the screening of innovative ideas, and supports the selection of high-quality ideas for open innovation projects	(Sahoo et al., 2024)
Technology-level capabilities (Wu et al., 2021)	Automation and efficiency improvements; alignment with social and technical structures	Increases operational efficiency, frees up employee time for strategic innovation, and enables optimal human-AI collaboration, which strengthens internal and external partnerships essential for open innovation	(Sahoo et al., 2024)
The implementation and scalability. (Sjödin et al., 2021)	"automating the identification and evaluation of external ideas and technologies…" "access to new ideas, knowledge, and expertise…"	enhancing the efficiency of the inbound open innovation process. competitive advantages in the marketplace thereby culminating in higher business performance.	(Bahoo et al., 2023; Sahoo et al., 2024)
Resource-built capabilities (Mikalef & Gupta, 2021)	"examining an organization's internal resources and capabilities…"	identifying potential areas of collaboration with external partners, allowing organizations to develop more targeted and effective outbound open innovation strategies.	Cui et al., 2022; Sahoo et al., 2024)

2.2.4. KACAP from RBV and KBV

RBV was rooted in economic insights from Penrose (1959) and Richardson (1972), expanded and refined by Barney (1991) and Conner (1991), then it is widely applied across business and management (Bals & Rosca, 2022). Wernerfelt (1984) initially introduced the RBV of firms. The fundamental issue of interest in management studies focuses on understanding how firms can leverage internal resources and capabilities to achieve sustained competitive advantage (Barney, 1991; Teece et al., 1997), with a focus on the economic performance of the focal firm and its shareholders (Bals and Rosca, 2022). The RBV posits that "resources and capabilities are simultaneously valuable, rare, imperfectly imitable, and non-substitutable" (Easterby-Smith & Prieto, 2008, p. 236). RBV offered resources and capabilities proven in prior studies, such as tangible and intangible resources (Hunt & Davis, 2012; Jawed & Siddiqui, 2019; Khattak & Ullah, 2021), resource advantages (Hunt & Davis, 2008, 2012), and dynamic capabilities (Eisenhardt & Martin, 2000; Y. Lin & Wu, 2014; Teece et al., 1997). As previously mentioned, several studies employ RBV to in technology adoption studies (Bag et al., 2021; Maroufkhani et al., 2020; Maroufkhani, Tseng, et al., 2020; Pillai et al., 2022). RBV is suitable in acknowledging firm technological activities through the theoretical standpoints of organizational resources and capabilities (Ramdani and Kawalek, 2007). It is aligned with the study of Maroufkhani et al. (2020), drawing on RBV and capability building view to examine the effect of BDA adoption on SMEs' performance.

The KBV of a firm originated from RBV (Grant, 2015). KBV highlights the importance of knowledge management in organizational innovation as it constitutes "the most strategically important of the firm's resources" (Grant, 1996, p. 110). Prior studies defined KBV from various key themes, including the distinction between knowledge and information (Aamodt & Nygård, 1995; Nonaka, 1994), explicit and tacit knowledge(Grant, 1996; Nonaka, 1994, 1998; Nonaka et al., 2006; Nonaka & Takeuchi, 1995), knowledge creation and transfer (Grant, 1996; Levitt & March 1988), knowledge conversion mechanism (Nonaka, 1994), building organizational capability (Levitt & March, 1988), organizational learning (Abbasi, 2015; Levitt & March, 1988), and absorptive capacity (ACAP) (Cohen & Levinthal, 1990; Grant, 1996).

KACAP stems from ACAP (Zahra & George, 2002). ACAP was first introduced by Cohen and Levinthal (1990, p. 128), which refers to "the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends", including identifying valuable external knowledge, effectively absorbing it, and transforming it into innovative outcomes or improvements to existing processes within the organization." This definition highlights the process of acquiring and exploiting externally generated knowledge (Camisón & Forés, 2010). Zahra and George (2002, p. 198) ground the concept that ACAP is "a set of organizational routines and strategic processes by which firms acquire, assimilate, transform, and exploit knowledge for the purpose of value creation". Compared with the study of Cohen and Levinthal (1990), this definition emphasizes dynamic capabilities geared toward strategic change and flexibility wherein firms create and exploit new knowledge by transforming acquired knowledge and sustaining competitive advantage by managing external knowledge, highlight the importance of external knowledge (Camisón & Forés, 2010; Zahra & George, 2002). Thus, based on the ACAP's definitions, the KACAP can be understood that a firm's external KACAP involves the usage of mechanisms through which knowledge outside the firm is identified, acquired, assimilated, transformed and applied (Camisón & Forés, 2011).

Recently, there has been an increasing consensus about integrating firm innovation and KBV perspectives, suggesting that KACAP significantly impacts firm innovation performance. Given the research context of Industry 4.0 and 5.0, it becomes essential to understand how KBV influences firm innovation, which involves examining the extent to which the knowledge resources of advanced technologies drive firm performance from both individual and organizational perspectives. Therefore, firm innovation performance is defined here as "the results of transforming existing applications, products, and services and/or developing new ones" from technology-enabled perspectives (Benitez et al., 2022, p. 6). Many prior studies have investigated the direct or mediate effect of KACAP toward firm innovation performance at a firm level. For example, in line with the study of Wang et al. (2017), the work of Duan et al. (2020) empirically shows that ACAP mediates the impacts of organizational slacks on innovation performance in Chinese high-tech manufacturing firms. Abou-Foul et al. (2023) investigate AI capabilities and servitization innovation performance from 185 manufacturing firms in the US and EU, highlighting the positive moderating roles of KACAP in their relationships. Khan & Tao (2022) reveal a positive relationship between the KACAP, agility, and firm innovation performance mediated by big data analytics and digital platform capabilities from 325 manufacturing firms in Pakistan. From a cognitive perspective, Usai (2021) emphasizes that new avenues for innovation processes necessitate specialized absorptive capacities for acquiring the necessary information/knowledge facilitated by technological advancements.

2.2.5. Hypotheses Development and the Conceptual Model of *Study 1*

This part delves into the constructs of the proposed model (**Figure 2.4**), starting with the foundational elements of technological, organizational, and environmental factors and then depicting the main drives of AI adoption toward open innovation through the mediators of knowledge absorptive capacity. The following subparagraphs will provide a detailed explanation of all variables, with the related emerging hypotheses outlined in **Table 2.6**. More in-depth assessments and measurements at the item level of each latent construct are provided in the next chapter.

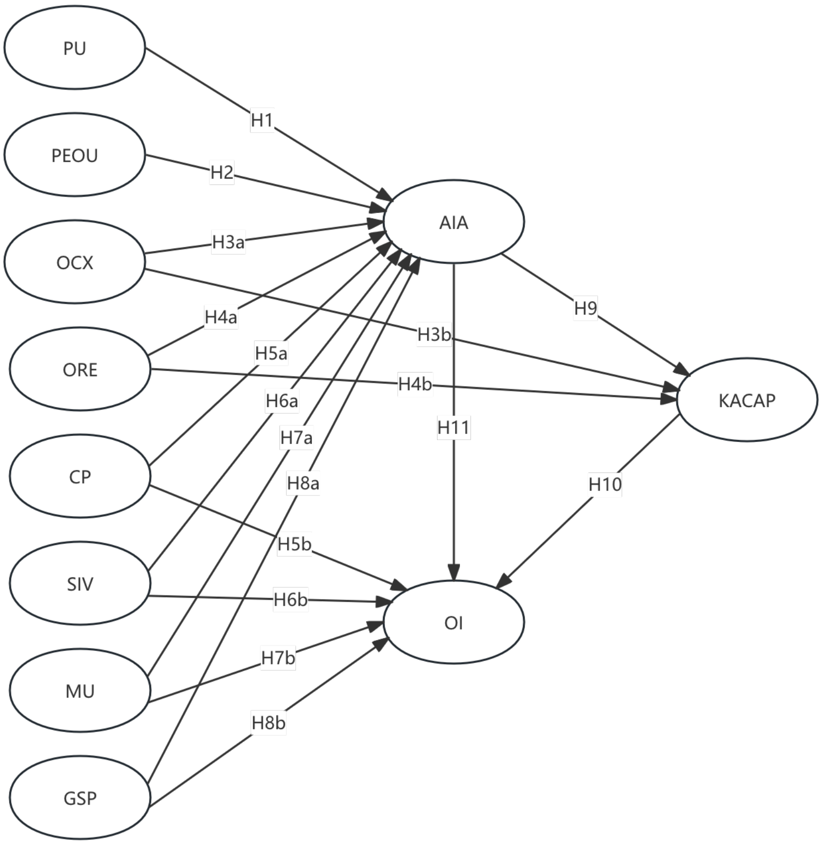

Figure 2.4 Research Model of Study 1

Legend: PU=perceived usefulness; PEOU=perceived ease of use; OCX=organizational complexity; ORE=organizational readiness; CP=competitive pressure. SIV=supplier involvement; GSP=government support and policy; AIA=AI adoption; KACAP=knowledge absorptive capacity; OI=open innovation

Table 2.6 Hypothesis Summary

Hypothesis	**Independent variable**	**Dependent variable**	**Explanation**
H1	Perceived usefulness	AI adoption	Perceived usefulness will positively influence AI adoption.
H2	Perceived ease of use	AI adoption	Perceived ease of use will positively influence AI adoption.
H3a	Organizational complexity	AI adoption	Organizational complexity will negatively influence AI adoption.
H3b	Organizational complexity	Knowledge absorptive capability	Organizational complexity will negatively influence knowledge absorptive capability.
H4a	Organizational readiness	AI adoption	Organizational readiness will positively influence AI adoption.
H4b	Organizational readiness	Knowledge absorptive capability	Organizational readiness will positively influence knowledge absorptive capability.

Table 2.6 Cont.

Hypothesis	Independent variable	Dependent variable	Explanation
H5a	Competitive pressure	AI adoption	Competitive pressure will positively impact AI adoption.
H5b	Competitive pressure	Open innovation	Competitive pressure will positively impact open adoption.
H6a	Supplier involvement	AI adoption	Supplier involvement will positively influence AI adoption.
H6b	Supplier involvement	Open innovation	Supplier involvement will positively influence open innovation.
H7a	Market uncertainty	AI adoption	Market uncertainty will positively influence AI adoption.
H7b	Market uncertainty	Open innovation	Market uncertainty will positively influence open innovation.
H8a	Government support and policy	AI adoption	Government support and policy will positively influence AI adoption.
H8b	Government support and policy	Open innovation	Government support and policy will positively influence open innovation.
H9	AI adoption	Knowledge absorptive capacity	AI adoption will positively influence knowledge absorptive capacity.
H10	Knowledge absorptive capacity	Open innovation	Knowledge absorptive capacity will positively influence Open innovation.
H11	AI adoption	Open innovation	AI adoption will positively influence Open innovation.
H12			Knowledge absorptive capacity will positively mediate AI adoption and open innovation.

2.2.5.1. Technological Antecedents from TAM

Perceived Usefulness and Perceived Ease of Use are the two main drivers in TAM that can explain a firm's AI adoption (Davis,1989). Perceived usefulness refers to "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). This belief is a subjective norm within the firm's context, and a linear relationship between usefulness and intention has been demonstrated in Chatterjee et al.'s (2021) study. The predictors of perceived usefulness, such as "subjective norms, image, job relevance, output quality, and result demonstrability", prompted to construe that individuals form perceptions of a system's usefulness, in part, by cognitively comparing the system's capabilities with the requirements of their job tasks (Venkatesh & Bala, 2008, p. 276; Venkatesh & Davis, 2000). It is therefore perceived that a sense of usefulness would lead an individual to intend to use a new technology (Chatterjee, Rana, Dwivedi, et al., 2021). Perceived ease of use is defined as "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320; Venkatesh et al., 2003, p. 451), which predicts users' intention to use a new system or technology. It includes the concepts of self-efficacy, perception of external control, anxiety, playfulness, enjoyment, and objective usability, which present individual traits and emotions (Venkatesh & Bala, 2008). However, Venkatesh and Bala (2008) suggest that these determinants of perceived ease of use will not influence perceived usefulness in explaining the different concepts and determinants. Perceived ease of use is primarily determined by individual factors such as control beliefs, intrinsic motivation (e.g., playfulness), and emotions (e.g., anxiety), affecting how easily or difficult a user finds a system to use. However, these factors do not directly contribute to the actual utility or effectiveness of the system in improving job performance, which is what perceived usefulness measures. Thus, while a system may be easy to use, this does not necessarily mean it will enhance job performance or have significant utility. Given this view, our conceptual model has not considered the effect of perceived ease of use on perceived usefulness.

Zain (2005) examined the influence of information technology acceptance on organizational performance in terms of how the acceptance of technology contributes to a firm's ability to be an agile competitor. Employing the TAM, the result shows that perceived usefulness and perceived ease of use are the main determinators of manufacturing managers' attitudes toward using, thus significantly impacting organizational agility. Na et al.(2022) compared cross-national attitudes on AI adoption to understand how organizations accept technologies from employees' attitudes. Therefore, when studying organizational decisions in technology adoption, it is required that organizations consider individual use perception. Consequently, employees' perceptions toward AI-integrated technologies are expected to assist organizations in making adoption decisions. Thus, this study proposes the following hypothesis:

H1: Perceived usefulness will positively influence AI adoption.

H2: Perceived ease of use will positively influence AI adoption.

2.2.5.2. Organizational Antecedents

Organizational complexity is derived from the definition of complexity that refers to the "degree to which an innovation is perceived as relatively difficult to understand and use", which is lead to be a barrier to adoption (Roger, 2003, p. 257). Thus, it has a negative impact on technology adoption (Horani et al., 2023). This means that if the complexity of technology increases, the employees may perceive difficulty with ease of use. Various studies have demonstrated complexity as a determinant of technological antecedents when referencing AI's complexity attribute (Badghish & Soomro, 2024; W. Guan et al., 2023; Horani et al., 2023; Kinkel et al., 2022). However, the complexity of AI is an internal organizational issue (Chatterjee, Rana, Dwivedi, et al., 2021) in that AI is rarely characterized as easy to deploy or use, with non-technical challenges, such as a lack of top management support, which can emerge both during and after implementation (Jöhnk et al., 2021). Moreover, if an organization's system is complex, employees may encounter difficulties in using new technology integrated into this complex system, which can hinder their ability to perceive the usefulness of the new system (Sonnenwald et al., 2001). From the employees' perspectives, organizational complexity is posited to the following hypothesis:

H3a: Organizational complexity will negatively influence AI adoption.

In addition, complexity in organization studies refers to an organization's structural complexity where the degree of differentiation exists (Ali et al., 2018; Robbins, 1990, cited as in Ali et al., 2018). This understanding highlights the effect of complexity on the extent and intensity of knowledge within organizations (Kim, 1980), which provides subsequent research on the complexity's role in facilitating the flow of development thanks to prior knowledge supporting the new knowledge absorption (Cohen & Levinthal, 1990). Previous studies have investigated the relationships between complexity (advanced technology (Winkelbach & Walter, 2015) and internal organizational structure (Ali et al., 2018)) and knowledge ACAP. Thus, from the perspectives on knowledge management in organizations, the hypothesis is:

H3b: Organizational complexity will negatively influence knowledge absorptive capacity.

The understanding of Organizational Readiness comes from various literature. Lacovou (1995) defined organizational readiness as the accessibility of the required organizational resources for adoption, including firms' financial and technological resources. Technical resources include both tangible and intangible assets (Horani et al., 2023). Tangible assets represent a firm's cooperative resources for ensuring a scalable and flexible foundation for business applications (Aboelmaged, 2014). Intangible assets include "application processes, collaboration strategies, IT development plans, and the technical knowledge/skills that can successfully incorporate new technologies" (Garrison et al., 2015, as cited in Horani et al., 2023, p. 7). Financial resources are crucial to cover ongoing expenses during technology implementation and usage (Kuan and Chau, 2001). These resources have been suggested to be considered by the organization's size, which directly determines the organization's readiness to adopt innovative technology (Rogers, 2003). For example, small organizations tend to lack capital, talent, and technological resources, thus lacking the ability to receive all strategic benefits of the technology, whereas larger organizations rely on more technical and financial resources to adopt it (Aboelmaged, 2014). Chatterjee et al. (2021) further support this and emphasize that adopting AI is impacted by the specific size and the availability of the organization's resources in their studies. Thus, a higher level of organizational readiness in large firms indicates adequate resources and a higher intention to adopt AI. These studies also subscribe to Rogers's view (2003). Besides, Hossain et al. (2024) argue that some typical industries in emerging economies also impact the adoption of advanced technologies. Machado et al. (2021) described readiness as the ability to adjust to digital transformation when digitalization appears in an organization. Digital organizational readiness is defined by Lokuge et al. (2019, p. 446) "as an organization's assessment of its state of being prepared for effective production or adoption, assimilation and exploitation of digital technologies for innovation." As AI is classified as digital technology, Jöhnk et al. (2021) apply digital readiness to understand the precursors of AI adoption. Thus, in terms of AI-involved organizational readiness, in addition to the financial and technological resources, the management commitment that describes organizations' willingness and support for innovation initiatives (Cao et al., 2021; Hashem & Aboelmaged, 2023) is a key attribute to building digital readiness for AI adoption. This internal environment for the readiness of new knowledge assimilation and acquisitions in organizations indirectly influences the development of its absorptive capacity (Van den Bosch et al., 1999, as cited in Vega-Jurado et al., 2008). Thus, this study proposes the following hypothesis:

H4a: Organizational readiness will positively influence AI adoption.

H4b: Organizational readiness will positively influence knowledge absorptive capacity.

2.2.5.3. Environmental Antecedents

Competitive Pressure was accepted as an external environmental aspect affecting managers' decisions (Gutierrez et al., 2015; Sayginer & Ercan, 2020), especially in SMEs in which AI adoption can be attributed to the SMEs' desire for competitiveness and survival in the industry 4.0 (Ghobakhloo, 2019). The definition of competitive pressure is "the degree of pressure felt by the firm from competitors within the industry" (T. Oliveira & Martins, 2010, p. 1341). The present study refers to the extent to which manufacturing firms perceive themselves as threatened by their counterparts within apparel industries. It can be explained by how pressure factors influence AI use and adoption by their competitors. This threat includes customer unloyalty and market share loss (Ghobakhloo, 2019). Also, the most referred to competitive pressure's definitions as the motivation of innovation diffusion and adoption by the threat of losing competitive advantage (Aboelmaged, 2014; Z. Yang et al., 2015). Thus, when considering that manufacturing digitalization may strengthen their competitive position and assist them in achieving superior firm performance, the competitive pressure affects technology adoption (Ghobakhloo, 2019). Additionally, the potential benefits of digitalization, including enhanced operational efficiency and stronger market positioning, further reinforce the need for AI adoption. Thus, competitive pressure compels firms to adopt AI as a defensive strategy and encourages proactive innovation to maintain and strengthen their competitive edge in a rapidly evolving business landscape, which enhance an organization's open innovation. According to the understanding of competitive pressure in the AI age, this study proposes the following hypotheses:

H5a: Competitive pressure will positively impact AI adoption.
H5b: Competitive pressure will positively impact open innovation.

Supplier Involvement has been suggested as an external environmental factor (Jöhnk, 2021; T. Oliveira & Martins, 2011). Thus, when referencing the adoption of technology that involves the participation of multiple business partners, it is limited to focus on intra-organizational or employee perception factors (W. Guan et al., 2023). The factor of supplier involvement presents how suppliers engage with downstream organizations to develop competitive advantages in the local and global marketplace in the completed supply chain processes (Hashem & Aboelmaged, 2023; Rahman et al., 2022). This collaboration, in some studies, regarded as relationships between organizations with their partners, stakeholders, suppliers, or customers (W. Guan et al., 2023; Hradecky, 2022; Lokuge et al., 2019; T. Oliveira & Martins, 2010) plays a crucial role in enhancing agile SCM, as it enables firms to quickly address supply chain issues and implement necessary changes promptly (Hashem & Aboelmaged, 2023). The determinant of supplier involvement or partnership in AI adoption has been demonstrated in prior studies. Chatterjee et al. (2021) demonstrate partnership support can help to generate the innovation performance of an organization through knowledge exchange, highlighting that partner support would help share knowledge, and this would enrich the ability of employees to adopt any innovative technology, thus positively impacting AI adoption in the manufacturing sector. Horani et al. (2023) indicate that AI suppliers are expected to engage in an effective and efficient partnership to strengthen firms' competitive advantage. In AI fields, extensive research focuses on AI's roles in SCM, including supplier selection for sustainability (Cannas et al., 2023; Dey et al., 2023; Kassa et al., 2023; Qu & Kim, 2024b; R. Sharma et al., 2022). Guan (2023) considered supply chain-related determinants that influence blockchain technology adoption, as blockchain deployment requires multiple supply chain partners' participation to assure transparency. These findings are consistent with previous studies (H. Chen et al., 2021; Horani et al., 2023). Similarly, apparel manufacturing requires establishing ecosystems with suppliers and suppliers' suppliers (Huan et al., 2004), including textile and raw material suppliers, the facilitators of AI-based production systems, and AI vendors (Horani et al., 2023); therefore, it is indispensable to take supplier involvement determinants in AI adoption in the present study.

Meanwhile, suppliers' early integration into the innovation process can significantly increase innovation performance in most industries (Hagedoorn, 1993, 2002). As discussed above, partnership support can help generate an organization's innovation performance through knowledge exchange. Back to the previous literature review, open innovation provides a framework for utilizing external and internal knowledge, technology, and resources to accelerate internal innovation and expand markets for external innovation. This is consistent with the explanation of partner support, which helps knowledge sharing between suppliers and related stakeholders, enhancing firm open innovation. The definition of open innovation defined by Gassmann and Enkel (2004, p. 2) as "the company needs to open up its solid boundaries to let valuable knowledge flow in from the outside to create opportunities for co-operative innovation processes with partners, customers and/or suppliers". Consequently, this study proposes the following hypotheses:

H6a: Supplier involvement will positively influence AI adoption.
H6b: Supplier involvement will positively influence open innovation.

Market Uncertainty adapted from environmental uncertainty, which was defined by Duncan (1972) "as the shortage of information on the events and actions taking place in the business environment and/or the impossibility of predicting external changes and their impact on organizational decisions" (Duncan, 1972; López-Gamero et al., 2011, p. 428). This uncertainty in the external environment stems from a lack of sufficient knowledge about environmental dynamics and the inability of managers to predict future developments (Hashem & Aboelmaged, 2023). For example, managers may feel uncertain about the direction of future technologies (López-Gamero et al., 2011) and market (Hashem & Aboelmaged, 2023). On the other hand, this unpredictability, in turn, prompts a firm to make changes to grasp competitive opportunities (López-Gamero et al., 2011). As is known, the destroyed global production and business practices have increased the uncertainty of MSMEs' production and operation due to the COVID-19 pandemic, which led to the interruption of supply chains in manufacturing (X. Lu et al., 2022). In this context, firms start to find ways to cope with unstable customer demands and high market uncertainty (W. Guan et al., 2023). As previously defined, AI has information processing capabilities in knowledge innovation through leveraging data monitoring, evaluation, analysis, prediction, and decision-making (Bai & Li, 2020); thus many prior studies focus on AI's roles in manufacturing supply chain processes, especially in forecasting market trends and predicting uncertain customer demand for control disruption (Brau et al., 2023; Cannas et al., 2023; Chakraborty, Hoque, and Kabir 2020, as cited in Dey et al., 2023; Lima-Junior & Carpinetti, 2019; Ismagiloiva et al., 2020 as cited in Mukherjee, 2022; Perano et al., 2023). Therefore, AI allows firms to reduce demand uncertainty and enhances their knowledge regarding the actual level of demand (Horani et al., 2023). Based on the previous discussion, the proposed hypotheses are:
H7a: Market uncertainty will positively influence AI adoption.
H7b: Market uncertainty will positively influence open innovation.

Government support and policy refers to "assistance or facilitating conditions provided to the employees or organization to transform or implement technology diffusion within the firm" (Badghish & Soomro, 2024, p. 6). Governments have supported adopting new technology through directed incentives, manifested in policy documents and regulations, such as providing monetary incentives, scientific resources, pilot projects, handbooks, and training programs. Prior studies state that facilitating conditions offered by government support have been identified as driving factors for firms to adopt new technology and innovation (Jun et al., 2019). Legesse et al. (2024) validated the government support and policies to perceived ease of use to suggest that government initiatives and policies can influence individuals' perception of how easy it is to use blockchain technology. Badghish and Soomro (2024) examine that government support and policies significantly impacts AI adoption. Patil et al. (2023) argue that government policies will create a favorable predisposition toward the usefulness of IoT technology, thereby enhancing firm growth. However, some research considers government intervention as an external pressure, especially in the aspects of regulation initiatives, such as environmental regulatory pressure that pushes firms to adopt green innovation (Jun et al., 2019). Moreover, in sustainable manufacturing, due to the government and public pressure, manufacturers have more recently started taking initiatives regarding sustainable SCM, it remains difficult for SMEs to compete in the market while also adopting green innovation due to time and resource constraints (Cordeiro & Vieira, 2012). Thus, they need AI-integrated technologies to tackle sustainable issues in environments (Akbari & Hopkins, 2022; Allahham et al., 2023; Bag & Pretorius, 2022; Dadi et al., 2021; Javaid et al., 2022; S. Kumar & Barua, 2022; S. Sharma et al., 2021; Tang et al., 2023; Vernier et al., 2021), economics (Bodendorf et al., 2022; Lechner & Reimann, 2020; Z.-J. Wang et al., 2023), and society (B. Gupta et al., 2008; S. Gupta et al., 2023; Jararweh et al., 2023). From this point of view, appropriate government policies and regulations (especially those related to privacy, security, and data access) that provide a supportive environment for AI adoption can help keep the AI ecosystem growing (Horani et al., 2023). Thus, the developed hypotheses are:

H8a: Government support and policy will positively influence AI adoption.

H8b: Government support and policy will positively influence open innovation.

2.2.6. AI Adoption, Knowledge Absorptive Capacity (KACAP), and Open Innovation (OI)

Based on the understanding of various literature steam on ACAP, KACAP aligns with the theory of KBV, as previously mentioned. From the perspective of the KBV, knowledge is a crucial input and a significant source of value in manufacturing (Chatterjee et al., 2021; Legesse et al., 2024; Tasnim et al., 2023). Building on this perspective, ACAP is a critical mechanism enabling firms to leverage their knowledge-based resources effectively, ensuring that external knowledge contributes meaningfully to their innovation outcomes (Moilanen et al., 2014; Zahra & George, 2002). Back to the highlights of open innovation theory previously reviewed, open innovation is the process based on the intentional management of knowledge flows across organizational boundaries (Chesbrough & Bogers, 2014, as cited in Arias-Pérez & Huynh, 2023), which provides a framework for utilizing external and internal knowledge, technology, and resources to accelerate internal and external innovation. Thus, ACAP would leverage purposive inflows and outflows of knowledge to achieve innovation performance.

Thus, as AI-integrated technologies are technical assets of organizational knowledge-based resources, prior studies have focused on the role of digital skills and the design of appropriate indicators to measure companies' absorptive capacity to adopt AI (Kinkel et al., 2022) and how AI adoption influences ACAP and, thus, innovations (Kastelli et al., 2024). The previously defined innovation types include open innovation as AI-enabled antecedents (Mariani et al., 2023); thus, this study attempts to investigate the impact of AI adoption on open innovation, the effect of AI adoption on KACAP, and KACAP's impacts on open innovations. More importantly, as the KACAP has the leverage to accelerate AI knowledge resources in the process of open innovation (Adamides & Karacapilidis, 2020; Tallarico et al., 2024), it is essential to identify the KACAP's effects between AI adoption and open innovation. Therefore, the proposed hypotheses are:

H9: AI adoption will positively influence knowledge absorptive capacity.

H10: Knowledge absorptive capacity will positively influence open innovation.
H11: AI adoption will positively influence open innovation.
H12: Knowledge absorptive capacity will positively mediate AI adoption and open innovation.

2.3. Literature Review for *Study 2*

2.3.1. Innovation Ecosystem

Innovation ecosystems, typically involving strategy, innovation, and entrepreneurship, have become a focal point during the last two decades (Adner, 2006; Adner & Kapoor, 2010; Gomes et al., 2018; Granstrand & Holgersson, 2020). There has been much debate on its definitions in academia; furthermore, it has had different meanings and purposes in various contexts. The concept of innovation ecosystems as distinct from the ecosystem is increasingly used to address endeavors for joint value creation (Pushpananthan & Elmquist, 2022). From a business ecosystem perspective, Moore (1993, p. 76) proposes that innovation drives companies "cooperatively and competitively to support new products, satisfy customer needs, and eventually incorporate the next round of innovations". Autio and Thomas (2014) define an innovation ecosystem as a network combining production with side participants connected to a focal firm or a platform and capturing new value through innovation. Granstrand and Holgersson (2020) identify 21 definitions of innovation ecosystems through a systematic review of 120 publications and find that the four most common components occurring in definitions are actors, collaboration, activities, and institutions. In contrast, other scholars have also highlighted both the importance of collaboration and competing actors (Dedehayir et al., 2018; Li-Ying et al., 2022; Mercan & Gökta, 2011; Rohrbeck et al., 2009) as well as the importance of artifacts (Curley & Donnellan, n.d.; Li-Ying et al., 2022; Pipek et al., 2012). Moreover, fewer mentions of the components of technologies and products as artifacts exist in many definitions; therefore, Granstrand and Holgersson (2020. p3) proposed a new and holistic definition of an innovation ecosystem that consists of "actors, activities, and artifacts, and the institutions and relations", which include "products and services, tangible and intangible resources, technological and non-technological resources, and other types of system inputs and outputs, including innovations". This definition is aligned with Chesbrough (2003)'s open innovation theory, highlighting the importance of external knowledge flows, where firms leverage ideas and technologies from outside sources to enhance their internal innovation capabilities with the collaboration with stakeholders. As we hypothesized that AI adoption drives open innovation in ***Study 1***, the understanding of how firms leverage AI to build an innovation ecosystem from open innovation perspectives is crucial. Thus, in the thesis, Granstrand and Holgersson's definition of innovation ecosystem is employed as the grounded AI-enabled innovation ecosystem theory. Also, Granstrand and Holgersson (2020) found that the most common elements in the definitions of innovation ecosystems are actors, collaboration, activities, and institutions, aligning well with the principles of open innovation. Other scholars have emphasized the dual nature of collaboration and competition within open innovation ecosystems (Dedehayir et al., 2018; Rohrbeck et al., 2009), as well as the importance of artifacts, or tangible assets, within these ecosystems (Curley & Donnellan, n.d.; Pipek et al., 2012). In this context, open innovation ecosystems are defined not only by their participants and collaborative activities but also by the interactions and institutional structures that support knowledge sharing and co-creation. In such ecosystems, organizations actively seek knowledge and technology from external sources, such as other firms, research institutions, and public entities, integrating these resources to create new products and services. This approach aligns with the RBV and KBV, which suggest that a firm's competitive advantage arises from its unique resources and knowledge. Within open innovation ecosystems, RBV and KBV frameworks help explain how firms leverage external knowledge as a critical resource to enhance their competitive advantage. Furthermore, dynamic capabilities (DC) theory complements this perspective by highlighting a firm's ability to adapt and reconfigure resources in response to environmental changes, essential for effectively integrating external knowledge within an open innovation ecosystem. As well as the concept of knowledge-based dynamic capabilities (KBDC), an extension of DC and KBV, underscores the importance of knowledge acquisition, integration, and transformation in rapidly changing environments (Denford, 2013). In the context of open innovation ecosystems, KBDC provides insight into how firms dynamically adapt their knowledge processes to maximize the value of both internal and external knowledge resources (Teece, 1997; Zhen et al., 2011). This framework is particularly relevant in Industry 4.0 and 5.0, where manufacturing organizations leverage AI and other advanced technologies to facilitate knowledge sharing, enhance collaboration, and foster innovation within the ecosystem. Based on these understandable concepts of open innovation ecosystem, the integration of RBV, KBV, DC, and KBDC provides a comprehensive theoretical foundation for analyzing open innovation ecosystems, particularly in manufacturing sectors transitioning to Industry 4.0 and 5.0. These findings underscore the importance of ecosystem-level knowledge exchange and creating a learning environment that enhances firms' dynamic capabilities, strengthening the innovation ecosystem as a whole. These theories also collectively support an understanding of how firms strategically harness external knowledge and adapt dynamically to changes within the ecosystem, thereby creating a robust framework for joint value creation. This theoretical foundation not only enriches the analysis of open innovation ecosystems but also reinforces the constructs of ***Study 1*** and ***Study 2*** by providing a systematic framework for knowledge-related factors.

2.3.2. Revisiting AI Capabilities and Open Innovation Ecosystem

Open innovation, in turn, plays a pivotal role in fostering a vibrant national innovation ecosystem (Ahn et al., 2020). Therefore, establishing an AI-enabled open innovation ecosystem requires an integrated approach, drawing from AI capabilities, RBV and KBV, ACAP, combinative capacity, and knowledge-based capability to gain competitive advantages and enhance innovation performance

AI capabilities have been found to be related to open innovation (Sahoo et al., 2024), and open innovation is one of the core factors establishing a vibrant national innovation ecosystem (Ahn et al., 2020). Thus, building an AI-enabled open innovation ecosystem needs to cover a holistic view from the previous dimensional theories, such as AI capabilities, RBV and KBV, ACAP and combinative capacity, and knowledge-based capability, thus gaining competitive advantages and increasing innovation performance, but not limit to it, in dynamic environments. Some studies on AI capabilities and organizational performance are available from a RBV. For example, Mikalef and Gupta (2021) grounded AI capability definitions and empirically supported a tangible and intangible resource-based AI capability results in increased organizational creativity and performance. Chen et al. (2022) applied RBV to e-commerce firms and demonstrated AI capabilities indirectly affect firm performance through creativity, AI management, and AI-driven decision-making. However, open innovation ecosystems are networks of organizations that work together to create new products, services, or applications based on the increasing digitalization of society and economy (Kuzior et al., 2023), although organizations are actively engaging in innovation activities using their AI capabilities to ensure that they continue to thrive in an increasingly volatile and saturated industry (Magas & Kiritsis, 2022; Petrescu, Krishen, Kachen, & Gironda, 2022, cited Sahoo et al., 2024). Thus, these ecosystems are defined by their openness, which allows organizations to tap into a variety of resources to achieve their goals, including tangible and intangible (Kuzior et al., 2023). On the other hand, open innovation relies on ecosystems to generate value within and between value chains, highlighting a close link between the digital tools that drive innovation and the innovation strategies companies employ (Kuzior et al., 2023). Essentially, digital technologies form the backbone of today's innovation ecosystem.

2.3.3. TH in Innovation Ecosystems

As previously mentioned, Enkel and his co-authors propose to establish a co-innovating ecosystem where partners outside the industry co-create values from external knowledge to drive innovation in the digital age, thus requiring a framework of triple helix (TH) (Enkel et al., 2009, 2020) because innovation is increasingly based upon university- industry- government interactions (Etzkowitz, 2003). In this theoretical lens, there is an increasing focus on the TH model in innovation ecosystem studies (Etzkowitz and Leydesdorff, 2000, as cited in Arenal et al., 2020), which is widely adopted for the environment and characterizing the relationships among the main stakeholders of the innovation ecosystem (Chinta and Sussan, 2018; Pique et al., 2018, as cited in Arenal et al., 2020). The TH model as a "descriptive and prescriptive model" (Heaton et al., 2019, p. 922) was first proposed for the university-industry-government relationship by (Etzkowitz & Leydesdorff, 1995) and aims to highlight how the interaction between the three key institutions of university, industry, and government evolves in the process of knowledge-based innovation.

2.3.3.1. The Roles of University-Industry Linkages based on TH

The concepts of ecosystems come into being in universities (Adner, 2006; Arenal et al., 2020). Universities act as one kind of innovation stakeholder and follow the paradigm of open "science" (Becker & Eube, 2018; Frenkel & Maital, 2014). Also, universities, as external resources, contribute knowledge to building open innovation ecosystems for industries. Prior studies emphasized universities' innovation contributions exist in entrepreneurial universities (Audretsch, 2014). The entrepreneurial university maintains its traditional academic roles of social reproduction and knowledge extension while expanding its new roles in promoting innovation (Etzkowitz, 2003). This emphasizes the university's role as an entrepreneur in society based on the organizing principle of the TH (Etzkowitz, 2003).

University-industry linkages, where academic institutions collaborate with industry to address challenges and drive innovation, play a crucial role in a knowledge-based economy by transferring technological knowledge to firms, thereby fostering innovation, entrepreneurship, and economic growth (Hailu, 2024). Hailu (2024) highlights several aspects. First, these linkages enable universities to align their research and educational programs with the needs of the industry, and second, the collaborative approach through fostering technological innovation enables universities to contribute to advancing technology and scientific infrastructure, which in turn supports economic growth. According to TH systems, co-creating an innovation ecosystem requires an exchange of knowledge and the ability to connect all the actors involved, and each role of each institution contributes its competencies to each other, thus stimulating open innovation (Neves et al., 2021). Extensive research on the significance of both linkages using the TH model to emphasize and analyze each role in these interactions. For example, Cai and Liu (2015) emphasize the third role of universities in university-industry-government as having a synergistic effect. This is consistent with the studies of Heaton et al. (2019), Li & Chu (2022), and Zhang et al. (2019). (Etzkowitz, 2003, p. 303) points out that TH is dynamic in that “the university, industry, and government are conceptualized as intertwined spirals with different relations to each other in the classic innovation regimes”. This implies that in a laissez-faire TH regime, industry leads with academia and government in supporting roles, whereas in a statist regime, the government takes the lead, guiding both academia and industry (Etzkowitz, 2003). Noya et al. (2023) found that the collaboration between government, large companies, and universities within the TH ecosystem significantly enhances SME performance, and the SME community strategically facilitates the impact of TH interventions on SME performance by its mediating roles in the relationships. Qu and Kim(2022) applied the theory of dynamic capabilities to “organizations-universities” (Frank, 2009, p. 1) in their study to understand that the core idea of the theories of dynamic capabilities echoes the need to explain the value capture within an ecosystem better from university-lead perspectives.

2.3.3.2. Government Interventions for University-Industry Linkage based on TH

The concept of government interventions originates from institutional theory, which suggests that institutional pressures, like coercive legal mandates from institutional environments, have a greater impact on shaping a firm’s formal structures than market forces (Joo et al., 2018). However, a new relationship paradigm between government and industry intervention associated with knowledge is TH (De Lima Figueiredo et al., 2023). Recent studies have recognized that the government’s role in the TH model extends beyond merely being a funder or enforcer; it now actively promotes regulations, programs, and actions and participates in various stages of the university-industry-government (Guerrero & Urbano, 2017).

Prior studies have demonstrated the roles of government interventions based on the TH model. An example is the research on the evolution of university-industry collaboration (UIC) policies in Japan from the mid-1990s to the present and analyze of their role in shaping Japan’s innovation ecosystem (Ranga et al., 2017). They attempt to identify that entrepreneurial culture, intermediator between universities and industries, and ACAP are the factors in lagging the US. Therefore, there is a need for government policies with a broader global outlook that strongly support partnerships with leading international actors, while universities, companies, and the government collaborate to enhance innovation networks by involving more local entrepreneurs in education, research, and business plans, and by consolidating their entrepreneurial focus (Ranga et al., 2017). Noya et al. (2023) argue that the government's role as a regulator and facilitator is crucial in emerging economies for building a triple helix innovation ecosystem, where the commitment of government officials through policies and funding support significantly influences its dynamics. Guerrero and Urbano (2017) provide a better understanding of the influence of TH stakeholders on the entrepreneurial innovation performance of enterprises located in emerging economies from diverse perspectives and research fields, including knowledge-based open innovation and entrepreneurship).

2.3.3.3. Triple Helix in AI Innovation Ecosystems

The studies applied TH to focus on universities, industry, and government in the age of AI, presenting technological knowledge as a role in their interactions and breaking the balance of the three agents. Under the national government interventions through AI policies, the roles of universities, enterprises, and even the national and regional governments are dynamic. Therefore, the TH model is not necessarily enough for research on the AI innovation ecosystem, especially in some statist regimes where the government takes the lead, guiding both academia and industry (Etzkowitz, 2003). Given that the key areas for AI development are China, the United States, and the European Union (Jacobides et al., 2021), several studies focus on TH in these countries' innovation ecosystems. The study of Jacobides et al. (2021) used China as a case study to analyze how China's political context contributes to the vibrancy of AI ecosystems. In China, the government encourages tech giants to create AI libraries and platforms to strengthen ecosystem partnerships and provide SMEs with affordable access to AI technology (Jacobides et al., 2021). This closer collaboration between government and business enables Chinese tech companies to lead ecosystem development across various industrial sectors, supporting their transformation through AI. Arenal et al. (2020) developed an asymmetric triple helix (ATH) model for the AI ecosystem in China from the country and industry levels based on Cai and Liu's (2015) TH model, which focuses on capturing a regional innovation system. Their framework emphasizes the central position of governments but leaves more room for regional and local governments to conduct their policy experiments (Arenal et al., 2020). Arenal et al. (2020) re-examined the types of companies and highlighted the role of universities in producing new knowledge and training people. Unlike the TH model, in which government intervention comes after the initial university-industry collaborations, in the ATH model, the central government draws up a strategic plan and pools a range of resources to support AI development across the country before AI clusters begin to emerge on their own (Arenal et al., 2020).

2.4. Summary of the Reviewed Literature

The above literature thoroughly reviews the theories, concepts, and key models and frameworks related to this thesis. While the prior research has contributed to empirical discoveries or grounded theories in each, no study holistically orchestrated some overlapped concepts in different perspectives and domains, such as AI capabilities and enabling roles, AI adoption and KBV, open innovation, knowledge management, and innovation ecosystems, and all of these throughout TH in the age of AI. Therefore, the gaps in the current research need to be addressed; this also provides more room for re-examining their associations and revisiting these theories and models. **Figure 2.5** depicts the synthesized research framework through reviewing the literature.

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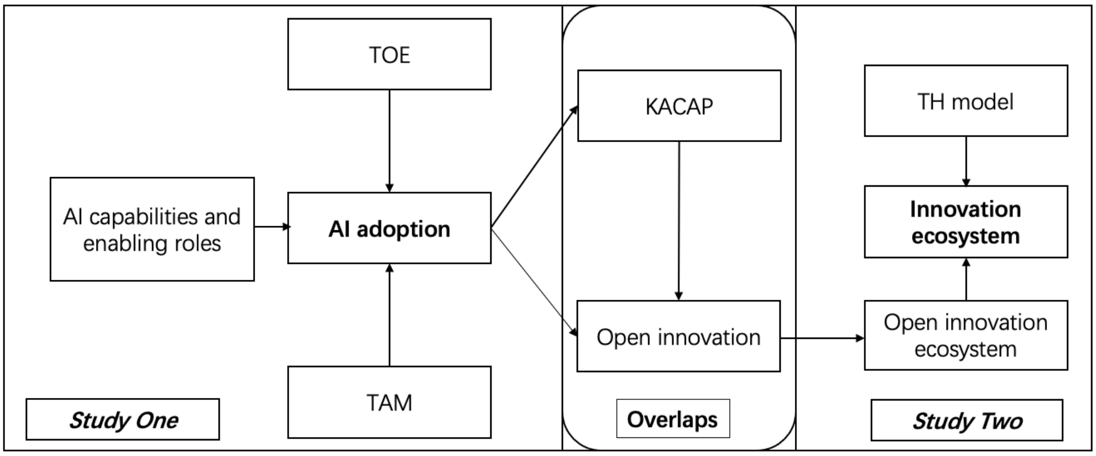

Figure 2.5 The Current Theoretical Lens in the Thesis

The reviewed literature highlights that, despite firms acknowledging AI's capabilities, the factors driving its adoption and its outcomes have yet to be thoroughly examined. The reviewed literature indicates that although firms are aware of AI's capabilities, the antecedents of AI adoption and consequences have not been fully explored, with several research gaps and unanswered research questions identified, which is not surprising, given that the research field is not yet mature. Moreover, the factors contributing to converting AI adoption into open innovation are not comprehensively identified. Studies have suggested that identifying the antecedents of AI adoption from the perspective of integrating the TOE model (Davis, 1989; Venkatesh, 2022; Venkatesh & Davis, 2000) is perceived to be helpful, as this model has been applied successfully in organizational and environmental contexts with a focus on technological issues (Brem et al., 2023; Chatterjee, Rana, Dwivedi, et al., 2021; Z. Yang et al., 2015). Studies have also emphasized the TOE framework's role in identifying the determinants of the AI adoption focus in the context of organizations. These studies reordered the TAM and TOE framework's constructs and variables. However, the studies that employed the hybrid TAM and TOE framework have not extended to other latent constructs associated or expanded with them. For example, while Chatterjee et al. (2021) employed TAM (PU and PEOU) as technological factors mediating organizational factors and intention to adopt AI, an environmental factor of government interventions is missing. The study of Chatterjee et al. (2021) focuses on Indian manufacturing, but they have not deployed the construction of government and policy support in their proposed TAM-TOE model because India is one of the AI-developing countries with the comprehensive support of AI policies (Chatterjee, 2020; Rizvi et al., 2021). The same limitation exists in the study of Kamble et al. (2021).

Several studies focus on AI-integrated technologies, such as blockchain and IoT in manufacturing using a hybrid TAM and TOE (Kamble et al., 2021; Legesse et al., 2024; Patil et al., 2023; Tasnim et al., 2023). However, they have yet to focus on the ACAP of these emerging technologies entering organizations. While organizational readiness was used to measure the manager's perception of his organization's competency to adopt the technology, the criterion is mainly focused on financial readiness organizational readiness (Kamble et al., 2021). They have yet to mention organizational absorptive capacities, which is consistent with Legesse et al. (2024), Patil et al. (2023), and Tasnim et al. (2023). In addition, as the research focuses on manufacturing sectors, most research specifies the contribution to supply chains and SCM (W. Guan et al., 2023; Kinkel et al., 2022; Legesse et al., 2024; Patil et al., 2023; Pillai et al., 2022; Tasnim et al., 2023). Nevertheless, they have not considered suppliers' involvement as an external environmental factor to determine the adoption intentions, except the study of Tasnim et al. (2023), Pillai et al. (2022), and Guan et al. (2023).

Following the above limitations in current studies, our thesis will fill the gaps in the aspects of determinants toward AI adoption from the hybrid TAM-TOE. In addition, AI adoption and organizational open innovation have an interactive relationship. Some debate exists in the current studies on whether AI adoption influences open innovation or whether open innovation impacts AI adoption. According to previously introduced AI capabilities, comprehensive studies have demonstrated AI enables open innovation in organizations through advanced AI techniques (Bahoo et al., 2023; Broekhuizen et al., 2023; Cui et al., 2022; Sahoo et al., 2024). This positive impact may manifest in enhanced resource integration capabilities, improved innovation efficiency, and accelerated innovation processes. By adopting AI technologies, organizations can better leverage external knowledge and technological resources, fostering continuous innovation practices. However, from open innovation theory, very little research defined open innovation's impacts on the adoption of AI. The study of Obradović et al. (2021) and Lepore et al. (2023) has mentioned the effect of open innovation on the adoption of Industry 4.0 technologies, but many prior studies have demonstrated open innovation has a positive influence on organizational performance (Greco et al., 2016; Oltra et al., 2018; Rumanti et al., 2023; Singh et al., 2021; Wang et al., 2021). Therefore, we assert that if open innovation positively impacts on organizational performance, this success may encourage the company to adopt AI technology more actively. By enhancing their resource integration capabilities and innovation momentum through open innovation, firms are more likely to incorporate AI technology into their innovation systems, thereby further strengthening their competitive advantages. Thus, this thesis will combine the debates and fill the gap in interactive relations in ***Study 1,*** initially attempting to empirically define the inter-effect between AI adoption and open innovation.

In addition to the above theoretical gaps, a limited number of factors have yet to be deployed to the specific domain, such as the apparel manufacturing sector. As prior introduced, the Chinese apparel manufacturing sector faces many challenges in the labor market shift, increasing workforce reduction due to the COVID-19 pandemic (Leal Filho et al., 2023; Tan et al., 2022). Also, the traditional apparel manufacturing environment has experienced a drastic reduction that warrants intelligence for obtaining sustainable production and manufacturing systems befitting this status and phenomenon. The survival of apparel manufacturers relies on steady and substantial global orders and qualified production makers, such as sewing makers and pattern cutters, and, more importantly, a favorable environment and strong decision-making organizations. As mentioned above, AI-embedded technology, such as robot-assisted making and fabrication and big data analytics for digital manufacturing, have revolutionized apparel production processes instead of a partial workforce (Giri et al., 2019). These AI-embedded technologies have facilitated manufacturing process systems for developing intelligent, agile, and eco-friendly production ecosystems (Chaudhuri et al., 2022; Giri et al., 2019). Existing literature on digital transformation in open innovation in the manufacturing sector shows limited research scope in China's manufacturing sector, let alone the apparel industry. China posits a leadership position in AI development (Arenal et al., 2020; Barton et al., 2017), but there is minimal research on how China's government, universities, and apparel manufacturing firms can co-create values in AI ecosystems. Also, the origins of this research idea of building AI-enabled innovation ecosystems stem from the researcher's genuine interest in how Chinese apparel manufacturing leverages AI capabilities to build an innovation ecosystem. However, prior studies have not grounded the definitions of AI capabilities in innovation ecosystems parameters and the apparel manufacturing sector with specific propositions and a theoretical framework. Thus, based on the results of ***Study 1***, ***Study 2*** conducts ground theory to build an AI-enabled innovation ecosystem to propose propositions and a theoretical framework for open innovation and AI adoption in ***Study 2***.

Regarding methodological gaps, the reviewed literature uses quantitative methods for AI adoption-related studies using a cross-sectional method and primary survey. In contrast, both qualitative and quantitative methods are employed for open innovation-related studies using a longitude method and secondary panel data. This thesis employs a quantitative method, using PLS-SEM analysis in ***Study 1***, and qualitative ground theories, using coding analysis in ***Study 2.***

2.5. Chapter Summary

This chapter initially presented the construction of AI capabilities in application areas and their enabling roles in different innovation types. It then introduced the theoretical lens and hypotheses derived from the proposed conceptual model, focusing on factors influencing the adoption of AI-integrated technologies to foster open innovation in Chinese manufacturing firms. The integration of TAM and TOE has been applied in numerous studies cited in this thesis, providing valuable strategic insights into how manufacturing firms' choices regarding AI adoption drive open innovation within their business landscape. Moreover, the KBV is a crucial theory running through TOE, AI adoption, and open innovation constructs, as the roles of knowledge management in this mechanism cannot be ignored. Therefore, to study the antecedents of AI adoption, thus driving open innovation based on the TAM-TOE framework, the KBV was considered suitable as the core theory for examining this research correlation within the Chinese apparel manufacturing sector.

This approach has ensured that the research provides a solid background on adopting technology that drives firms' open innovation in ***Study 1***. The result is a structural equation model (SEM) developed based on previous technology adoption frameworks, incorporating constructs that best represent AI adoption. The research model, along with its latent constructs and relevant relationships, has been formulated to establish the foundation for the next stage of the thesis, where the methodology for concept validation will be detailed in the following chapter. The reviewed literature for ***Study 2*** proposed open innovation from something-based perspectives, such as RBV, KBV, innovation ecosystems, and TH, which inform the ***MRO*** of studying AI-enabled innovation ecosystems from these dimensional concepts. These theoretical lenses of AI-integrated technologies adoption, open innovation, and innovation ecosystems literature have been analyzed to uncover contributions and limitations, leading to the identification of the research gap that serves as the core focus of this study.

3. Methodology

3.1. Introduction

As defined by Collis and Hussey (1997), methodology refers to the approach to the research process, from the theory of how research should be undertaken to data collection and analysis. This chapter provides comprehensive research approaches to address research questions derived from ***Study 1*** and ***Study 2,*** thereby fulfilling the ***MRO and SROs***. To achieve the ***MRO*** of developing AI-enabled innovation ecosystems with propositions for Chinese apparel manufacturing industry, ***Study 1*** was designed as a quantitative investigation to fulfill ***SRO 1***, which aims to examine the antecedents of AI adoption and their impact on KACAP and open innovation in Chinese apparel manufacturing firms. By adopting a positivist paradigm and a deductive approach, ***Study 1*** examined a structured model using the integrated TAM-TOE framework and positioned KACAP as a critical mediator, providing empirical insights into how technological, organizational, and environmental factors drive AI adoption and enable open innovation. This quantitative foundation is essential for establishing statistically significant relationships that confirm the framework's relevance within the apparel industry context. Building on the quantitative findings of ***Study 1***, ***Study 2*** adopted a qualitative, inductive approach to achieve ***SRO 2***, which focused on categorizing and specifying the required AI capabilities in apparel production innovation processes, and the challenges and barriers to adoption AI, thereby developing a theoretical framework and generating propositions to explain how Chinese apparel manufacturing enhance internal organizational resources and external collaborations with universities, associations, and government. Through grounded theory, ***Study 2*** explored deeper dimensions of AI-driven collaboration by analyzing interview data from key stakeholders. This qualitative approach complements the quantitative insights of ***Study 1*** by providing context-specific insights, thus forming a comprehensive understanding of how AI adoption interacts with organizational and external resources to drive innovation. The two studies create a synergistic research design, where ***Study 1*** provides empirical validation for foundational constructs, and ***Study 2*** offers a theoretical lens to broaden the findings and contextualize them within a collaborative innovation ecosystem. By integrating these approaches, the research ensures that both the main and specific research objectives are thoroughly addressed, offering a robust framework for AI-enabled innovation in the apparel manufacturing sector.

Section 3.2 presents the corresponding methodological research procedures based on Saunders et al. (2015, p.164) "research onion", providing together with the rationale for the research philosophy and approaches of this thesis. This guidance aims to support the processes for validating the conceptual model introduced earlier. Section 3.3 outlines the research design, including methodology choices, strategies, and time horizons. Sections 3.4 and 3.5 describe the data collection and procedure in ***Study 1*** and ***Study 2***, respectively. Section 3.6 covers the ethical considerations, and Section 3.7 summarizes the logic of the two studies. **Figure 3.1** shows the flow chart of Chapter 4.

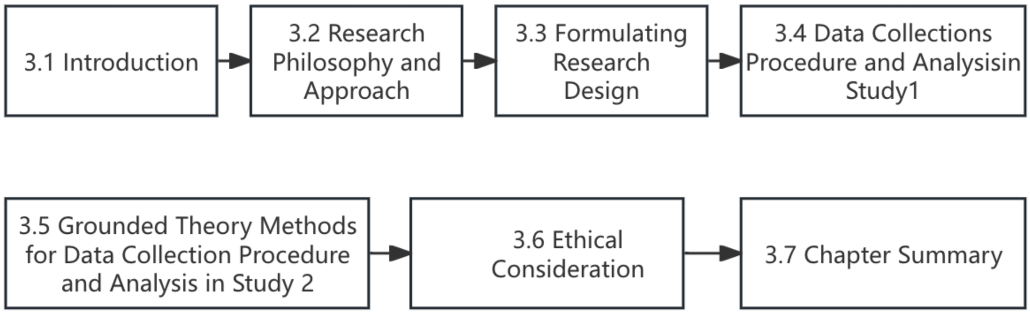

Figure 3.1 Flow Chart of Chapter 3

3.2. Research Philosophy and Approach

Developing and presenting an idea requires systematic measurement and analysis of inputs, which are gathered as data (Dobre, 2022). The selection of research methods is guided by their relevance to the knowledge being generated and the steps involved in its development (Saunders et al., 2015). The research paradigm plays a crucial role in shaping the approach and determining the appropriate methodology. To ensure alignment with the objectives of this thesis, various research philosophies and approaches were critically evaluated, leading to the adoption of the most effective method for achieving the desired outcomes. Thus, the following paragraph first peels away the outer two layers of the research 'onion', which are research philosophies and approaches.

3.2.1. Research Philosophy

The research philosophy contains essential assumptions about how the researcher views the world (Saunders et al., 2015). These assumptions help clarify the research questions, choose research strategies, and conduct the whole research process coherently (Easterby-Smith et al., 2002; Saunders et al., 2009; Blaikie, 2000). The research philosophy of this thesis encompasses ontology and epistemology (Saunders et al., 2015), each of which is examined below to provide distinct insights into the nature of reality, the concept of knowledge, and the methods for acquiring empirical evidence.

Ontology concerns the nature of reality and includes objectivism and subjectivism (Bell et al., 2022; Bhattacherjee, 2012; Saunders et al., 2016). Objectivism is an ontological stance claiming that social phenomena and their meanings exist independently of the individuals involved (Bell et al., 2022); in contrast, subjectivism asserts that social reality is shaped by individual perceptions and subsequent actions of social actors (Saunders et al., 2015). Subjectivism embraces constructionism (Bell et al., 2022; Clark et al., 2021; Saunders et al., 2016). It is vital to identify that ***Study 1*** is dominated by objectivism because understanding the meanings individuals attach to social phenomena, such as the objects of organizations and management. ***Study 2*** employs constructionism, asserting that social reality is constructed through human interaction and social processes. It emphasizes that reality is not an objective, independent entity but is continuously constructed and reconstructed by social actors through shared understanding and practices (Clark et al., 2021; Saunders et al., 2016).

Epistemology concerns “assumptions about knowledge, what constitutes acceptable, valid and legitimate knowledge, and how we can communicate knowledge to others” (Burrell and Morgan 1979, as cited in Saunders et al., 2015, p. 127), and is the relationship between reality and the people (Carson et al., 2001; Perry et al., 1999). Saunders et al. (2015) suggested three primary positions: positivism, realism, and interpretivism. The focus of positivism on what is “posited” highlights its commitment to a strictly scientific method aimed at producing pure data and facts, free from human interpretation or bias. (Saunders et al., 2015). This requires researchers to apply natural sciences methods to study the social world (Dobre, 2022). Thus, researchers explain and predict organizational behavior and events by looking for causal relationships from data that can be observable and measurable facts (Primecz, 2020; Saunders et al., 2016). Saunders et al. (2015) suggest positivist researchers use existing theories to develop hypotheses, emphasizing quantifiable observations that lend themselves to statistical analysis. However, positivism has its critics. These critics contend that positivism excessively prioritizes objectivity and quantitative data, thereby overlooking the intricate complexity and diversity of social phenomena and how social context profoundly shapes and influences these phenomena (Orlikowski & Baroudi, 1990). Critical realism explains what we see and experience regarding the underlying structures of reality that shape observable events. Different from positivism, critical realism emphasizes uncovering the deeper structures and mechanisms that shape observable phenomena (Saunders et al., 2015). Thus, it advocates moving beyond surface-level empirical data in research to explore deeper realities, revealing the true nature and complexity of things (Bhattacherjee, 2012). However, it has critiques for “neglecting other factors equally important in social relationships, such as gender and race, thus critical realism being viewed as limited to the way the world is sensed as opposed to how it is” (Orlikowski and Baroudi, 1991 as cited in Dobre, 2022, p. 112). In contrast to positivism, interpretivism posits that social reality is constructed through human interactions and subjective experiences, necessitating a focus on individuals’ subjective experiences, cultural contexts, and social environments when studying social phenomena (Saunders et al., 2015). Within the interpretive framework, researchers typically employ qualitative methods, such as in-depth interviews, observations, and case studies, to comprehend individuals’ behaviors, beliefs, and values. This methodological approach contends that social phenomena cannot be fully understood through objective data alone; instead, it requires interpreting and understanding participants’ subjective meanings to uncover the deeper layers of social reality. Therefore, interpretive research aims to create new, richer understandings and interpretations of social worlds and contexts, for example, by looking at organizations from the perspectives of different groups of people so that they could arguably be seen as experiencing different workplace realities (Saunders et al., 2016).

Therefore, according to these positions suggested by Saunders et al. (2015), ***Study 1*** selects positivism, which facilitate the validation of independent research findings and enhance the understanding of research phenomena by conducting hypothesis testing. ***Study 2*** adopts interpretivism, emphasizing the differences between conducting research among people (Bell et al., 2022). Interpretive researchers use qualitative data to understand how social reality is constructed by people interacting with others (Hackley, 2003).

3.2.2. Research Approaches

The second layer of the "onion" is "approaches to theory development" (Saunders et al., 2016, p. 164). Different perspectives link theory and research, with the main approaches represented by the deductive, inductive, and abductive approaches (Bell et al., 2022; Bhattacherjee, 2012; Saunders et al., 2016). A deductive approach uses data to test theory with various statistical analyses, thereby validating the hypotheses made (Bell et al., 2022). However, it may incorporate an inductive approach, using data to develop theory (Saunders et al., 2016). An inductive approach is driven by the gap of knowledge, thus requiring the accumulation of facts and data that lead to generating and building theory where "data collection is used to explore a phenomenon, identify themes and patterns and create a conceptual framework" (Saunders et al., 2016, p. 145). Similarly, as deduction often entails an element of induction, the inductive process likely involves some deduction, such as grounded theory (Bell et al., 2022). Thus, selecting which approaches in research needs to consider each binding principle as none of both is exhaustive (Dobre, 2022). The third approach is the abductive approach, where theory generation or modification incorporates existing theory where appropriate to build new theory or modify existing theory (Saunders et al., 2016). This approach highlights that generating or modifying theory must rely on the existing theories, and the modified frameworks must be tested through additional data collection (Saunders et al., 2016).

Based on the evaluations of research approaches to theory development, ***Study 1*** follows a deductive approach, utilizing statistical analysis to empirically test the proposed hypotheses (Bell et al., 2019). It addresses ***SRQ 1*** and ***SRQ 2***, building upon previously validated theoretical concepts through hypothesis testing. ***Study 2*** adopts an inductive approach, in which the researcher generates theories and gains insights to create new conceptual possibilities (Saunders et al., 2016), thus addressing ***SRQ 3*** and ***SRQ 4***.

3.3. Formulating Research Design

The previous section peels away the research philosophy and approaches, which are two outer layers of the "onion" to theory development and influence the research design (Saunders et al., 2015). Thus, building on the determined ontological objectivist perspective and epistemological positivist approach (***Study 1***), as well as the ontological constructivist perspective with epistemological interpretivism and inductive reasoning (***Study 2***), this section delves into three additional layers: methodological choice, research strategy, and time horizon. Thus, following the determined ontological objectivist perspective with epistemological positivist direction, a deductive approach (***Study 1***), and an ontological constructivist perspective with epistemological interpretivism and an inductive approach (***Study 2***), this section further uncovers the following three layers: methodological choice, research strategy, and time horizon for this research.

3.3.1. Methodological Choices

The third layer of the "onion" contains two main methodological choices: quantitative and qualitative research (Saunders et al., 2015). Quantitative research typically employs a deductive approach focused on theory testing, aligning with the practices and norms of the natural scientific model and positivism, and perceives social reality as an external, objective entity (Bell et al., 2022; Clark et al., 2021; Saunders et al., 2016). Qualitative research usually emphasizes words and images rather than quantification, which typically adopts an inductive approach to theory and research focused on theory generation, rejects the norms of the natural scientific model and positivism in favor of understanding how individuals interpret their social world and view social reality as a dynamic, emergent property shaped by individual creation (Bell et al., 2022; Clark et al., 2021; Saunders et al., 2016).

However, in business and management research, researchers tend to combine both elements (Saunders et al., 2016). Thus, except quantitative or qualitative in one research, a mixed method is defined as "the branch of multiple methods research that combines quantitative and qualitative data collection techniques and analytical procedures" (Saunders et al., 2016, p. 169). This thesis adopts "double-phase research design"; specifically, it is a "sequential explanatory research design" (quantitative followed by qualitative) (Saunders et al., 2016, p. 170), as ***Study 1*** adopts quantitative research, and ***Study 2*** adopts qualitative research in this thesis. The quantitative results of ***Study 1*** provide an empirical basis for qualitative research in ***Study 2***. A quantitative research design may use a single data collection technique, such as a questionnaire or a corresponding quantitative analytical procedure. In contrast, data collection is non-standardized in a qualitative research design.

3.3.2. Research Strategies

Research strategy is "the methodological link between philosophy and subsequent choice of methods to collect and analyze data" (Denzin and Lincoln 2011, as cited in Saunders et al., 2015, p. 177). The "onion" illustrates eight elements in the "strategy layer": experiment, survey, archival research, case study, ethnography, action, grounded theory, and narrative inquiry (Saunders et al., 2016, p. 164). In general, this thesis adopts a case study of Chinese apparel manufacturing sector, but specifically, it employs survey and grounded theory strategies for quantitative and qualitative research, respectively, since the survey strategy is usually associated with a deductive research approach and grounded theory is particularly well suited to organizational research, associated with an inductive research approach with theorizing process, and a theoretical framework is generated and built (Bell et al., 2022; Saunders et al., 2016). The detailed research procedures of both strategies in ***Study 1*** and ***Study 2*** are presented in Section 4.4.

3.3.3. Time Horizon

Due to time constraints, this thesis reserved a case study strategy within a cross-sectional research design, collecting data at a single time (Clark et al., 2021). Although it often employs the survey strategy to describe the incidence of a phenomenon, many case studies are based on interviews conducted over a short period (Saunders et al., 2016).

3.4. Data Collections Procedure and Analysis in *Study 1*

This section peels away the last layer of the "onion," which focuses on the specific data collection and analysis procedures (Saunders et al., 2016). To clearly describe the different procedures of ***Study 1***and ***Study 2***, following the sequential explanatory research design, i.e., quantitative followed by qualitative, the following paragraph first presents ***Study1***'s quantitative data collection and analysis procedure, followed by ***Study 2***'s qualitative data collection and analysis procedure in **section 1.5**.

Survey strategies using questionnaires are cost-effective for collecting standardized quantitative data from large populations, enabling easy comparison and analysis using descriptive and inferential statistics (Saunders et al., 2015). Thus, this thesis employs a questionnaire for data collection and questions derived from prior research on TAM-TOE antecedents that influence the adoption of AI-integrated technologies, thus driving open innovation. Prior studies employed questionnaires to validate models on TAM-TOE framework for AI-integrated technologies adoption, such as IoT-based smart manufacturing systems (Patil et al., 2023), AI-based manufacturing and production system (Chatterjee, Rana, Dwivedi, et al., 2021), blockchain (Kamble et al., 2021; Legesse et al., 2024; Tasnim et al., 2023). Therefore, ***Study 1*** decides to employ the questionnaire as the most appropriate technique for data collection.

3.4.1. Designing the Questionnaire Survey Instruments

Questionnaires tend to be used for descriptive or explanatory research (Saunders et al., 2015). Explanatory research is usually deductive, using data to test a theory or theories to examine and explain cause-and-effect relationships (Saunders et al., 2016). Therefore, ***Study 1*** decided to adopt explanatory research, as it aimed to examine and explain relationships between antecedents of the adoption of AI-integrated technologies and its impacts on open innovation. ***Study 1***'s questionnaire (see **Appendix B**) was carefully designed to minimize respondent confusion, bias, and hesitancy in completing the survey. To achieve this, the questions were organized into two sections that align with the structure of the model, guiding respondents smoothly from one section to the next, thereby increasing their awareness as they progressed through the survey. A Participant Information Sheet was provided before answering questions. It presents the scope of the research, followed by a request to the respondents to confirm their consent to participate (Dobre, 2022). The first section is associated with questions on demographics, addressing the firm age, size, annual sales, production capacity, production types, and customer regions.

Also, explanatory research requires the researcher to review the literature carefully, discuss ideas widely, and conceptualize research before designing the questionnaire (Ghauri &Gronhaug, 2005; Saunders et al., 2015). Thus, the questionnaire survey instrument must be developed based on the support of the theory. To develop the survey, an appropriate measurement scale was created to assess the constructs identified in ***Chapter 4***. Further steps were taken to carefully select and structure the wording of the questions, determine their sequencing, specify the expected response format, and incorporate the measurement of additional variables into the survey instrument (Dobre, 2022).

To create a measuring scale, constructs must first be identified and then translated into measurable variables through specific items (Bhattacherjee, 2012). To confirm the suitability of the selected constructs and items for this thesis research model, additional evaluation was performed by reviewing prior literature and existing questions from previous studies, with proper citations included as necessary, where "the corresponding construct and items have been initially used" (Bell et al., 2022, p. 886). For double-confirmed and careful selection and inclusion, the measurement scale and questionnaire construction were initially reviewed by two experts experienced in knowledge science and apparel production in the AI area. Subsequently, the questionnaire was designed using all the items representing the constructs selected in ***Study 1***'s measurement instrument (see **Table 3.1)**.

Table 3.1 The measurement instrument and sources

Construct	**No.**	**Indicator**	**Indicator Description**	**Reference**
Perceived Usefulness (PU)	1	pu_1	Using AI-based manufacturing and production systems can enhance work efficiency.	(Davis, 1989; Venkatesh & Davis, 2000)
	2	pu_2	Using AI-based manufacturing and production systems can improve the quality of task completion.	
	3	pu_3	Using AI-based manufacturing and production systems can increase productivity.	
	4	pu_4	Using AI-based manufacturing and production systems can save a significant amount of time.	
	5	pu_5	AI can provide valuable decision support for our organization.	
Perceived Ease of Use (PEOU)	6	peou_1	An AI operation process is easy to understand.	(Davis, 1989; G. C. Moore & Benbasat, 1991)
	7	peou_2	The time required to learn AI is reasonable.	
	8	peou_3	Our employees can easily operate an AI-based manufacturing and production system.	
	9	peou_4	Our employees can quickly learn about the usage of AI in their work processes.	
Organizational Complexity (OCX)	10	ocx_1	Integrating AI technology with the existing legacy system is difficult for our organization.	(Chatterjee et al., 2021; Rogers, 2003)
	11	ocx_2	Resistance to change is high regarding migrating from the legacy system to an AI-	

			based manufacturing and production system.	
Organizational Readiness (ORE)	12	ore_1	Our company has complete infrastructure to develop AI in manufacturing and production processes.	(Chatterjee, Rana, Dwivedi, et al., 2021; Iacovou et al., 1995a; Rogers, 1995)
	13	ore_2	Our employees have the necessary skills and knowledge to use the AI-based system.	
	14	ore_3	Our management has a high level of support for AI in manufacturing and production systems.	
Competitive Pressure (CP)	15	cp_1	Using an AI-based manufacturing and production system will bring a competitive advantage to our organization.	(Chatterjee et al., 2023; Gutierrez et al., 2015)
	16	cp_2	The apparel industry has increasingly applied an AI-based manufacturing and production system.	
	17	cp_3	I am aware that many firms are moving towards AI-based manufacturing and production.	
Supplier Involvemen (SIV)t	18	siv_1	SP2-Our suppliers provide satisfying products and services.	(Islami, 2023; Lemke et al., 2003)
	19	siv_2	SP3- Our suppliers respond quickly to our demands.	
	20	siv_3	SP4- We have close relationships with our suppliers.	
Market Uncertainty (MU)	21	mu_1	Our market demand frequently experiences significant changes.	(Chau & Tam, 1997)
	22	mu_2	Our customers' needs are variable and unpredictable.	
	23	mu_3	The pace of technological development in our industry is very fast.	
	24	mu_4	The emergence of new technologies has a significant and unpredictable impact on our industry.	
Government Support and Policy	25	gsp_1	The AI-related policies and regulations is important for apparel manufacturing transformation.	(Edquist & Hommen, 2000)

(GSP)	26	gsp_2	The government provides adequate financial support for developing and applying AI-integrated technology to my company.	
	27	gsp_3	The government's support and help are very important when applying AI technologies.	
AI Adoption (AIA)	28	aia_1	We plan to adopt AI technology for manufacturing and production.	(Akhtar, 2020; Davis, 1989; Rogers, 1995; Yang et al., 2021)
	29	aia_2	We plan to adopt AI technology to solve problems in SCM.	
	30	aia_3	We plan to adopt AI technology to reduce risks in our manufacturing and production processes.	
	31	aia_4	We plan to adopt AI technology to be agile in an uncertain environment.	
Knowledge Absorptive Capacity (KACAP)	32	kacap_1	Our company can effectively identify and acquire important new knowledge and information within and outside the industry to support the application of AI technology.	(Cohen & Levinthal, 1990; Denford, 2013b; Jiménez-Barrionuevo et al., 2011; Verona & Ravasi, 2003) (Nonaka & Takeuchi, 1995); (Grant, 1996; Verona & Ravasi, 2003)
	33	kacap_2	We actively acquire knowledge from external sources and integrate it with internal knowledge.	
	34	kacap_3	Our company can understand and analyze the acquired knowledge and information within and outside the industry, ensuring compatibility with existing knowledge.	
	35	kacap_4	We provide sufficient technical training for our employees to help them absorb and apply AI technology.	
Open Innovation (OI)	36	oi_1	Our company culture encourages knowledge sharing.	(Enkel et al., 2009; Laursen & Salter, 2006; Lichtenthaler &
	37	oi_2	Our company extends sources with our customers.	
	38	oi_3	Our company extends sources with our suppliers.	

39	oi_4	Our company extends sources with institutions or universities.	Lichtenthaler, 2009)
40	oi_5	Our collaboration with external partners facilitates the adoption of new technologies.	

3.4.2. Response Format

The questionnaire included structured closed questions to ensure that the collected data is in a format that allows future analysis (Dobre, 2022). According to Bhattacherjee (2012), responses to structured survey questions are captured using one of the following response formats: dichotomous, nominal, ordinal, interval-level, and continuous response. The designed questions of the questionnaire were structured to include nominal, ordinal, and interval-level response formats among those available in the literature, as described below.

Nominal response refers to selecting options in a measurement tool that belong to different categories, with no inherent order or numerical relationship between these categorical variables, such as the industry types, business types, etc. (Bhattacherjee, 2012). This survey includes two nominal responses where respondents are presented with unordered options, such as: What is your firm's business type: OEM/ODM/OBM, and What is your primary market or markets: Asia- Japan, Korean /Asia-Singapore/Europe/North America- Canada/North America- the U.S. / China domestic. The two nominal questions in the survey aim to categorize and group the companies in the sample. This categorization facilitates a deeper analysis of the sample composition, providing a foundation for subsequent research or data analysis, particularly for potential future grouping or comparisons between different categories. The survey also included four ordinal questions, such as the firm's age in years: "0-5/6-10 /11-15/15+", and the years the managers own the company: "0 <5years 0 6-10years 0 11-15years 0 >15years", but the intervals between them are not equal, aiming to encourage actual answers from respondents by the anonymity of their feedback. The ordinal question allows the researcher to categorize and rank data, facilitate group comparisons, and simplify complex information for more accessible analysis and interpretation (Bhattacherjee, 2012). The third type of response format is the interval-level response using a five-point Likert scale (Bell et al., 2022; Bhattacherjee, 2012; Saunders et al., 2016), which is more likely to reflect respondents' actual subjective evaluation of a usability questionnaire item (Taherdoost, 2019). Thus, the constructs' measurement was carried out using the five-point Likert scale: "1= strongly disagree, 2= disagree, 3= neutral, 4= agree, and 5= strongly agree", which usually comprises a series of statements (known as items) that focus on an issue or theme. Each item describes the relationships between the constructs and their corresponding indicators based on the measurement models in Partial least squares-Structural Equation Modeling (PLS-SEM), which is primarily used to develop theories in exploratory research (Hair et al., 2017).

3.4.3. Sampling Procedure

3.4.3.1. Target Respondents Identification

Based on ***SRO 1*** focused on examining the antecedents of AI adoption, thus driving open innovation in Chinese apparel manufacturing sector, emphasizing the significant mediating role of knowledge absorptive capacity (KACAP) in innovation processes, the target respondents of ***Study 1*** were identified as top managers in Chinese apparel manufacturing firms.

There were 170 thousand apparel and textile manufacturers in China as of January 2022 (China Textile Industry Federation). While conducting the literature review, which led to the conceptual model in ***Chapter 2***, it has been noticed that most of the studies frequently focus on the manufacturing sector (Bag et al., 2021; Chatterjee, Rana, Dwivedi, et al., 2021; Kamble et al., 2021; J. M. Kim & Park, 2024; Kinkel et al., 2022; Maroufkhani et al., 2023; Maroufkhani, Wan Ismail, et al., 2020a, 2020b; Patil et al., 2023; Pillai et al., 2022; Ronaghi, 2023). However, prior research has hardly studied apparel manufacturing, which provides a gap in the focused industrial samples. Therefore, to ensure a broad possible representation of apparel industries in ***Study 1*** and to maximize the number of respondents, the survey did not impose any limitations on the firm size or location in China. The research is set such that the sample is representative of the apparel manufacturing sector in China.

3.4.3.2. Sampling Frame

The sampling frame is "an accessible section of the target population (usually a list with contact information) from where a sample can be drawn" (Bhattacherjee, 2012, p. 66). The source of ***Study 1*** comes from the China National Garment Association (CNGA) databases (https://www.cnga.org.cn/), which lists the association members' addresses, websites, e-mail addresses, firm age, number of employees, and business types. However, these association members include not only the manufacturing sector but also design and retail. These findings challenge quickly reaching a sufficient number of respondents to secure the minimum required responses. In addition, the member directory covers only subscribers who pay to be listed; the sample will, therefore, be biased toward businesses that have chosen to subscribe (Saunders et al., 2016). Furthermore, the database information might be outdated soon (Saunders et al., 2016). Considering the above issue, the organizations with garment production businesses presented with the updated associate member list have been selected as the sampling frame. In addition, the source of the Alibaba Group database (https://www.alibaba.com) was targeted, which lists the firm profile.

3.4.3.3. Sampling Techniques

Probability sampling and non-probability techniques are grouped in the sampling techniques (Bhattacherjee, 2012). Probability sampling involves the random selection of samples, ensuring that each unit in the population has a known, non-zero chance of being selected to obtain a representative sample that allows for generalization to the entire population (Bhattacherjee, 2012). Non-probability sampling is a sampling technique in which some units of the population have zero chance of selection or where the probability of selection cannot be accurately determined, including convenience sampling (easily accessible to respondents), quota sampling (the proportion of respondents in each subgroup should match that of the population), expert sampling (judge mental sampling), and snowball sampling where researchers rely on the initial respondents to recruit additional participants from their social networks (Bhattacherjee, 2012, pp. 69-70). Studies in the technology adoption literature often employ quota sampling, utilizing demographic information obtained through trade associations (Cao et al., 2021; Gangwar et al., 2015). While quota sampling is non-probabilistic, it ensures that specific demographic groups are represented, though it does not provide every member an equal chance of selection. In ***Study 1***, a quota sampling technique was employed to select specific manufacturers, and a simple random sampling technique was then applied to ensure representativeness among apparel manufacturing companies in China. **Table 3.2** shows the proportion of geographic locations (industry cluster) (J. Wu et al., 2018), firm size (Standards of National Bureau of Statistics, 2017), and production types in the CNGA database. It is necessary to explain that in terms of firm size, this study initially employed quota sampling with a target distribution of 92% MSMEs and 8% large enterprises. However, due to the small proportion of large enterprises and the challenges in obtaining responses, the sampling design was adjusted to focus exclusively on MSMEs. This change in sampling strategy is acknowledged as a necessary adaptation to the data collection process and is discussed further in the limitations section.

Table 3.2 Quota Sampling Criteria (Source from the CNGA WeChat Mini App, as of 2024, May)

Criteria	**Quota**	**Characteristics**
Industry Cluster (Geographic		
Yangtze River Delta	42%	Major apparel manufacturing hub in China.
Pearl River Delta	31%	Key export-oriented manufacturing region.
North China	12%	Traditional industrial area with declining but still significant production.
Western China	15%	Developing region with increasing investment.
Firm Size (China national textile and apparel council, as of 2022)		Upper-scale and lower- scale (/www.cntac.org.cn).
Large (>1000 employees)	8%	High production capacity, significant market influence.
Micro Small Medium (<1000 employees)	92%	Flexibility and adaptability in market changes.
Business Type		
OEM (Original Equipment Manufacturer)	25%	Major production model, primarily focused on manufacturing for other brands
ODM (Original Design Manufacturer)	40%	Companies that design and manufacture products, typically for other brands
OBM (Original Brand Manufacturer)	35%	Companies that design, manufacture, and sell their own brand products

3.4.3.4. Sample Size

The sample size indicates the number of elements to be included in the study, ensuring that it is sufficiently large to meet the requirements of the statistic (Dobre, 2022; Saunders et al., 2016). The small sample sizes used in existing quantitative studies on technology adoption, Partial Least Square Structural Equation Modelling (PLS-SEM), is recommended for use, especially when the research involves a complex conceptual model with many constructs and a large number of items (Hair et al., 2017, as cited in Dobre, 2022). Several methods are used to calculate the minimum sample size, including the 10 times rule and the statistical power of the estimates (Hair, 2017). The 10 times rule requires the maximum number of arrowheads pointing at a latent variable anywhere in the PLS path model, but this rule offers a rough guideline (Hair et al., 2022). To determine the scientifically appropriate sample size, this study utilized G*Power software, setting the power at 0.8 and the effect size f*2* at 0.15 (medium effect). Based on these parameters and considering eight constructs in the model, the required total sample size was calculated to be 109. However, the minimum sample size resulting from these calculations may still be too small (Kock & Hadaya, 2018, as cited in Hair et al., 2022). Thus, based on Kock and Hadaya (2018), Hair et al. (2022) recommend the " 'inverse square root method', which considers the probability that the ratio of a path coefficient and its standard error will be greater than the critical value of a test statistic for a specific significance level" (Hair et al., 2022, p. 54). As the example shown (Hair et al., 2022, p. 54), assuming a significance level of 5% and a minimum path coefficient of 0.2, the minimum sample size is 155. Therefore, after conducting the pilot testing, the ***study 1*** sample size is 269, which satisfies the "10 times rule", the "statistical power of the estimates," and the "inverse square root method" (Hair et al., 2022).

3.4.4. Pilot Testing

The questionnaire of ***Study 1*** should be pilot-tested before distributing (Bell et al., 2022; Saunders et al., 2016) with respondents to ensure that respondents have had no problems understanding or answering questions and have followed all instructions correctly and the minimum number for the pilot is 10 (Fink 2013, as cited in Saunders et al., 2015). Therefore, this study initially conducted expert validation by two academics specialized in knowledge science and intelligent design and production management to help establish content validity and make necessary amendments before pilot testing (Saunders et al., 2015). The questionnaire was also validated through a WeChat group to assess its content and the time needed for completion. A pre-test was conducted to evaluate the questions' content and sequence, addressing any unclear or ambiguous statements. Also, to ensure the reliability of the measurement model, the questionnaire was again piloted with 23 managers with expertise in apparel manufacturing production management to ensure they understood the measures and what technologies integrated with AI-integrated technologies would be applied in apparel manufacturing. This prior test assessed the constructs' consistency by computing Cronbach's alpha (α), composite reliability (rho_a), and average variance extracted (AVE) for each construct.

3.4.5. Data Collection

Ethical research protocol approval was obtained prior to data collection. Considering that the data collection procedure of ***Study Two*** has yet to be explained, the ethical considerations are presented in section 4.10, which comprises the two studies.

After confirming the minimum sample size, the first step was to conduct the survey distribution. As the designed questionnaire is a self-completion questionnaire usually completed by the respondents, this survey can be distributed to respondents through the Internet (Internet questionnaire), a web browser using a hyperlink (Web questionnaire), a mobile questionnaire using a QR (quick response) code (Saunders et al., 2015), and email (Bell et al., 2022). Respondents have been reached through online surveys through email (Cao et al., 2021) and web questionnaire (Kinkel et al., 2022)and offline through mail or telephone (Gangwar et al., 2015; T. Oliveira & Martins, 2010) in technology adoption studies, and both (Chatterjee, Rana, Dwivedi, et al., 2021). Bhattacherjee (2012) recommends that more than one data collection method be used to reach the minimum sample size in a practical timeframe (Dobre, 2022). Therefore, for the cost-effectiveness of the collection, this study used direct phone calls and an online website to distribute the survey and access the maximized size of the samples.

All participants in this study provided informed consent before their inclusion. To ensure that they were adequately informed about the research purpose and intent and that their anonymity was respected (Bell et al., 2019), informed consent was written on the first page of the questionnaire, and prospective respondents were informed that the aim of this study was purely academic. They were assured that their anonymity and confidentiality would be strictly preserved, and they were asked to respond within eight weeks of receiving the messages. Also, to ensure that top managers from the apparel manufacturing industry understand the meaning of AI, as referenced in the questionnaire, a definition of AI tools was provided in Chinese on the first page of the questionnaire.

The office phone number is listed in the China National Garment Association database. However, the managers' contacts are not shown, and the firm's receptionists refused to answer the questionnaire, resulting in only 19 responses out of 358 manufacturing firms accepting the survey by direct phone. The researcher is a Dalian Textile and Apparel Association member, so accessing Dalian's apparel manufacturing firm is relatively easy. Thus, 13 responses accepted the survey through WeChat. However, one location's sample cannot be satisfied with probabilistic sampling techniques; therefore, the researcher decided to collect the rest of the data through "the services of a third-party agency" (Dobre, 2022, p. 170). The researchers commissioned Beijing Fengling Digital Intelligence Information Technology Co., LTD (https://www.powercx.com/) to collect data from Alibaba Group's database of apparel manufacturing members. Also, a cover letter (Appendix E) has been provided to this third-party agency to ensure that the participants to whom they are distributed are aware of the research content, including detailed research purposes, researchers, and corresponding academic information.

Subsequently, 47 questions were distributed to managers with expertise in production management to gain feedback. From Jun to August 2024, 269 responses were received after three follow-ups, which met the minimum sample size requirement of 155, as discussed above.

3.4.6. Statistical Data Analysis

Partial least squares-SEM (PLS-SEM) is primarily used to develop theories in exploratory research, which is suitable for the large and complex research model (Hair et al., 2017). It has often been used in many technology adoption studies (Cao et al., 2021; Chatterjee, Rana, Dwivedi, et al., 2021; T. Oliveira & Martins, 2010). This study employed this method and tested the hypotheses empirically using SmartPLS4 software, Vision 4.1.0.3. The integrated TOE-TAM framework comprises complex interrelationships among eight independent variables and 40 indicators. Thus, it is appropriate that PLS-SEM is employed to validate the research model.

The PLS-SEM is preferred over other structural equation modeling, such as CB-SEM (Covariance-Based Structural Equation Modeling), as it eliminates the "imposed distributions of data" (Hair et al., 2022, cited as in Dobre, 2022, p. 149). In addition, PLS-SEM does not require data to meet normal distribution assumptions, making it advantageous for handling non-normally distributed data (Hair et al., 2022). Moreover, it is particularly suitable for analyzing small sample sizes and non-normally distributed data (Hair et al., 2022). Thus, in this study, the PLS-SEM was employed to test theoretical frameworks with complex structural models through the SmartPLS 4.0 software version 4.1.0.3.

3.4.7. Preliminary Data Assessment

It is crucial to examine the data before initiating the analysis (Hair et al., 2022). The consistency and accuracy of the outcomes rely on the integrity of the data. When using multivariate approaches, these methods depend on specific premises and are highly sensitive to anomalies and incomplete data. This study employs PLS-SEM, which does not necessitate concern for data normality. However, Hair et al. (2022) suggest performing a Kolmogorov-Smirnov test to ascertain whether any variables deviate from a normal distribution, thereby supporting the findings of this research.

This study uses a quota sampling technique with a probabilistic approach inside the target population segment (Dobre, 2022). "The most important aspect of a probability sample is that it represents the target population"(Saunders et al., 2016, p. 281). Although the researcher initially received 19 responses out of 358 apparel manufacturing firms from the CNGA database through direct phone calls and an additional 13 respondents from apparel manufacturing firms located in the Dalian area, the third-party agency assisted in collecting the rest of the samples from Alibaba Group (acquired by Ant Group). Thus, the sample can be regarded as a representative sample representing the target population (Saunders et al., 2016). The third-party agency collected the remaining 237 responses with 237 tokens, which ensured that each sample response was validated. However, research studies suffer in quality because of missing data that could yield biased conclusions (Hair et al., 2022) (Dobre, 2022). There is no missing data because even in the case of self-completion questionnaires, the answer website has set mandatory questions. Otherwise, the answer paper cannot be completed. The answers in this survey have also been checked for trends and suspicious patterns (Hair et al., 2022) and for the same reason, there is no suspicious response (Dobre, 2022).

As the measurement instrument uses a Likert scale to measure variables that are more likely to be detected, outlier analysis is recommended to remove data deviations that could manifest as an extreme value for one or several variables that alter the statistics, leading to an inaccurate analysis outcome (Bell et al., 2022; Saunders et al., 2016). Given this context, it is recommended to use SPSS to calculate the z-scores for each variable, and outliers were identified according to the criteria of eliminating observation if their corresponding z-scores are outside the +/-3.29 interval and as well out of the verification of the corresponding plots (Dobre, 2022). However, Pallant (2020, as cited in Dobre, 2022) suggested no significant differences in the variable's indicator values or path coefficients variables have been noticed. Therefore, the researcher kept all the respondents' answers in the dataset.

PLS-SEM does not make distributional assumptions, as it is a non-parametric statistical method; however, it is recommended that a Kolmogorov-Smirnov test be conducted to identify which variables are out of a normal distribution, in support of an accurate statistical analysis that should support the outcomes of this research. Thus, each variable's kurtosis and skewness have been evaluated (Mardia, 1970; Romeu and Ozturk, 1993). Given that there are no values higher than +/- 2 for either skewness and kurtosis in the data set, this indicates that kurtosis and skewness statistics tests perform well (Mardia, 1970) with good statistical power for testing for multivariate normality. As such, the data set is included in the statistical analysis (Dobre, 2022).

Armstrong and Overton (1977) suggest that in cases where late respondents resemble those who did not respond, the last 25% of respondents should be compared with the first 75%. However, this assumption does not hold true for non-probability samples, as the final quarter may not have replied despite receiving follow-up reminders. In the present study, data collection was carried out by an external agency, which prevented late responses and facilitated the testing of nonresponse bias.

The partial correlation procedure was used to examine the potential common method bias, followed by Simmering et al. (2015). It uses a marker variable theoretically unrelated to at least one of the key constructs in the questionnaire for "priori justification for predicting a zero correlation" (Lindell & Whitney, 2001, p. 115). In this study, the demographics of respondents are not theoretically related to the proposed model constructs; therefore, these parts of information can be seen as marker variables. Thus, the result of the partial correlation procedure indicated no significant changes in any of the study correlations, suggesting that common method bias was not a severe problem in this study.

3.4.8. Evaluating the Measurement Model and the Structural Model

According to Hair et al. (2022), model estimation generates empirical values that reflect the relationships between indicators and constructs in the measurement models and between constructs in the structural model. These estimates allow us to assess the quality of the measures and determine whether the model effectively explains and predicts the constructs of interest. ***Chapter 3*** has indicated that the measurement model is reflective, i.e., the specified indicators represent the effects of the underlying latent variables; therefore, the researcher evaluated indicator reliability, internal consistency reliability (Cronbach's alpha, composite reliability, reliability coefficient), convergent reliability (average variance extracted), and discriminant validity (HTMT and Fornell-Larcker) according to Hair et al.'s (2022) Confirmatory Composite Analysis (CCA) process (see **Table 3.3**).

If the measurement model criteria are met, the model evaluation continues by assessing whether the structural model provides satisfactory results in explaining and predicting the target constructs (Hair et al., 2022). Table 3.4 illustrates the criteria of each structural model assessment, including collinearity assessment, significance and relevance of path coefficients, model explanatory power (R^2), and predictive power ($PLS_{predict}$ procedure) (Hair et al., 2022) (see **Table 3.4**).

Table 3.3 The measurement model evaluation (Source; Hair et al., 2022)

Criteria	**Explanation**
Indicator Reliability	Indicator reliability refers to the correlation between each observed variable (indicator) and its corresponding latent variable. It is typically assessed using the outer loading values, with a recommended threshold of greater than 0.7, indicating that the indicator reliably measures the construct.
Internal Consistency Reliability	Internal consistency reliability evaluates the correlation among indicators within a latent variable. Traditionally measured by Cronbach's Alpha, and Composite Reliability (CR). Cronbach's Alpha values between 0.6 and 0.7 are acceptable in exploratory research, while CR values should also be above 0.7. The reliability coefficient rho_A is suggested as a balanced measure between the two.
Convergent Reliability	Convergent validity assesses whether multiple indicators of a latent variable are theoretically measuring the same construct. It is typically measured by the Average Variance Extracted (AVE). An AVE value of 0.5 or higher indicates that the construct explains at least 50% of the variance of its indicators.
Discriminant Validity	Discriminant validity examines whether a latent variable is distinct from other latent variables. It is usually assessed using the Fornell-Larcker criterion, cross-loadings, and the Heterotrait-Monotrait Ratio (HTMT). The Fornell-Larcker criterion requires that the square root of the AVE of a latent variable should be greater than its correlations with all other latent variables. HTMT is considered a more robust method, with values below 0.90 (or 0.85) indicating good discriminant validity.

Table 3.4 The structural model evaluation (Source; Hair et al., 2022)

Criteria	Explanation
Collinearity	Collinearity is when two or more predictor variables in a model are highly correlated, leading to redundancy. In PLS-SEM, collinearity is assessed using the Variance Inflation Factor (VIF). Recommended Range: VIF values should ideally be below 3.3, with values above 5 indicating problematic levels of collinearity.
Significance and relevance of path coefficients,	This criterion assesses whether the relationships (path coefficients) between constructs are statistically significant and relevant. Significance is typically evaluated using t-values, with a threshold of $t > 1.96$ for a 5% significance level ($p < 0.05$). Relevance is assessed by the magnitude of the path coefficients, with values around 0.10 indicating a small effect, around 0.30 indicating a medium effect, and above 0.50 indicating a large effect.
Model explanatory power in sample model fit (R^2)	R^2 (coefficient of determination) indicates the proportion of variance in the dependent variable explained by the model's independent variables. Recommended Range: R^2 values can vary based on the field, but generally, 0.25 indicates weak, 0.40 moderate, and 0.60 substantial explanatory power.
Predictive power ($PLS_{predict}$ procedure)	The predictive power is evaluated using the $PLS_{Predict}$ procedure to assess how well the model predicts the outcomes for new cases (out-of-sample). Recommended Range: The goal is to have Q^2 predict values greater than 0 and as close to 1, indicating high predictive accuracy for new data. Also, the PLS-SEM model should have a lower Root Mean Squared Error (RMSE) than the linear regression model (LM) to demonstrate predictive relevance.

3.4.9. Measurement and Structural Model Evaluation in Mediation Analysis

Mediation occurs when a third construct, known as a mediator, intervenes in the relationship between two other constructs (Dobre, 2022). Specifically, in the PLS path model, variations in the exogenous construct trigger changes in the mediator construct, impacting the endogenous construct. (Hair et al., 2022, cited in Dobre, 2022). Thus, the mediator construct plays a crucial role in shaping the relationship between two constructs by revealing the underlying mechanism or process through which the influence occurs, thereby enhancing the understanding of the direct relationship and how it changes in the mediator's presence. The bootstrapping method enables the evaluation of relationships between variables with mediating effects (Hair et al., 2022). A bootstrapping procedure (5000 resamples) from PLS-SEM was employed to derive a distribution of the HTMT statistic, as recommended in the reviewed studies

(Cao et al., 2021; Chatterjee, Rana, Dwivedi, et al., 2021). This study employed a segmentation method to test hypothesis H11 (refer to ***Chapter 2***, section 2.2.6), examining the impact of AI adoption as the independent variable on the dependent variable, while also assessing the mediating role of KACAP in the relationship between AI adoption and open innovation.

3.5. Grounded Theory Methods for Data Collections Procedure and Analysis in *Study 2*

Study 2 followed the principles of Grounded Theory (GT). The qualitative grounded theory of ***Study 2*** aims to theorize an AI-enabled open innovation framework and subsequent propositions. GT refers to the discovery of theory from data and the inductive development of theory through qualitative analysis of data (Glaser & Strauss, 2017; Greguletz et al., 2019; Saunders et al., 2016). This definition focuses on the GT process, but according to (Chamberlain-Salun et al., 2020, as cited in Lawler, 2023, p. 36), it is "the product of a constructed understanding of the world that forms and refines during the phases of analysis (GT process), which ultimately resolves as a substantive theory (GT product)". Thus, GT consists of "duality" with both a process and a product (Lawler, 2023, p.36).

Thus, the purpose of employing a GT is to address ***SRO 2***. Since data analysis is central to GT, this section proposes a systematic approach to concept development, focusing on data collection from interviews, which includes sampling, pilot testing, interviewing, transcribing, coding procedures, data analysis, and conceptual framework development. This approach emphasizes an interpretive rather than a logico-deductive process (Suddaby, 2006). Derived from Bryant (2019), Bryant and Charmaz (2008), and Glaser and Strauss (2017), **Figure 3.2** presents the core activities of GT and the theory construction process. These activities indicate that the core GT practices are both cyclic and frequently simultaneous rather than sequential, involving concurrently collecting, constant comparison, memo-writing, theoretical sensitivity, and coding data and analysis until the researcher concludes that they have reached a state where all threads of analysis have been identified (Birks & Mills, 2015; Bryant, 2019; Bryant & Charmaz, 2008; Glaser & Strauss, 2017; Lawler, 2023). However, it is worth noting that Glaser and Strauss's original idea—that categories would naturally emerge from data through constant comparison by theoretically sensitive researchers—proved challenging in practice, leading to multiple refinements and the introduction of complex concepts like theoretical coding in the development of GT (Bryant & Charmaz, 2008), which is introduced in ***Section 3.5.3***. Bryant and Charmaz (2008) suggest conducting a literature review for orientation in the theoretical construction process; thus, the previous literature on innovation ecosystems guides the completed GT in theory building. The previous literature, particularly Granstrand and Holgersson (2020, p.3), has provided a clear definition of the innovation ecosystem, which this study adopts as the theoretical foundation for AI-enabled innovation ecosystems.

The theory-building process (see **Figure 3.2**) can be extended to any data (Bryant & Charmaz, 2008), such as secondary data, observations, and interviews (Makri & Neely, 2021). Interviews aim to collect data for the researcher to "probe deeply to uncover new clues, open up new dimensions of a problem and to secure vivid, accurate inclusive accounts that are based on personal experience" (Burgess, 1982, p. 107). Interviews are a critical method for gathering valid and reliable data, as emphasized by

Kahn and Cannell (1957, p.318), who define an interview as "a purpose discussion between two or more people." This method allows researchers to collect data directly relevant to their research questions and objectives (Saunders et al., 2016). Interviews can be categorized as standardized or non-standardized, with the latter being particularly useful in qualitative research designs like GT. The non-standardized interviews include structured, semi-structured, and unstructured (in-depth interviews) (Saunders et al., 2016). Makri and Neely (2021) summarized these interviews for different use purposes. For example, structured interviews are often used in surveys like questionnaires (Leavy, 2014, as cited in Makri& Neely, 2021). Unstructured interviews are recommended for fieldwork or ethnography research, where participants are expected to discuss the topic without pre-identified questions (Jamshed, 2014, as cited in Makri& Neely, 2021). Although there is a pre-identified guide in semi-structured interviews, the researcher can flexibly improve their open-ended questions or change direction as new themes emerge and the research progresses (Jamshed, 2014, as cited in Makri& Neely, 2021).

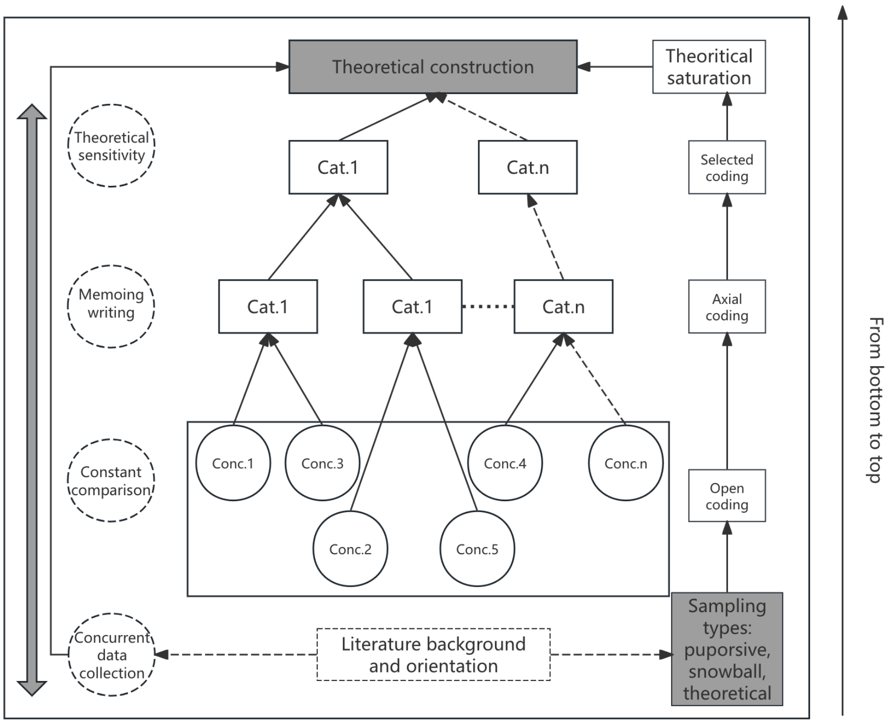

Figure 3.2 Grounded Theory Procedural Framework and Core Activities (Source: Birks & Mills, 2015; Bryant, 2019; Bryant & Charmaz, 2008; Glaser & Strauss, 2017; Lawler, 2023)

Thus, a semi-structured interview method was employed due to its several advantages. First, this study is exploratory in nature, focusing on understanding the current context and discovering new concepts, aiming to explore how to build an innovation ecosystem for apparel manufacturing. Second, semi-structured interviews facilitate in-depth exploration by encouraging participants to elaborate on or expand their responses (Saunders et al., 2016). Third, the flexibility of semi-structured interviews allows the researcher to adjust the order and logic of questions based on the interviewees' responses while remaining within the scope of the original theme (Saunders et al., 2016). Given that ***Study 1*** has already established key themes by identifying the extent to which AI adoption drives open innovation through KACAP, semi-structured interviews are an essential tool for gathering further exploratory qualitative data, especially in research designs that adopt an inductive approach like GT (Saunders et al., 2016). These interviews allow for an open-ended exploration of the research topic, critical for developing new theories grounded in empirical data (Brinkmann & Kvale, 2015). This approach supports inductive reasoning, where the researcher constructs theories based on collected data rather than testing predefined hypotheses. Subsequently, the sampling, pilot testing, and interviewing actions are described in the following sub-sections.

3.5.1. Sampling Techniques

"Most qualitative research entails purposive sampling of some kind" (Bell et al., 2022, p. 1236). As previously presented, purposive sampling is a type of non-probability sampling where participants are selected not through randomization (Clark et al., 2021). Thus, at the initial stage of participant selection, purposive sampling was employed, targeting individuals from the apparel industry, universities, and associations who could provide rich information to address the research questions and reveal the essence of the phenomenon (Bryant & Charmaz, 2008). However, since managers in the apparel manufacturing industry are a specific and hard-to-reach professional group, snowball sampling was used through introductions by apparel associations to expand the participant pool. Snowball sampling is also often recommended when networks of individuals are the focus of attention (Coleman, 1958, as cited in Clark et al., 2021). Theoretical sampling is another type of GT, where participants are selected according to the descriptive needs of the emerging concepts and theory (Bryant & Charmaz, 2008). It is "the process of data collection for generating theory whereby the analyst jointly collects, codes, and analyzes this data and decides what data to collect next and where to find them, in order to develop his theory as it emerges" (Glaser and Strauss, 1967, p.45, as cited in Clark et al., 2021). In this study, as preliminary data analysis and theoretical concepts began to emerge during the research process, theoretical sampling was applied, guiding the selection of participants from the Yangtze River Delta, Pearl River Delta, and North regions to develop the theory further.

This study is purposive sampling research with theoretical sampling and snowball sampling because the targeted interview participants, such as organizations and people (or whatever the unit of analysis is) within sites, are selected because of their relevance to the research questions, thus theorizing from the collected qualitative data (Bell et al., 2022).

3.5.2. Interviewing Action Procedures

Brinkmann and Kvale (2015) outline that an interview investigation consists of seven stages: thematizing, designing, interviewing, transcribing, analyzing, verifying, and reporting. Following their guidelines, the first step of thematizing involves formulating research purposes and questions and providing theoretical clarification of the theme under investigation, which is crucial for ensuring that the interview remains focused and relevant. An interview question can be evaluated concerning both a thematic (producing knowledge) and a dynamic dimension (the interpersonal relationship in the interview). Brinkmann and Kvale (2015, p. 157) emphasize that “a good interview question should contribute thematically to knowledge production and dynamically to promoting a good interview interaction”. Thus, the interview questions were derived from research purposes and questions with the both dimensions.

Study 2 consists of three research questions: 1) What are the emerging concepts of AI capabilities that Chinese manufacturing firms need? 2) What are the emerging concepts of challenges of AI adoption in China’s manufacturing sector? 3) 3): How to build an AI-enabled innovation ecosystem to explain the mechanisms through which enterprises, universities, associations, and government leverage AI to enhance their collaboration in China’s manufacturing sectors?

Thus, when designing the interview, it is necessary to develop an interview guide that ensures the questions revolve around the research questions while maintaining flexibility to accommodate the characteristics of semi-structured interviews. Since the target interviewees are associated with the fashion industry, education, and associations, each group of interviewees was provided with the research purpose and corresponding interview questions (**Appendix D**).

Before the formal interview, the researcher conducted pilot interviews of three interviewees in the apparel industry, universities, and associations as soon as the supervisor approved the interview guidelines. With the help of them, the guidelines could be adjusted. Subsequently, a total of 15 interviewees participated in the interview (**Table 3.5**). The participants included eight apparel manufacturing managers and their suppliers and customers in top leadership positions at large enterprises and MSMEs across China’s three apparel industry clusters: the Yangtze River Delta (advanced), the Pearl River Delta (advanced), and North China (traditional); five scholars engaged in teaching and research at universities or institutions; and two leaders serving as deputies of apparel associations. These interviewees were contacted through the researcher’s present colleagues, previous colleagues in fashion firms, and the deputies of DTAA through the private networks or, in a secondary phase, via other interviewees’ networks (i.e., snowball sampling) (Greguletz et al., 2019). All interviewees had over ten years of experience in the fashion industry and academy. Six interviews ranged from approximately 40 to 80 minutes and were conducted through face-to-face meetings at different places, such as offices and cafes. Nine interviews were conducted by phone and lasted 20-50 minutes, aligning with most semi-structured interview time durations (Lin, 2018). Interviewees’ names were kept anonymous due to pre-interview agreements of anonymity. All participants in this study provided informed consent before being interviewed and were offered the purpose of the research to ensure all the interviewees consented to the procedures (**Appendix D**). The interviews were conducted by a single researcher between June and September 2024. All interviews were audio recorded in Chinese, transcribing in a total of 99,448 Chinese characters. Given that the original data was in Chinese, the researcher translated key quotations into English during the coding process. Yangtze River Delta (YRD) (advanced), Pearl River Delta (PRD) (advanced), and North China (traditional)

Table 3.5 Preliminary Interviewee Informants

Interviewee ID. # (actors)	Organizational Affiliations	Positions	Working Experience	Firm Location
A1	Associations	Secretary-general	16-20 years	North
A2		Director	16-20 years	North
I1	Industries	Production manager	>20 years	North
I2		OEM business manager	10-15 years	North
I3		Fabric supplier	16-20 years	YRD
I4		ODM business manager	10-15 years	PRD
I5		Customer (retail)	10-15 years	PRD
I6		ODM business manager	10-15 years	North
I7		Customer (retail)	16-20 years	North
I8		OBM business manager	16-20 years	North
U1	Universities	Dean/Professor	>20 years	North
U2		Professor	>20 years	North
U3		Dean/Professor	16-20 years	YRD
U4		Specialized Course Instructor	10-15 years	North
U5		Specialized Course Instructor	10-15 years	YRD

Legend: A=Association; I=Industry; U=University; YRD= Yangtze River Delta; PRD= Pearl River Delta; OEM = Original Equipment Manufacturers; ODM= Original Design Manufacturers; OBM=Original Brand Manufacturers

3.5.3. Coding for Data Analysis

Several scholars have defined coding. For example, Charmaz (2006) defined coding as the process whereby researchers define what the data are about, and it is the first step in data analysis. Köhler et al., (2022) state that coding means labeling and systematizing data with systematic, simplified, and repeatable characteristics (Köhler et al., 2022). It is the first step for the researchers to move beyond tangible data to make analytic interpretations (Holton, 2007; Corbin, 2008; Boeije, 2009; Saldana, 2009, cited Liamputtong, 2009), and it is used in projects allows researchers to understand more about iterating as a part of the analytical process (Locke, et al., 2020). It can help researchers give meaning to the raw data, make the data understandable (Elliott, 2018), and enrich the ideas and theories by engaging more with the data (Locke et al., 2022). Thus, it is a core process in classic GT methodology (Holton, 2007). There are two streams of coding methods in GT methods. Saunders (2015) mentioned one is from Strauss and Corbin (1998), and the other one is from Charmaz (2006), which advocates theory building from different coding procedures. The data was manually coded using NVivo (Version 15.0.0) software, employing Strauss and Corbin’s (1998) open, axial, and selective coding in three levels: setting nodes, encoding with software, and validity test.

Therefore, the first step in data analysis was an open coding analysis. It involves breaking down, comparing, conceptualizing, and categorizing the collected data using either words informed by the language of actors in the field (referred to as “in vivo codes”) or notions derived from sociological terminology (which Glaser calls “sociological constructs”) (Bryant & Charmaz, 2008). It also involves deconstructing a large volume of data according to specific principles, assigning concepts to the data, and then recombining it in a new way (Chen, 2000; Bryant & Charmaz, 2008). Open coding in ***Study 2*** aims to identify similar or related types from the collected the raw interview transcripts, assign names to the types, and determine the concepts and dimensions of these types. According to Chen (2000), open coding involves three steps: (1) Conceptualization—extracting content from the raw data, breaking it down into independent sentences, and identifying coding elements from these sentences, thereby transforming colloquial language into refined language and forming preliminary concepts; (2) Concept Classification—optimizing, analyzing, and selecting concepts, grouping similar concepts, analyzing the connections between terms, and forming conceptual clusters that belong to the same category; (3) Categorization—further abstracting and naming the conceptual clusters. This study used NVivo (Version 15.0.0) for line-by-line reading and manual coding for every piece of transcript, highlighting phrases and passages related to the overarching what AI capabilities firm needs (***SRQ3***) and barriers to adoption AI (***SQ4***), thereby constructing an open innovation ecosystem through collaborations with stakeholders to absorb knowledge in innovation activities in China's government's supportive policies (***MRQ***). By coding the common words, phrases, terms, and labels mentioned by respondents, we set first-order categories of nodes that reflect the views of the respondents in their own words, and encode with the NVivo (Version 15.0.0) software.

The second step is axial coding analysis, aiming to "produce concepts that seem to fit the data," the "axial coding" phase is a more advanced stage of open coding (Strauss, 1987, p. 28, as cited in Bryant & Charmaz, 2008, p. 201), occurring in coding paradigms. It involves an in-depth analysis of a single category to further examine the first-order open nodes to detect links and patterns among them. It serves as the central axis for further coding and category development, potentially evolving into the core category of the emerging theory (Bryant & Charmaz, 2008). This iterative process yielded second-order themes that represent theoretically distinct concepts created by combining first-order nodes (Sjödin et al., 2021). These themes relate to the required AI capabilities and specific barriers to adopting AI in real-world project scenarios within apparel manufacturing. In accordance with validity considerations raised in the literature, the themes were further refined using insights from the literature and data from interviews (Kumar, et al., 1993, as cited in Sjödin et al., 2021). This step was further resulted in a list of coding labels and categories as the software shown to thoroughly discuss the data structure, and each concept should be explained from the understanding of interview

The last step is selected coding analysis, involving the generation of aggregate dimensions that represented a higher level of abstraction in the coding. As the process continues, with the main concern being continually processed or resolved, the core concept becomes the focus of further selective data collection and coding efforts (Bryant & Charmaz, 2008). Here, we used insights from the literature to form theoretically sound dimensions relating to capabilities and barriers to adoption. Thus, the aggregate dimensions built on the first-order categories and second-order themes to present a theoretically and practically grounded categorization.

3.5.4. Saturation in Qualitative Research

In GT, the emphasis is on achieving saturation, where sampling continues until conceptual categories and their relationships are thoroughly developed (Clark et al., 2021). It originated from the theoretical sampling process, which is part of the GT method of qualitative research (Nelson, 2017). Glaser and Strauss (1967, p. 45) define theoretical sampling as "the process of data collection for generating theory whereby the analyst jointly collects, codes and analyzes his data and then decides what data to collect next and where to find them, in order to develop his theory as it emerges". In the words of Glaser and Strauss (1967, p. 61) "'Saturation' means that no additional data are being found whereby the sociologist can develop properties of the category. As the similar instances over and over again, the researcher becomes empirically confident that a category is saturated". Therefore, the validity of the research is ensured through the test of theoretical saturation (Nelson, 2017), as failing to achieve data saturation can negatively affect the research's quality and compromise content validity (Fusch and Ness, 2015, as cited in Nelson, 2017). In the study, after interviewing 15 participants and completing the three stages of coding (open, axial, and selective coding), an additional 5 interviews were conducted through a semi-structured phone interview to examine theoretical saturation (**Table 3.6**). Similarly, all the five interviews were conducted by phone and lasted approximately 30-60 minutes. Interviewees' names were kept anonymous and each provided informed consent. The interviews were conducted by a single researcher in October 2024. All interviews were audio recorded in Chinese, transcribing in a total of 42853 Chinese characters.

Table 3.6 The Interviewee Informants for Saturation Examination

Interviewee ID. # (actors)	Organizational Affiliations	Positions	Working Experience	Locations
I9	Industries	ODM business manager	10-15 years	North
I10		OEM production manager	>20 years	YDT
I11		OBM CEO	>20 years	YDT
U6	Universities	Specialized Course Instructor	10-15 years	North
U7		Specialized Course Instructor	10-15 years	North

Legend: A=Association; I=Industry; U=University; YRD= Yangtze River Delta; PRD= Pearl River Delta; OEM = Original Equipment Manufacturers; ODM= Original Design Manufacturers; OBM=Original Brand Manufacturers

3.6. Ethical Considerations

Ethics refers to the behavior that is related to the rights of participants, the question about how the research is formulated, designed, gained access, collected, processed, and stored, and the impact of results or conclusion from the research (Easterby-Smith et al., 2002; Gill et al., 2010; Saunders et al., 2009; Collis & Hussey, 1997). Ethical considerations were made throughout the process, involving privacy, voluntary nature, consent, deception, confidentiality, anonymity, embarrassment, stress, harm, discomfort, pain, objectivity, and quality of research in light of the principle and procedure statement.

This thesis focuses on the antecedents of AI-integrated technologies, thereby driving open innovation in the apparel manufacturing sector without threats to the researcher or the respondents. However, ethical issues must be considered in this research, such that the credibility of the researcher and the represented research institution's credibility and reputation are maintained (Dobre, 2022). Thus, an ethical research protocol approval was obtained before data collection. Also, before conducting the survey and interview with the participants, "informed consent forms" were provided (Bryman, 2008) (see **Appendix C** and **Appendix D**). In this thesis, when approaching potential participants, the aim of the research was given first, as well as the explanation of complete information about participation rights and the use of data (Saunders et al., 2006). Furthermore, informed consent should be obtained from every participant, and no stress was given (Saunders et al., 2009; Collis & Hussey, 1997). The survey was conducted through an online questionnaire platform, with the informed consent form embedded at the beginning of the home page. Thus, no physical informed consent was obtained, but completing the questionnaire implies informed consent. Meanwhile, confidentiality and anonymity have been addressed in the previous data collection sections of ***Study 1*** and ***Study 2***.

A complete set of information on researchers and institutions was provided, and respondents could withdraw from the survey at any time. They were assured of confidentiality and anonymity, with all results adhering to ethical standards (Bhattacherjee, 2012). Audio records of semi-structured interviews were securely stored, and personal data was used solely for academic purposes, ensuring honest presentation of findings.

3.7. Chapter Summary

This chapter discusses the research philosophy according to the research "onion" (Saunders et al., 2016). As shown in Figure 4.2, this thesis employs a systematic research paradigm, design, and data collection and analysis procedures to explore the AI-integrated technologies applied in apparel manufacturing firms comprehensively and to what extent and how they drive organizations' open innovation to achieve the thesis' ***MRO***: building AI-enabled innovation ecosystems for Chinese apparel manufacturing. ***SRO 1*** aims to examine the antecedents of AI adoption, thus driving knowledge KACAP and open innovation in Chinese apparel manufacturing firm. ***SRO 2*** aims to theorize frameworks and propositions by categorizing how AI drives organizations' open innovation to build innovation ecosystems through enhancing internal organizational resources and external collaborations with actors from universities and associations. ***SRO 1*** provides a causal relationship by what and why questions, which provides a foundation for grounded theory to address ***SRO 2***, demonstrating the close relationships between both. Consequently, this thesis comprises two studies to achieve the ***MRO*** (see **Figure 4.3**).

Study 1 (to achieve ***SRO 1***) predominantly utilized a quantitative research approach, leveraging PLS-SEM to empirically validate the antecedents of AI adoption and its consequential effects on knowledge absorptive capacity and open innovation capability. Through the rigorous statistical analysis of a substantial dataset, this study examined the causal relationships underpinning AI adoption and these critical innovation-related constructs, thereby furnishing robust empirical evidence that substantiates the proposed hypotheses.

Study 2 (to achieve ***SRO 2***) adopted a qualitative research approach, grounded in the principles of grounded theory, to explore the intricate processes through which organizations architect an AI-driven open innovation ecosystem. By conducting semi-structured interviews, this study constructed an interpretive framework that explicate the specific mechanisms and pathways through which AI catalyzes the development of innovation ecosystems within organizational settings.

Thus, ***Study 1*** has a strong relationship with ***Study 2***. The empirical insights of ***Study 1*** serve as a foundational basis for the theoretical framework developed in ***Study 2***, enhancing its credibility and generalizability. Vice versa, the qualitative inquiry of ***Study 2*** provides a rich, theoretical context that deepens the understanding of the causal relationships identified in ***Study 1***. The subsequent chapters separately present the results of these methods in the two studies.

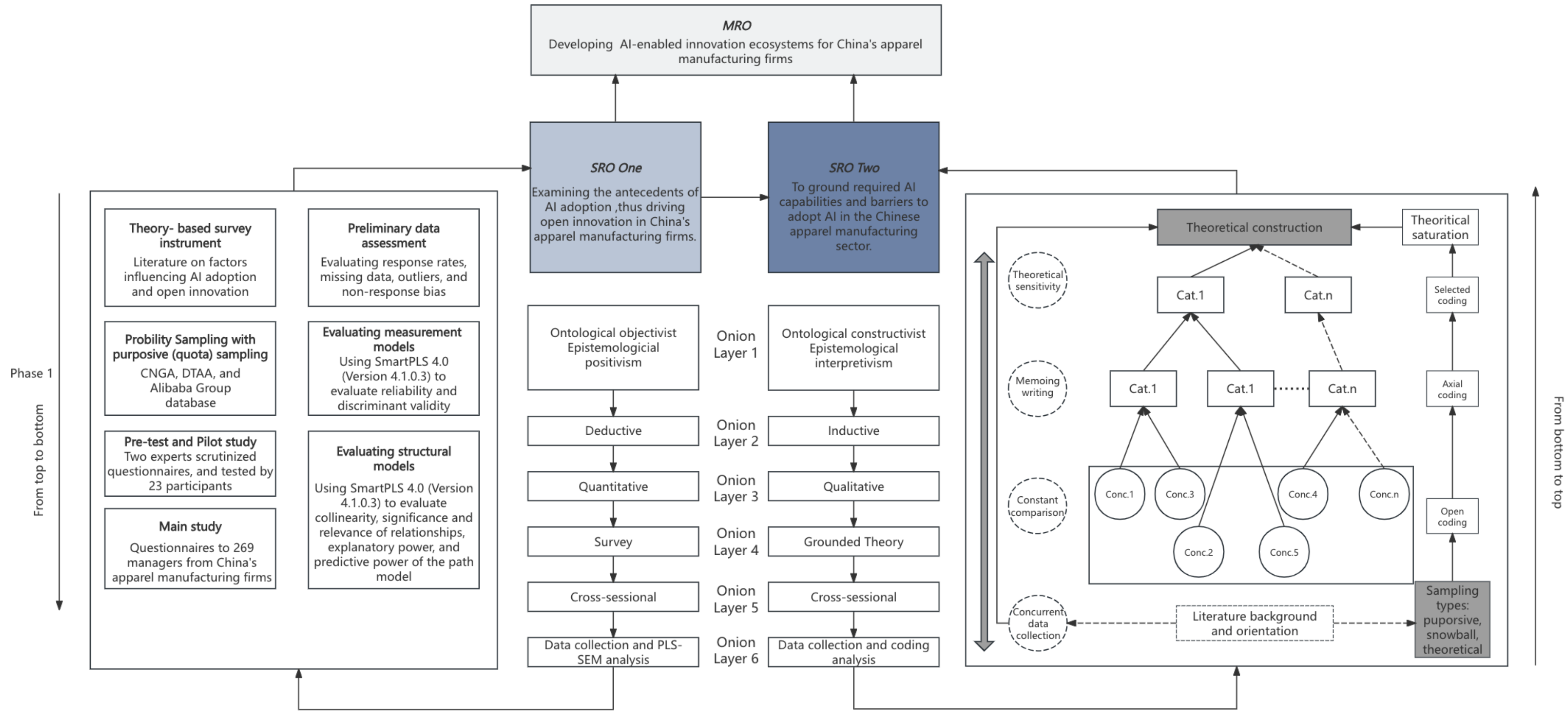

Figure 3.3 Frameworks of Methodology

4. Results of *Study 1* and Analysis

4.1. Introduction

The results of ***Study 1*** will be presented in this chapter according to the research methods in ***Chapter 3***. This study focuses on the managers in the apparel manufacturing industry, utilizing the “key informants” approach (Klein et al., 2024). As key decision-makers or managers within their organizations, these respondents provide valuable insights into the impact of AI technologies on traditional industries. The research sample consists of owners and managers with decision-making authority, reflecting the current state of technology adoption in the apparel manufacturing sector and how these technologies influence both internal and external knowledge resources absorption, ultimately affecting the firms’ open innovation practices. This chapter is structured in a series of subsections, beginning with the introduction. Section 4.2 then outlines the outcomes of the pre-test and the pilot study. In Section 4.3, the focus shifts to AI adoption and open innovation, presenting initial data analysis, summary statistics, and PLS-SEM modeling in its respective subsections. The chapter's final thoughts are discussed in Section 4.4. **Figure 4.1** depicts the order of these sections.

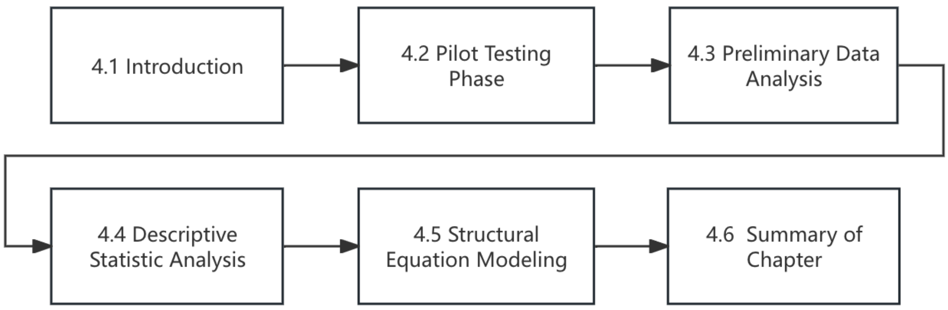

Figure 4.1 Research Flow of Chapter 4

4.2. Pilot Testing Phase

Two specialists in intelligent design and production management, whose research concentrates on AI adoption, implementation, and utilization, have conducted a preliminary evaluation of the survey for the conceptual model. In addition, the survey was pretested by 23 apparel firm owners and managers in OBM, OEM, and ODM manufacturing using the same sampling frame as the previous chapter. The feedback revealed that pre-test participants were able to finish the survey in 8 to 15 minutes, deeming the survey length appropriate. Respondents also indicated that they comprehended the research's aim, which is to explore the adoption of AI-integrated technologies to enhance both current and future business performance. All the pilot participants have confirmed that they understood the term AI-integrated technology scopes and how they perform in apparel production areas. The feedback similarly appreciated the responses given, as participants maintained a neutral position when they could not relate the question to their specific situations.

The pilot study gathered 23 responses, and the analysis of Cronbach's alpha for each construct demonstrated satisfactory reliability, with all values exceeding 0.7. (**Table 4.1**). The pilot study results were conducted, and the scale's reliability was initially tested, so it was decided that the survey for the main study should be proceeded with. However, given the small sample size used in the pilot study, the data should be preliminary tested once a complete number of answers is collected. Thus, the following section will conduct a preliminary data analysis after collecting the full samples.

In the analysis, the reverse-coded items have been properly recoded, ensuring that all items are now aligned in the same direction as the construct. This adjustment ensures accurate calculation of descriptive statistics, such as the mean and standard deviation, and prevents any potential distortion in validity or reliability assessments due to inconsistent item coding.

Table 4.1 Construct reliability and validity for the pilot study

Constructs	**Abb.**	**Cronbach's alpha**	**Composite reliability (rho_a)**	**Average variance extracted (AVE)**
Perceived Usefulness	PU	0.867	0.935	0.709
Perceived Ease of Use	PEOU	0.876	0.901	0.729
Organizational Complexity	OCX	0.848	0.945	0.758
Organizational Readiness	ORE	0.885	0.885	0.814
Competitive Pressure	CP	0.872	0.885	0.725
Supplier Involvement	SIV	0.877	0.912	0.803
Market Uncertainty	MU	0.758	0.774	0.582
Government Support and	GSP	0.816	0.817	0.731
AI Adoption	AIA	0.909	0.909	0.787
Knowledge Absorptive	KACAP	0.832	0.852	0.678
Open Innovation	OI	0.829	0.863	0.600

4.3. Preliminary Data Analysis

4.3.1. Outliers

The outliers have been assessed concerning the z-score criterion of +/- 3.29 (Dobre, 2022) through SPSS (**Table 4.2**), and the author has not considered these outliers being removed from the data set because there were no significant differences in the variable's indicator values or path coefficients variables have been noticed through "5% trimmed mean test" even though the pruning method was applied to reduce the impact of outliers, the overall distribution of the data was not significantly affected, and the original mean is very close to the pruned mean (Pallant, 2020). Therefore, all the respondents' answers in the dataset were kept. As per **Table 4.3**, the outliers initially considered for removal had minimal differences between the mean and the 5% trimmed mean. Therefore, the researcher has decided to retain them in the data set. This is aligned with the decision of Dobre (2022).

Table 4.2 Construct items' highest and lowest standard scores

Construct	Item	Minimum	Maximum	Recommended Action
PU	Zscore(pu_1)	-2.818	1.324	Retain
	Zscore(pu_2)	-3.702	1.315	Discard
	Zscore(pu_3)	-3.928	1.214	Discard
	Zscore(pu_4)	-2.611	1.145	Retain
	Zscore(pu_5)	-2.944	1.377	Retain
PEOU	Zscore(peou_1)	-3.523	1.579	Discard
	Zscore(peou_2)	-3.797	1.537	Discard
	Zscore(peou_3)	-3.062	1.308	Retain
	Zscore(peou_4)	-3.270	1.336	Retain
OCX	Zscore(ocx_1)	-1.660	2.633	Retain
	Zscore(ocx_2)	-1.521	2.665	Retain
ORE	Zscore(ore_1)	-3.044	1.443	Retain
	Zscore(ore_2)	-3.216	1.337	Retain
	Zscore(ore_3)	-3.551	1.292	Discard
CP	Zscore(cp_1)	-3.842	1.169	Discard
	Zscore(cp_2)	-3.739	1.303	Discard
	Zscore(cp_3)	-3.933	1.410	Discard
SIV	Zscore(siv_1)	-2.939	1.437	Retain
	Zscore(siv_2)	-2.504	1.338	Retain
	Zscore(siv_3)	-2.900	1.235	Retain
MU	Zscore(mu_1)	-3.740	1.446	Discard
	Zscore(mu_2)	-3.030	1.288	Retain
	Zscore(mu_3)	-3.783	1.255	Discard
	Zscore(mu_4)	-3.470	1.292	Discard
GSP	Zscore(gsp_1)	-3.889	1.504	Discard
	Zscore(gsp_2)	-3.430	1.388	Discard
	Zscore(gsp_3)	-3.905	1.232	Discard
AIA	Zscore(aia_1)	-4.205	1.353	Discard
	Zscore(aia_2)	-2.377	1.305	Retain
	Zscore(aia_3)	-3.630	1.198	Discard
	Zscore(aia_4)	-2.667	1.386	Retain
KACAP	Zscore(kacap_1)	-3.828	1.406	Discard
	Zscore(kacap_2)	-3.945	1.283	Discard
	Zscore(kacap_3)	-3.882	1.250	Discard
	Zscore(kacap_4)	-4.061	1.307	Discard
OI	Zscore(oi_1)	-4.034	1.171	Discard
	Zscore(oi_2)	-4.128	1.315	Discard
	Zscore(oi_3)	-4.050	1.271	Discard
	Zscore(oi_4)	-3.216	1.337	Retain
	Zscore(oi_5)	-4.051	1.194	Discard

Legend: PU=perceived usefulness; PEOU=perceived ease of use; OCX=organizational complexity; ORE=organizational readiness; CP=competitive pressure. SIV=supplier involvement; GSP=government support and policy; AIA=AI adoption; KACAP=knowledge absorptive capacity; OI=open innovation

Table 4.3 Outliers - Items Means and 5% Trimmed Means Comparison

Construct	**Item**	**Mean**	**5% Trimmed mean**	**Absolute difference**	**Decision**
PU	Zscore(pu_2)	3.95	4.00	0.050	Retain
	Zscore(pu_3)	4.06	4.10	0.040	Retain
PEOU	Zscore(peou_1)	3.76	3.80	0.040	Retain
	Zscore(peou_2)	3.85	3.86	0.010	Retain
ORE	Zscore(ore_3)	3.93	3.98	0.050	Retain
CP	Zscore(cp_1)	4.07	4.12	0.050	Retain
	Zscore(cp_2)	3.97	4.00	0.030	Retain
	Zscore(cp_3)	3.94	3.98	0.040	Retain
MU	Zscore(mu_1)	3.88	3.93	0.050	Retain
	Zscore(mu_3)	4.00	4.05	0.050	Retain
	Zscore(mu_4)	3.91	3.97	0.060	Retain
GSP	Zscore(gsp_1)	3.88	3.90	0.020	Retain
	Zscore(gsp_2)	3.85	3.89	0.040	Retain
	Zscore(gsp_3)	4.04	4.09	0.050	Retain
AIA	Zscore(aia_1)	4.03	4.05	0.020	Retain
	Zscore(aia_3)	4.01	4.05	0.040	Retain
KACAP	Zscore(kacap_1)	3.93	3.97	0.040	Retain
	Zscore(kacap_2)	4.02	4.06	0.040	Retain
	Zscore(kacap_3)	4.03	4.06	0.030	Retain
	Zscore(kacap_4)	4.03	4.07	0.040	Retain
OI	Zscore(oi_1)	4.10	4.15	0.050	Retain
	Zscore(oi_2)	4.03	4.07	0.040	Retain
	Zscore(oi_3)	4.04	4.07	0.030	Retain
	Zscore(oi_5)	4.09	4.12	0.030	Retain

Legend: PU=perceived usefulness; PEOU=perceived ease of use; OCX=organizational complexity; ORE=organizational readiness; CP=competitive pressure. SIV=supplier involvement; GSP=government support and policy; AIA=AI adoption; KACAP=knowledge absorptive capacity; OI=open innovation

4.3.2. Normality

According to Hair et al. (2022), the Kolmogorov-Smirnov test was recommended in SPSS to assess the normality of the dataset, with significant results observed for all statistics (**Table 4.4**), suggesting that none of the items adhered to a normal distribution. However, the values of kurtosis and skewness for all items fell within the acceptable range of +/-2 (Hair et al., 2010). As a result, all items were retained for further analysis, as Partial Least Squares Structural Equation Modeling (PLS-SEM) was chosen as the method for statistical analysis.

Table 4.4 Normality Assessment

	Mean	Std.	Skewness		Kurtosis		Kolmogorov-	
	Statistic	Statistic	Statistic	Std.	Statistic	Std.	Statistic	Sig.
pu_1	4.04	0.72	-0.48	0.15	0.18	0.30	0.29	0.00
pu_2	3.95	0.80	-0.63	0.15	0.44	0.30	0.29	0.00
pu_3	4.06	0.78	-0.77	0.15	1.11	0.30	0.28	0.00
pu_4	4.09	0.80	-0.60	0.15	-0.10	0.30	0.25	0.00
pu_5	3.72	0.93	-0.54	0.15	0.13	0.30	0.25	0.00
peou_1	3.76	0.78	-0.44	0.15	0.45	0.30	0.29	0.00
peou_2	3.85	0.75	-0.22	0.15	0.01	0.30	0.27	0.00
peou_3	3.80	0.92	-0.54	0.15	-0.30	0.30	0.28	0.00
peou_4	3.84	0.87	-0.41	0.15	-0.29	0.30	0.25	0.00
ocx_1	2.55	0.93	0.30	0.15	-0.56	0.30	0.26	0.00
ocx_2	2.45	0.96	0.56	0.15	0.06	0.30	0.26	0.00
ore_1	3.71	0.89	-0.52	0.15	0.04	0.30	0.27	0.00
ore_2	3.83	0.88	-0.65	0.15	0.34	0.30	0.28	0.00
ore_3	3.93	0.83	-0.52	0.15	0.23	0.30	0.25	0.00
cp_1	4.07	0.80	-0.74	0.15	0.82	0.30	0.26	0.00
cp_2	3.97	0.79	-0.44	0.15	0.01	0.30	0.26	0.00
cp_3	3.94	0.75	-0.50	0.15	0.51	0.30	0.29	0.00
siv_1	4.01	0.69	-0.44	0.15	0.42	0.30	0.31	0.00
siv_2	3.96	0.78	-0.30	0.15	-0.46	0.30	0.26	0.00
siv_3	4.10	0.73	-0.40	0.15	-0.29	0.30	0.26	0.00
mu_1	3.88	0.77	-0.54	0.15	0.46	0.30	0.30	0.00
mu_2	3.81	0.93	-0.54	0.15	-0.22	0.30	0.26	0.00
mu_3	4.00	0.79	-0.59	0.15	0.33	0.30	0.27	0.00
mu_4	3.91	0.84	-0.79	0.15	0.89	0.30	0.30	0.00
gsp_1	3.88	0.74	-0.37	0.15	0.31	0.30	0.29	0.00
gsp_2	3.85	0.83	-0.54	0.15	0.49	0.30	0.26	0.00
gsp_3	4.04	0.78	-0.69	0.15	0.65	0.30	0.28	0.00
aia_1	4.03	0.72	-0.40	0.15	0.36	0.30	0.27	0.00
aia_2	3.94	0.82	-0.47	0.15	-0.21	0.30	0.27	0.00
aia_3	4.01	0.83	-0.53	0.15	-0.07	0.30	0.24	0.00
aia_4	3.97	0.74	-0.52	0.15	0.28	0.30	0.30	0.00
kacap_1	3.93	0.76	-0.58	0.15	0.59	0.30	0.30	0.00
kacap_2	4.02	0.77	-0.69	0.15	1.05	0.30	0.28	0.00
kacap_3	4.03	0.78	-0.52	0.15	0.20	0.30	0.26	0.00
kacap_4	4.03	0.75	-0.75	0.15	1.14	0.30	0.31	0.00
oi_1	4.10	0.77	-0.72	0.15	0.71	0.30	0.27	0.00
oi_2	4.03	0.74	-0.62	0.15	0.85	0.30	0.29	0.00
oi_3	4.04	0.75	-0.50	0.15	0.31	0.30	0.26	0.00
oi_4	3.83	0.88	-0.55	0.15	0.19	0.30	0.26	0.00
oi_5	4.09	0.76	-0.56	0.15	0.28	0.30	0.25	0.00

4.4. Descriptive Statistic Analysis

4.4.1. Firm Demographics

The findings on the firm demographics, as shared by the respondents, are summarized in **Table 4.5**. According to the quota sampling method, and measured with employees, all responses were from micro, small, and medium-sized enterprises (MSMEs), with a higher number of small and medium-sized firms (74.3%, 15.6%) answering the survey than micro-sized managers (10%).

Table 4.5 Firm Demographics (N=269)

Variable	Group	Frequency	%
Firm size	Micro	27	10%
	Small	42	16%
	Medium	200	74%
Firm age	<6year	52	19%
	6-10year	72	27%
	11-15year	63	23%
	>15year	82	31%
Business type	**Single**	187	**70%**
	OEM	49	26%
	ODM	76	41%
	OBM	62	33%
	Multiple	82	**30%**
	OEM &ODM	19	23%
	OEM &OBM	7	9%
	ODM&OBM	35	43%
	OEM &ODM&OBM	21	25%
Industry clusters	Northern	61	23%
	Western	52	19%
	Yangtze River Delta	87	32%
	Pearl River Delta	69	26%

Legend: OEM = Original Equipment Manufacturers; ODM= Original Design Manufacturers; OBM=Original Brand Manufacturers

Regarding the firm age, approximately one-third of manufacturing firms (31%) are over 15 years old. 27% of firms were established between six and ten years, followed by 11-15 years (23%) and below six years (19%).

As for represented business types in the sample, a single type (OEMs, ODMs, or OBMs) of the three accounts for 70%, over one-third of the multiple types (two or three included) (30%). Among the firms in single business type (70%), the highest proportion is ODM firms, accounting for 40.6%, followed by OBMs and OEMs, which take 33% and 26%, respectively. Regarding those firms that possess both or all business types, the number of OEMs with OBMs takes the minimum proportion (9%). In contrast, the number of firms with business types of ODMs and OBMs takes the highest percentage

(43%). The rest of the firms with OEMs and ODMs and the complete covering types of business signifies the middle ones, accounting for 23% and 26%, respectively.

As the initial 32 respondents' firm profiles show that the firm location from the CNGA and DTAA database, and the third agency provided the IP of respondents, all the firm location information was collected, showing that the Yangtze River Delta and Pearl River Delta have the most respondents and the former takes almost one-third proportion (32%). The latter number of firms is close to the Northern traditional apparel manufacturing clusters (23%), accounting for 26%. The Western apparel industry cluster shows the minimum number of firms (19%).

4.4.2. Variables Descriptive Statistics

The descriptive statistics evaluated the average and the variability for the observed variables, including both items and constructs, as shown in **Table 4.6**. The findings of the study are provided for the entire sample. Regarding constructs, respondents strongly agreed with supplier involvement (SIV: 4.025) and open innovation (OI: 4.019). The variability for these constructs is greatest for supplier involvement (SIV: 0.585) and least for open innovation (OI: 0.571). Constructs that respondents lean towards agreements are knowledge absorptive capacity (KACAP: 3.999), competitive pressure (CP: 3.993), AI adoption (AIA: 3.986), perceived usefulness (PU:3.972), government support and policy (GSP: 3.924), market uncertainty (MU: 3.902), organizational readiness (ORE: 3.824), and perceived ease of use (PEOU: 3.813). The variability for these constructs is greatest for organizational readiness (ORE: 0.709) and least for knowledge absorptive capacity (KACAP: 0.572). One construct that respondents lean towards disagreements is organizational complexity (OCX: 2.500), and the standard distribution for this construct is 0.831, which is the highest among all of the constructs.

4.5. Structural Equation Modelling

The preceding section outlined the initial analysis of the dataset, and the descriptive statistics provided a comprehensive understanding of the sample's responses to the items and constructs. This section details the findings from applying the PLS-SEM technique, which was employed to assess the empirical validation of the research model. The Kolmogorov-Smirnov test ($p<0.001$) revealed that the data did not conform to a normal distribution, thus validating the appropriateness of using PLS-SEM (Hair et al., 2022). PLS-SEM consists of two stages for evaluating the research model (Hair et al., 2022), including the assessment of the measurement model, also known as the outer model, and the evaluation of the structural model, referred to as the inner model (Hair et al., 2022).The measurement model assesses the construct validity and reliability of the indicators, and the structural model examines the hypothesized causal relationships between latent variables (Hair et al., 2022).

Table 4.6 Variables Descriptive Statistics (N=269)

Construct	Indicators	Minimum (Strongly Disagree)	Maximum (Strongly agree)	Mean	Std. Deviation	Mean	Std. Deviation
PU	pu_1	2	5	4.04	0.724	3.972	0.590
	pu_2	1	5	3.95	0.797		
	pu_3	1	5	4.06	0.778		
	pu_4	2	5	4.09	0.799		
	pu_5	1	5	3.72	0.926		
PEOU	peou_1	1	5	3.76	0.784	3.813	0.632
	peou_2	1	5	3.85	0.750		
	peou_3	1	5	3.80	0.915		
	peou_4	1	5	3.84	0.868		
OCX	ocx_1	1	5	2.55	0.932	2.500	0.831
	ocx_2	1	5	2.45	0.955		
ORE	ore_1	1	5	3.71	0.891	3.824	0.709
	ore_2	1	5	3.83	0.878		
	ore_3	1	5	3.93	0.826		
CP	cp_1	1	5	4.07	0.798	3.993	0.619
	cp_2	1	5	3.97	0.793		
	cp_3	1	5	3.94	0.749		
SIV	siv_1	2	5	4.01	0.686	4.025	0.585
	siv_2	2	5	3.96	0.781		
	siv_3	2	5	4.10	0.726		
MU	mu_1	1	5	3.88	0.771	3.902	0.612
	mu_2	1	5	3.81	0.926		
	mu_3	1	5	4.00	0.794		
	mu_4	1	5	3.91	0.840		
GSP	gsp_1	1	5	3.88	0.742	3.924	0.624
	gsp_2	1	5	3.85	0.830		
	gsp_3	1	5	4.04	0.779		
AIA	aia_1	1	5	4.03	0.720	3.986	0.577
	aia_2	2	5	3.94	0.815		
	aia_3	1	5	4.01	0.829		
	aia_4	2	5	3.97	0.740		
KACAP	kacap_1	1	5	3.93	0.764	3.999	0.572
	kacap_2	1	5	4.02	0.765		
	kacap_3	1	5	4.03	0.779		
	kacap_4	1	5	4.03	0.745		
OI	oi_1	1	5	4.1	0.769	4.019	0.571
	oi_2	1	5	4.03	0.735		
	oi_3	1	5	4.04	0.752		
	oi_4	1	5	3.83	0.878		
	oi_5	1	5	4.09	0.763		

Legend: PU=perceived usefulness; PEOU=perceived ease of use; OCX=organizational complexity; ORE=organizational readiness; CP=competitive pressure. SIV=supplier involvement; GSP=government support and policy; AIA=AI adoption; KACAP=knowledge absorptive capacity; OI=open innovation

4.5.1. Measurement Model

As previously presented in the criteria recommended by Hair et al. (2022), the measurement model results include convergent validity (**Table 4.7**), such as outer loadings, indicator reliability, and average variance extracted (AVE), internal consistency reliability (**Table 4.8**), such as construct reliability and validity, and discriminant validity (**Tables 4.9** and **4.10**). A summary of the measurement model's results is presented in **Table 4.11**.

4.5.1.1. Convergent Validity

The first step in reflective measurement model assessment involves examining the outer loadings of the indicators (Hair et al., 2022). Hair et al. (2022) state that the outer loadings should be 0.708 or higher, but 0.70 is considered close enough to 0.708 to be acceptable. However, these indicators were retained considering some indicators' (between 0.40 and 0.7) contribution to the content validity (mu_2:0.666, oi_4:0.653, pu_5: 0.670). These indicators were then conducted for internal consistency reliability and convergent validity (Hair et al., 2022). As the construct measures met the recommended thresholds, all indicators were retained. As shown in **Table 4.7**, the convergent validity of all the measurement models has been achieved, as the indicator reliability has been established, with the indicators' outer loadings meeting the required minimum threshold. Furthermore, the AVE values of all constructs are well above 0.50, confirming satisfactory convergent validity.

4.5.1.2. Internal Consistency

The second step is to evaluate internal consistency reliability (Hair et al., 2022). The ρA reliability metric usually lies between Cronbach's alpha and the composite reliability and is therefore considered a good compromise between these two measures (Hair et al., 2022). **Table 4.8** shows that both Cronbach's Alpha and the Composite Reliability (ρ_A) are above the 0.70 threshold, indicating that all construct measures exhibit high internal consistency reliability. Hair et al. (2022, p.151) state, "reliability values higher than 0.95 are not desirable", and the results show that both Cronbach's Alpha and the Composite Reliability (ρ_A) are below 0.95, signifying the internal consistency is satisfied.

Table 4.7 Results of Convergent Validity

Construct	Indicators	Outer Loadings	Indicator reliability	AVE
PU	pu_1	0.796	0.634	0.543
	pu_2	0.729	0.531	
	pu_3	0.769	0.591	
	pu_4	0.713	0.508	
	pu_5	**0.670**	**0.449**	
PEOU	peou_1	0.804	0.646	0.578
	peou_2	0.729	0.531	
	peou_3	0.734	0.539	
	peou_4	0.771	0.594	
OCX	ocx_1	0.834	0.696	0.771
	ocx_2	0.919	0.845	
ORE	ore_1	0.810	0.656	0.67
	ore_2	0.798	0.637	
	ore_3	0.845	0.714	
CP	cp_1	0.762	0.581	0.63
	cp_2	0.816	0.666	
	cp_3	0.802	0.643	
SIV	siv_1	0.807	0.651	0.64
	siv_2	0.795	0.632	
	siv_3	0.799	0.638	
MU	mu_1	0.750	0.563	0.536
	mu_2	**0.666**	**0.444**	
	mu_3	0.781	0.610	
	mu_4	0.726	0.527	
GSP	gsp_1	0.809	0.654	0.635
	gsp_2	0.750	0.563	
	gsp_3	0.829	0.687	
AIA	aia_1	0.780	0.608	0.552
	aia_2	0.713	0.508	
	aia_3	0.745	0.555	
	aia_4	0.734	0.539	
KACAP	kacap_1	0.775	0.601	0.56
	kacap_2	0.727	0.529	
	kacap_3	0.742	0.551	
	kacap_4	0.749	0.561	
OI	oi_1	0.759	0.576	0.541
	oi_2	0.780	0.608	
	oi_3	0.718	0.516	
	oi_4	**0.653**	**0.426**	
	oi_5	0.760	0.578	

Legend: PU=perceived usefulness; PEOU=perceived ease of use; OCX=organizational complexity; ORE=organizational readiness; CP=competitive pressure. SIV=supplier involvement; GSP=government support and policy; AIA=AI adoption; KACAP=knowledge absorptive capacity; OI=open innovation

Table 4.8 Results of Internal Consistency

Latent	**Indicators**	**Cronbach's**	**Composite**	**Composite**
PU	pu_1	0.788	0.793	0.855
	pu_2			
	pu_3			
	pu_4			
	pu_5			
PEOU	peou_1	0.757	0.761	0.845
	peou_2			
	peou_3			
	peou_4			
OCX	ocx_1	0.710	0.766	0.870
	ocx_2			
ORE	ore_1	0.754	0.762	0.859
	ore_2			
	ore_3			
CP	cp_1	0.706	0.708	0.836
	cp_2			
	cp_3			
SIV	siv_1	0.719	0.719	0.842
	siv_2			
	siv_3			
MU	mu_1	0.716	0.733	0.821
	mu_2			
	mu_3			
	mu_4			
GSP	gsp_1	0.712	0.718	0.839
	gsp_2			
	gsp_3			
AIA	aia_1	0.731	0.736	0.831
	aia_2			
	aia_3			
	aia_4			
KACAP	kacap_1	0.739	0.741	0.836
	kacap_2			
	kacap_3			
	kacap_4			
OI	oi_1	0.787	0.793	0.854
	oi_2			
	oi_3			
	oi_4			
	oi_5			

Legend: PU=perceived usefulness; PEOU=perceived ease of use; OCX=organizational complexity; ORE=organizational readiness; CP=competitive pressure. SIV=supplier involvement; GSP=government support and policy; AIA=AI adoption; KACAP=knowledge absorptive capacity; OI=open innovation

4.5.1.3. Discriminant Validity, Correlations, and AVE

The evaluation of the measurement model was concluded with an assessment of discriminant validity. This assessment determines whether a construct is separate and unique from other constructs (Hair et al., 2022), following the Fornell-Larcker Criterion, suggesting that the constructs discriminate well because the square root of the AVE of each reflective construct is larger than the correlations with the remaining constructs (see **Table 4.9**). To supplement the Fornell-Larcker Criterion, a heterotraitmonotrait (HTMT) correlational ratio test was performed (Henseler et al., 2015). **Table 4.10** shows that all the values of the constructs are lower than the suggested threshold value of 0.85 except competitive pressure (CP:0.880), which is acceptable for conceptually similar constructs (Hair et al., 2022). This indicates that the correlations between different constructs are relatively low, meaning each construct has a distinct concept, demonstrating high discriminant validity among the various constructs (Cao et al., 2021). **Table 4.11** summarizes the results of the measurement model.

4.5.2. Structural Model

The last step is to assess the structural model using the bootstrapping routine. As a component of the structural model evaluation, all required procedures (Hair et al., 2022) were performed. The model was analyzed for multicollinearity, the significance and relevance of path coefficients, the model's explanatory capability through in-sample fit (R^2) and out-of-sample fit (Q^2), along with an evaluation of its predictive ability using $PLS_{predict}$ (Hair et al., 2022). The final stage of the structural model evaluation involved comparing different models (Hair et al., 2022).

Table 4.9 Discriminant Validity (Fornell- Lacker ratios)

	AIA	CP	GSP	KACAP	MU	OI	OCX	ORE	PU	PEOU	SIV
AIA	**0.743**										
CP	0.641	**0.794**									
GSP	0.599	0.440	**0.797**								
KACAP	0.598	0.565	0.541	**0.749**							
MU	0.590	0.531	0.515	0.451	**0.732**						
OI	0.602	0.587	0.547	0.631	0.532	**0.735**					
OCX	-0.152	-0.165	-0.119	-0.020	-0.182	-0.071	**0.878**				
ORE	0.458	0.433	0.524	0.573	0.310	0.448	-0.032	**0.818**			
PU	0.642	0.587	0.533	0.508	0.498	0.560	-0.055	0.509	**0.737**		
PEOU	0.548	0.503	0.545	0.512	0.466	0.474	-0.074	0.622	0.559	**0.760**	
SIV	0.532	0.571	0.473	0.586	0.459	0.587	-0.147	0.444	0.520	0.507	**0.800**

Table 4.10 Discriminant Validity (HTMT ratios)

	AIA	CP	GSP	KACAP	MU	OI	OCX	ORE	PU	PEOU	SIV
AIA											
CP	**0.886**										
GSP	0.827	0.622									
KACAP	0.807	0.781	0.747								
MU	0.795	0.735	0.707	0.603							
OI	0.785	0.785	0.726	0.824	0.684						
OCX	0.200	0.227	0.188	0.082	0.272	0.098					
ORE	0.607	0.582	0.716	0.758	0.405	0.584	0.079				
PU	0.837	0.784	0.706	0.662	0.642	0.702	0.097	0.656			
PEOU	0.731	0.688	0.742	0.682	0.609	0.622	0.101	0.836	0.720		
SIV	0.729	0.801	0.662	0.801	0.620	0.771	0.205	0.591	0.690	0.687	

Table 4.11 Results summary for measurement models (N=269)

Construct	Indicator	Convergent validity			Internal Consistency		Discriminant
		Outer Loadings >0.7	**Indicator Reliability >0.5**	**AVE >0.5**	**Cronbach's Alpha >0.7**	**Composite Reliability (rho_a)>0.7**	**Validity HTMT<0.90?**
PU	pu_1	0.796	0.634	0.578	0.757	0.761	
	pu_2	0.729	0.531				
	pu_3	0.769	0.591				Yes
	pu_4	0.713	0.508				
	pu_5	0.670	0.449				
PEOU	peou_1	0.804	0.646	0.543	0.788	0.793	Yes
	peou_2	0.729	0.531				
	peou_3	0.734	0.539				
	peou_4	0.771	0.594				
OCX	ocx_1	0.834	0.696	0.771	0.710	0.766	Yes
	ocx_2	0.919	0.845				
ORE	ore_1	0.810	0.656	0.67	0.754	0.762	
	ore_2	0.798	0.637				Yes
	ore_3	0.845	0.714				
CP	cp_1	0.762	0.581	0.63	0.706	0.708	
	cp_2	0.816	0.666				Yes
	cp_3	0.802	0.643				
SIV	siv_1	0.807	0.651	0.64	0.719	0.719	
	siv_2	0.795	0.632				Yes
	siv_3	0.799	0.638				
MU	mu_1	0.750	0.563	0.536	0.716	0.733	Yes
	mu_2	0.666	0.444				
	mu_3	0.781	0.610				
	mu_4	0.726	0.527				
GSP	gsp_1	0.809	0.654	0.635	0.712	0.718	
	gsp_2	0.750	0.563				Yes
	gsp_3	0.829	0.687				
AIA	aia_1	0.780	0.608	0.552	0.731	0.736	Yes
	aia_2	0.713	0.508				
	aia_3	0.745	0.555				
	aia_4	0.734	0.539				
KACAP	kacap_1	0.775	0.601	0.56	0.739	0.741	Yes
	kacap_2	0.727	0.529				
	kacap_3	0.742	0.551				
	kacap_4	0.749	0.561				
OI	oi_1	0.759	0.576	0.541	0.787	0.793	Yes
	oi_2	0.780	0.608				
	oi_3	0.718	0.516				
	oi_4	0.653	0.426				
	oi_5	0.760	0.578				

Legend: PU=perceived usefulness; PEOU=perceived ease of use; OCX=organizational complexity; ORE=organizational readiness; CP=competitive pressure. SIV=supplier involvement; GSP=government support and policy; AIA=AI adoption; KACAP=knowledge absorptive capacity; OI=open innovation

4.5.2.1. Multicollinearity Assessment

First, the potential collinearity issues need to be examined to ensure that the estimated path coefficients are not biased. The results from running the PLS-SEM algorithm show that the VIF values (see **Table 4.12**) of all combinations of endogenous constructs (represented by the columns) and corresponding predictor constructs (represented by the rows) are lower than the conservative threshold of 3.0. Therefore, there are no collinearity issues, satisfying the criteria in place (Hair et al., 2022).

4.5.2.2. Significance and Relevance of Path Coefficients

The significance and relevance of the path coefficients (Hair et al., 2022) pertain to the assessment of how endogenous constructs are related to exogenous ones within the structural model. The bootstrapping method enables the evaluation of the proposed relationships between constructs. It tests the significance of the path coefficients by calculating the t-values and p-values within the structural model. A relationship is deemed significant when the t-statistic exceeds the critical threshold. **Figure 4.2** illustrates the estimated magnitudes of the path coefficients, while **Table 4.13** presents the significant findings for these coefficients. The critical values for two-tailed tests are 1.65 at a 10% significance level ($p < 0.10$), 1.96 at a 5% significance level ($p < 0.05$), and 2.57 at a 1% significance level ($p < 0.01$). It should be noted that when assuming a 5% significance level, the p-value must be lower than 0.05 to conclude that the relationship under investigation is statistically significant at the 5% level (Hair et al., 2022).

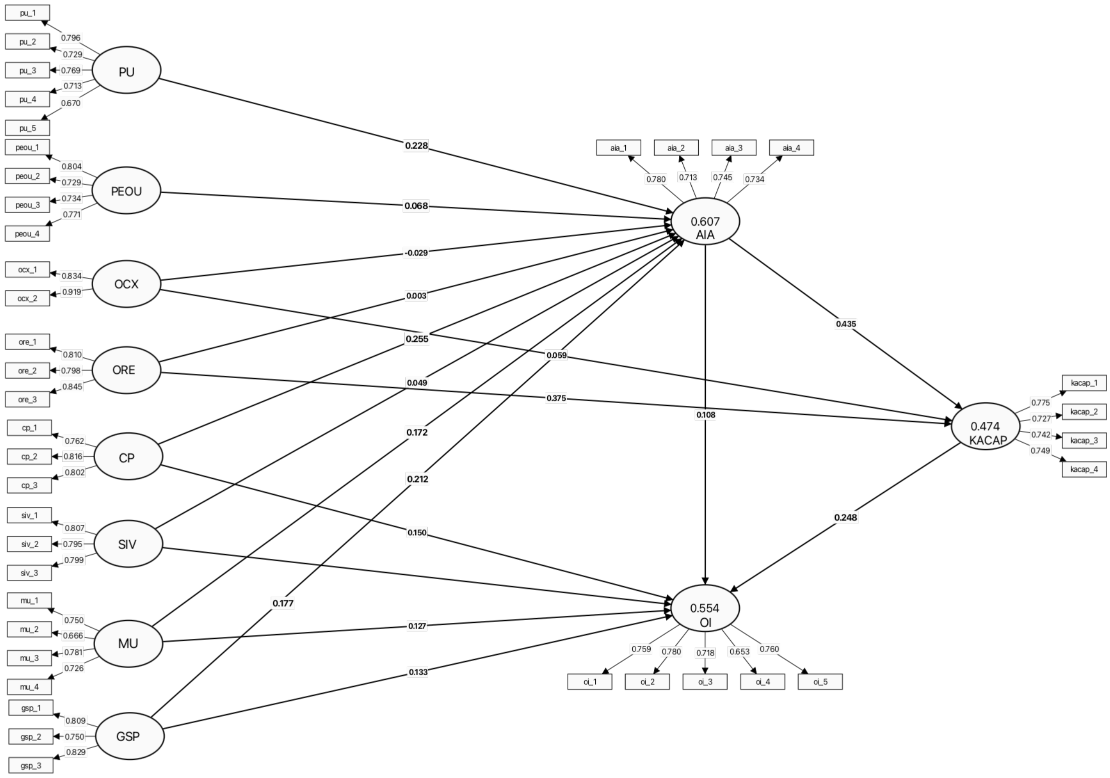

Figure 4.2 Structural Model Path Coefficients

Legend: PU=perceived usefulness; PEOU=perceived ease of use; OCX=organizational complexity; ORE=organizational readiness; CP=competitive pressure. SIV=supplier involvement; GSP=government support and policy; AIA=AI adoption; KACAP=knowledge absorptive capacity; OI=open innovation

Table 4.12 Item multicollinearity assessment:VIF

Indicator	VIF
aia_1	1.406
aia_2	1.348
aia_3	1.392
aia_4	1.355
cp_1	1.317
cp_2	1.434
cp_3	1.402
gsp_1	1.416
gsp_2	1.319
gsp_3	1.487
kacap_1	1.433
kacap_2	1.364
kacap_3	1.389
kacap_4	1.391
mu_1	1.413
mu_2	1.371
mu_3	1.347
mu_4	1.378
ocx_1	1.435
ocx_2	1.435
oi_1	1.603
oi_2	1.643
oi_3	1.495
oi_4	1.334
oi_5	1.61
ore_1	1.584
ore_2	1.439
ore_3	1.553
peou_1	1.552
peou_2	1.326
peou_3	1.498
peou_4	1.606
pu_1	1.755
pu_2	1.462
pu_3	1.541
pu_4	1.481
pu_5	1.311
siv_1	1.438
siv_2	1.395
siv_3	1.397

Table 4.13 Relevant Constructs for the Structural Model

Hypothesis	**Path**	**Path (β)**	**T statistics**	**P values**	**Significance (p<0.05)?**
H1	PU -> AIA	0.228	3.319***	0.001	Yes
H2	PEOU -> AIA	0.068	1.033ns	0.302	No
H3a	OCX -> AIA	-0.029	0.825ns	0.409	No
H3b	OCX -> KACAP	0.059	1.374ns	0.169	No
H4a	ORE -> AIA	0.003	0.046ns	0.964	No
H4b	ORE -> KACAP	0.375	4.610***	0.000	Yes
H5a	CP -> AIA	0.255	4.211***	0.000	Yes
H5b	CP -> OI	0.150	2.245**	0.025	Yes
H6a	SIV -> AIA	0.049	0.799ns	0.425	No
H6b	SIV -> OI	0.177	2.570***	0.010	Yes
H7a	MU -> AIA	0.172	2.897***	0.004	Yes
H7b	MU -> OI	0.127	2.333**	0.020	Yes
H8a	GSP -> AIA	0.212	3.257***	0.001	Yes
H8b	GSP -> OI	0.133	1.595ns	0.111	No
H9	AIA -> KACAP	0.435	5.443***	0.000	Yes
H10	KACAP -> OI	0.248	3.122***	0.002	Yes
H11	AIA -> OI	0.108	1.152ns	0.250	No

Note: t-values for two-tailed test: ***t-value 2.58 (Sig. level = 1%), **1.96 (sig. level = 5%) (Hair et al., 2022).

H1 proposes that perceived usefulness positively affects AI adoption, supported by the statistically significant effect, with a path coefficient of 0.228 (p<0.001). H2 posits that perceived ease of use positively influences AI adoption, but it is rejected since this effect is not statistically significant. H3a and H3b suggest organizational complexity negatively influences AI adoption and KACAP but is rejected as the linkages' path coefficients are nonsignificant (H3a=0.825ns, H3b=1.374ns). H4a suggests that organizational readiness positively influences AI adoption, but it is also rejected as the effect is not statistically significant, with a path coefficient of 0.046ns. However, Organizational readiness has a positive influence on KACAP, which support H4b, with path coefficients of 0.375 (t=4.610, p =0.000). The fifth group of hypotheses (H5a and H5b), addressing the positive association of the competitive pressure with the AI adoption and open innovation, is confirmed (H5a: β=0.225, t=4.211, p=0.000; H5b: β=0.150, t=2.245, p=0.025). H6a posits that supplier involvement positively impacts AI adoption, but this is rejected because the effect is not statistically significant (0.799ns). In contrast, H6b posits that supplier involvement positively open innovation with statistical significance (β=0.177, t=2.570, p=0.010). Both H7a and H7b have significant effects on AI adoption and open innovation, with path coefficients of 0.172 (p< 0.001) and 0.127 (p<0.05). H8a signifies a positive impact between government support and policies and AI adoption (β=0.212, t=3.257, p=0.001), but the positive effect of government support and policies on open innovation is rejected because the impact is not statistically significant (1.595ns). As for the ninth hypothesis (H9), AI adoption is also confirmed (β=0.435, t=5.443, p=0.000) of having a positive association with the apparel manufacturing firm's KACAP. H10 also supports the statistically significant effects of KACAP on open innovation, with a positive association confirmed ($\beta=0.248$, $t=3.122$, $p=0.002$). The last significance and relevance of the path coefficient is H11, showing a nonsignificant effect of AI adoption on open innovation.

4.5.2.3. Explanatory Power

The explanatory power of the model, as shown in **Table 4.14**, was analyzed using the coefficient of determination (R^2). This metric measures how much variance in the dependent (endogenous) construct can be explained by the independent (exogenous) constructs (Hair et al., 2022). The analysis revealed that the structural model accounted for 60.7% of the variance in AI adoption ($t=16.562$, $p<0.001$), 47.4% in KACAP ($t=8.894$, $p<0.001$), and 55.4% in open innovation ($t=10.154$, $p<0.001$). R^2 values are interpreted based on established thresholds: 0.60 or higher indicates strong explanatory power, 0.33 is moderate, and 0.19 is weak (Min et al., 2020). Furthermore, the Q^2 values, which assess the model's predictive relevance, consistently exceeded the benchmark of 0.5, confirming the model's substantial predictive accuracy (Hair et al., 2019).

Table 4.14 Structural model – coefficient of determination (R^2)

	R-square	**T statistics (|O/STDEV|)**	**P values**
AIA	0.607	16.562	0.000
KACAP	0.474	8.894	0.000
OI	0.554	10.154	0.000

4.5.2.4. Predictive Power

The Q^2 statistic measures the extent to which the model can predict variance in the constructs it examines, offering valuable insights into its predictive performance (Hair et al., 2022). In PLS-SEM, Stone-Geisser's Q^2 statistic is commonly applied to evaluate out-of-sample predictive power, though its applicability is somewhat constrained by the choice of dependent variables. **Table 4.15** highlights the predictive accuracy of the model, with AI adoption showing the highest Q^2 value (0.568), followed by open innovation (0.491) and KACAP (0.456). These results underscore the model's strong predictive capabilities, particularly in explaining AI adoption, a pivotal construct within the framework.

Table 4.15 Model Predictive Accuracy – Q^2 Value

	$Q^2_{predict}$	**RMSE**	**MAE**
AIA	0.568	0.664	0.515
KACAP	0.456	0.745	0.534
OI	0.491	0.719	0.532

For further evaluating the structural model's predictive power, Shmueli et al. (2016, as cited in Hair et al., 2022) created $PLS_{predict}$ as an improved method with 10 folds and 10 repetitions, i.e., k and r were set to 10 each, which is a primary approach to evaluate the predictive power of a PLS path model (Hair eta al., 2022). The $PLS_{predict}$ results (**Table 4.16**) are presented in the context of AI adoption, KACAP, and open innovation. The proposed model satisfies the $PLS_{predict}$ prerequisite condition where the Q^2 prediction should be >0 for all the indicators, and thus, the $PLS_{predict}$ method can be used.

The next step is to assess the model PLS-RMSE results against the naïve benchmark, i.e., linear regression model (LM) (Dobre, 2022). Hair et al. (2022, p. 214) highlight that "If all indicators in the PLS-SEM analysis have lower RMSE (or MAE) values compared to the "naïve LM benchmark", the model has high predictive power". As **Table 4.16** shows, the $PLS_{predict}$ results indicate that the model of the study has very high predictive power, given that for the dependent variables, all their corresponding items have the root mean squared error (RMSE) values lower than the naïve benchmark, described as the outcome of a LM.

Table 4.16 Model Predictive Power – $PLS_{predict}$

	$Q^2_{predict}$ >0	**PLS-SEM_RMSE**	**LM_RMSE**	**Predictive Power (<0)**
aia_1	0.384	0.566	0.621	-0.055
aia_2	0.230	0.717	0.766	-0.049
aia_3	0.314	0.688	0.738	-0.050
aia_4	0.309	0.616	0.659	-0.043
kacap_1	0.307	0.637	0.660	-0.023
kacap_2	0.227	0.674	0.728	-0.054
kacap_3	0.223	0.688	0.746	-0.058
kacap_4	0.259	0.643	0.688	-0.045
oi_1	0.303	0.643	0.663	-0.020
oi_2	0.314	0.610	0.653	-0.043
oi_3	0.206	0.671	0.712	-0.041
oi_4	0.203	0.786	0.790	-0.004
oi_5	0.288	0.645	0.689	-0.044

4.5.3. Measurement and Structural Model Evaluation in Mediation Analysis Structural Model

Evaluating mediations in the model should be assessed by considering all standard model evaluation criteria, such as convergent validity, discriminant validity, reliability, multicollinearity, explanatory power, and predictive power, resulting in incorrect implications regarding the mediation (Hair et al., 2022). As these relevant assessment criteria for measurement and structural model have been evaluated and met previously, the mediator analysis follows.

The mediation effect is associated with the intervention of the variable mediator in the relationship between two variables (Dobre, 2022). Hair et al. (2022) characterized several types of mediating effects. The first group consists of direct-only nonmediation (the direct effect is significant but the indirect effect is not), and no-effect nonmediation (neither the direct nor the indirect effect are significant), and the second group encompasses of complementary mediation, i.e. partial mediation (the indirect effect and the direct effect are both significant and point in the same direction), competitive mediation, i.e. suppressor variable (the indirect effect and the direct effect are both significant but point in opposite directions), and indirect-only mediation, i.e. full mediation (the indirect effect is significant but the direct effect is not). **Table 4.17** presents all specific indirect mediating effects using the SmartPLS bootstrapping outputs, and **Table 4.18**, where the author compares direct and indirect effects to classify the mediating impact in the model.

Table 4.17 Significance Analysis of the Specific Indirect Effects

	Specific Indirect effects T statistics	**P values**	**Significance ($p<0.05$)?**
PU -> AIA -> KACAP	2.901***	0.004	Yes
PU -> AIA -> OI	0.986	0.324	No
PU -> AIA -> KACAP -> OI	1.846	0.065	No
PEOU -> AIA -> KACAP	0.978	0.328	No
PEOU -> AIA -> OI	0.711	0.477	No
PEOU -> AIA -> KACAP -> OI	0.814	0.416	No
OCX -> AIA -> KACAP	0.815	0.415	No
OCX -> AIA -> OI	0.538	0.591	No
OCX -> KACAP -> OI	1.230	0.219	No
OCX -> AIA -> KACAP -> OI	0.706	0.480	No
ORE -> AIA -> KACAP	0.044	0.965	No
ORE -> AIA -> OI	0.036	0.971	No
ORE -> KACAP -> OI	3.10***	0.002	Yes
ORE -> AIA -> KACAP -> OI	0.039	0.969	No
CP -> AIA -> KACAP	3.479***	0.001	Yes
CP -> AIA -> OI	1.107	0.268	No
CP -> AIA -> KACAP -> OI	1.940	0.052	No
SIV -> AIA -> KACAP	0.766	0.444	No
SIV -> AIA -> OI	0.562	0.574	No
SIV -> AIA -> KACAP -> OI	0.679	0.497	No
MU -> AIA -> KACAP	2.593**	0.010	Yes
MU -> AIA -> OI	1.009	0.313	No
MU -> AIA -> KACAP -> OI	1.727	0.084	No
GSP -> AIA -> KACAP	2.615***	0.009	Yes
GSP -> AIA -> OI	1.039	0.299	No
GSP -> AIA -> KACAP -> OI	1.705	0.088	No
AIA -> KACAP -> OI	2.258**	0.024	Yes

Table 4.18 Types of Mediating Effects

Path	Direct effects T statistics	Significance (p<0.05)?	Indirect effects T statistics	Significance (p<0.05)?	Types of mediating effects
OCX -> KACAP	1.374ns	No			No-effect nonmediation
OCX -> AIA -> KACAP			0.815	No	
ORE -> KACAP	4.610***	Yes			Direct-only nonmediation
ORE -> AIA -> KACAP			0.044	No	
CP -> OI	2.245**	Yes			Direct-only nonmediation
CP -> AIA -> OI			1.107	No	
CP -> AIA -> KACAP -> OI			1.940	No	
SIV -> OI	2.570**	Yes			Direct-only nonmediation
SIV -> AIA -> OI			0.562	No	
SIV -> AIA -> KACAP -> OI			0.679	No	
MU -> OI	2.333**	Yes			Direct-only nonmediation
MU -> AIA -> OI			1.009	No	
MU -> AIA -> KACAP -> OI			1.727	No	
GSP -> OI	1.595ns	No			No-effect nonmediation
GSP -> AIA -> OI			1.039	No	
GSP -> AIA -> KACAP -> OI			1.705	No	
AIA -> OI	1.152ns	No			Indirectly-only mediation, i.e., Full mediation
AIA -> KACAP -> OI			2.258**	Yes	

Note: t-values for two-tailed test: ***t-value 2.58 (Sig. level = 1%), **1.96 (sig. level = 5%) ns =Not Significant (Hair et al., 2022).

As can be seen, AI adoption and KACAP are considered as two mediators. AI adoption mediates perceived usefulness and KACAP suggests a significance (t=2.901, p=0.004), as well as the exogenous variable CP (t=3.479, p=0.001), MU (t=2.593, p=0.010), and GSP (t=2.615, p=0.009) to the endogenous variable KACAP. However, there is no direct paths between these exogenous variables and KACAP, indicating the nonmediation effect. In addition, when examining the mediating role of AI Adoption, the results showing on the table 5.18 indicates that the direct effects that organizational readiness has on KACAP are significant (t=4.610, p=0.000), but its indirect effects on KACAP via merely AI adoption is not significant, and therefore, the type of mediating effects is found to be directly-only nonmediation. Similar results of direct-only nonmediation are observed in other relationships. For example, while the direct effects of competitive pressure on open innovation are significant, the indirect effects via AI adoption alone (CP → AIA → OI) or through the sequential mediation of AI adoption and KACAP (CP → AIA → KACAP → OI) are not statistically significant. A comparable trend is evident in the relationship between supplier involvement and open innovation. The direct effects of supplier involvement on open innovation remain significant, whereas the indirect effects through either AI adoption (SIV → AIA → OI) or the combined mediation of AI adoption and KACAP (SIV → AIA → KACAP → OI) do not achieve significance. Similarly, for market uncertainty and open innovation, the direct effects are significant, but the mediating roles of AI adoption and the sequential pathway involving both AI adoption and KACAP are not supported by the data. These findings suggest that while direct effects from competitive pressure, supplier involvement, and market uncertainty to open innovation are present, the mediating influence of AI adoption, whether independently or in combination with KACAP, does not significantly contribute to explaining these relationships.

The second mediating significance of KACAP between organizational readiness and open innovation is also a nonmediation effect. In this structural model, the hypothesized mediator variable in this thesis model is KACAP, supporting H12 that assesses that KACAP has a positive effect with significance between AI adoption and open innovation. This result explains Hair et al. (2022)'s states that when a change occurs in the exogenous variable (AI adoption), it leads to a shift in the mediator (KACAP), which subsequently affects the endogenous variable (open innovation). As shown in Table 5.18, the direct effects that AI adoption has on open innovation are statistically nonsignificant, but its indirect effects on open innovation via merely KACAP is significant. Accordingly, this type of mediating effect is found to be indirect-only mediation or full mediation.

4.6. Summary of Chapter

This chapter outlines the survey results collected from apparel manufacturing owners and managers in China, focusing on the factors influencing AI adoption and its role in driving open innovation. It begins with the results of the pilot testing, followed by an analysis of the survey data. The findings include descriptive statistics, with the remainder of the chapter dedicated to PLS-SEM analysis. Using the methodology outlined by Hair et al. (2022), the results for both the measurement model and structural model were presented.

The primary findings of ***study 1*** are that the knowledge absorptive capacity (KACAP) has a significant mediating role in firm open innovation. This suggests that in the context of Industry 4.0, which drives China's traditional apparel manufacturing digitalization, firms leverage AI-integrated technology that was significantly influenced by TAM and TOE factors to enhance firms' open innovation through improving their KACAP for surviving in this unpredicted market. However, these antecedents of AI adoption in firms have identified that all internal organizational factors (organizational complexity and organizational readiness) insignificantly impact AI adoption. In contrast, most external environmental factors (competitive pressure, market uncertainty, and government support and policy) have been found to affect AI adoption, either on open innovation significantly. These results are discussed in detail in ***Chapter 6***.

5. Findings of *Study 2* and Analysis

5.1. Introduction

This study applies grounded theory to conduct a qualitative data analysis through three steps: open coding, axial coding, and selective coding. In this study, interviews were independently coded twice by following a one-third proportion. Without influencing each other, the researcher first independently analyzed the interview transcripts, selected sentences closely related to the research questions for conceptualization, and categorized the concepts, further forming broader categories. Finally, the researcher compared their respective coding results, identifying both the similarities and differences between the two independent coding rounds. The identical coding content was adopted, while the differences were reviewed, deeply considered, and compared. This process allowed for the categorization and integration of the coding, the refinement of theoretical logic, and the gradual formation of the writing framework, as previously mentioned in ***Chapter3***. This coding scheme is consistent with several studies (Campbell et al., 2013; Chen, 2000), and any concepts that appeared less than twice and could not be categorized were eliminated during this process. Section 5.2 presents the results of data structure by coding steps. Section 5.3 and 5.4 presents the analysis of two parts of the data. Section 5.5 summarizes the chapter. The flow chart of Chapter 5 is presented in **Figure 5.1**.

Figure 5.1 Flow Chart of Chapter 5

5.2. Results of Data Structure

Figure. 5.2, and 5.3 illustrate the completed data structure that resulted from the data analysis, which is based on the open coding, axial coding, and selected coding results. As a final selected coding step, we theorized about the logic and linkages across aggregate dimensions, second-order themes, and first-order categories. Because we sought to address what AI capabilities the Chinese manufacturing firms required are developed and the challenges when adopting AI in manufacturing and production processes, and how to build an innovation ecosystem where the collaborated actors leverage resources in activities based on China's institutional (policies and standards) context, we contrasted lines of insight from the interviews. The initial results of ***study 2*** were presented to two key informants to validate the results through analysis. Constant comparison and memo writing were conducted during the processes, and data saturation was examined as relevant after the first follow-up (Birks & Mills, 2015; Bryant, 2019; Bryant & Charmaz, 2008; Foley et al., 2021; Makri & Neely, 2021; Orlikowski & Baroudi, 1990).

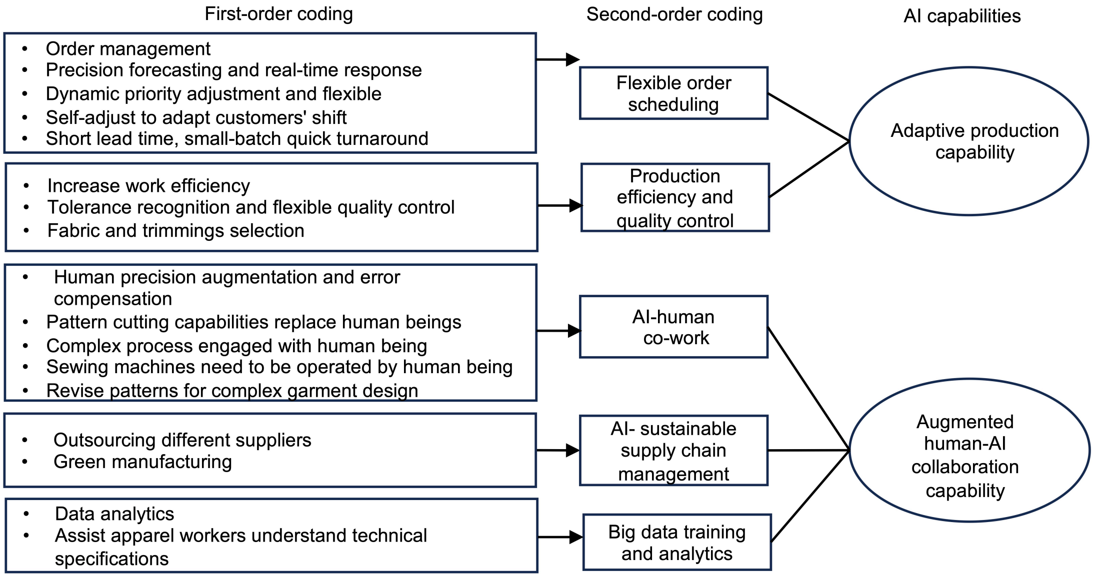

Figure 5.2 Data Structure-AI capabilities

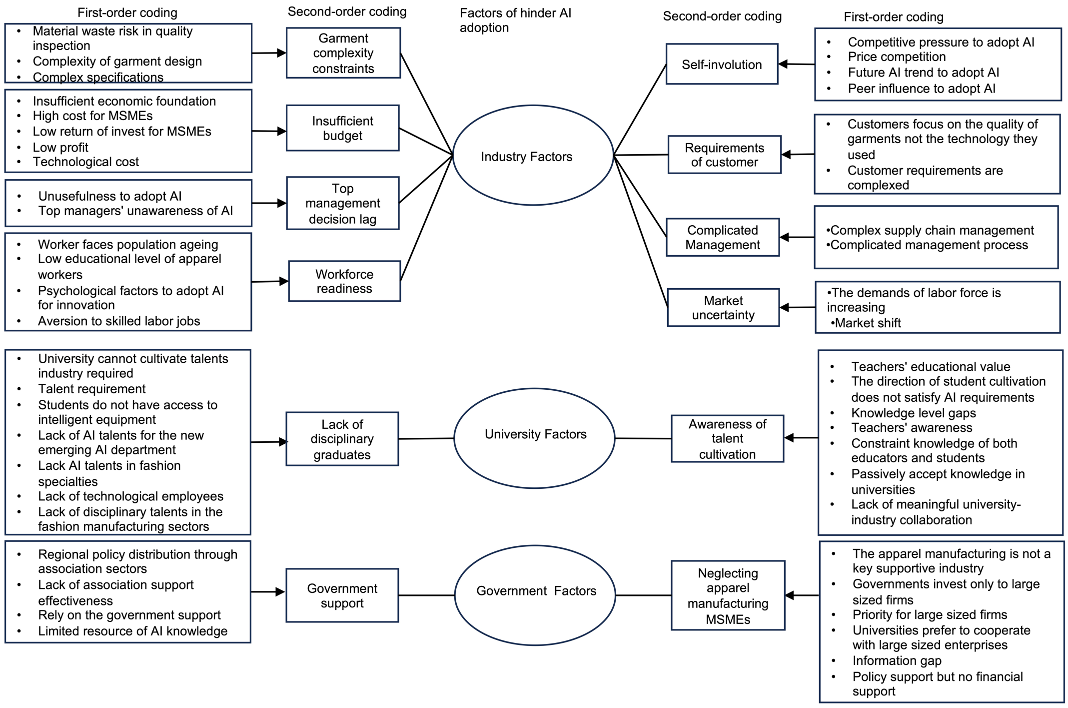

Figure 5.3 Data Structure-Barriers to AI adoption

Drawing on empirical data from 15 interviews, we identified and conceptualized core AI capabilities in apparel manufacturing practices, incorporating insights not only from managers, suppliers, and customers, but also from educators and apparel association leaders with expertise in the fashion industry. While foundational AI capabilities have been established in previous literature, our findings focus on unexplored capabilities, addressing gaps in AI applications within apparel production processes. To identify AI capabilities for apparel production, we focused initially on interview questions about current issues in traditional apparel production, then expanded to include AI technology awareness and the role of AI in addressing these issues, thereby exploring barriers and challenges to AI adoption. We present our findings and analysis in two parts, one relating to AI capabilities (**Table 5.1**), and the other dealing with the barriers to AI adoptions (**Table 5.2**). Following the presentation of findings, Chapter 6 will theorize the AI-enabled innovation ecosystem framework based on the two layers of results in this chapter.

5.3. Required AI Capabilities

The analysis of this section uncovers two interconnected AI-driven priorities that the apparel manufacturing industry in China must develop to fully leverage AI: adaptive production capability, and augmented human-AI collaboration capability.

5.3.1. Adaptive Production Capability

Adaptive production capabilities suggest that flexible production features are the basis of the integration of AI. These features enable manufacturers to meet the varying needs of small-batch production, fast order execution, and fluctuations in customer preferences. They also would allow companies to augment their flexibility by synchronizing production schedules, human resources, and outputs with customer-specific requirements in an elaborate yet streamlined way. AI in Chinese apparel manufacturing is in its infancy (Liu et al., 2020). Thus, the required capabilities initially focus on practical production capability, including flexible order scheduling, efficiency, and quality control. This demonstrates a distinct but interrelated set of needs, with the industry respondents' importance and level of demand linked to the frequency that the specific need was supported. The analysis of these frequencies to establish their implications for adaptive production and the relationships amongst these mechanisms is thus the focus of this section.

Table 5.1 shows order management and short lead time, small-batch quick turnaround have a frequency of five, making them the most frequently mentioned needs within flexible order scheduling. This finding shows that flexible order handling and fast response to small batch demand are the primary status quo that MSMEs have faced recently. Especially in the post-COVID-19 period, due to the factors of mass clothing consumption downgrade, the customer order characteristics of downstream clothing brands have become small and complex to meet the needs of personalized consumers in this period.

Table 5.1 Results of Required AI Capabilities of Apparel Manufacturing Sectors

Selected coding	**Axial coding**	**Open coding (18 nodes)**	**Frequency**	**Quotations**
Adaptive production capability	Flexible order scheduling	Order management	5	In production, AI can predict my needs, such as how many linings and trimming materials I require and their quantities when **orders come in**.(I8)
		Precision forecasting and real-time response	2	Manual order dispatching, for example, in my case as a central hub, not all incoming goods can be sent to every customer daily. Suppose today there are **50 customer orders** to be shipped, and among them, **10 are key customers** whose products can all be sent out, while the products for **another 10 key customers are incomplete.** (I5)
		Dynamic priority adjustment and flexible response capabilities	4	For trench coats or jackets, only basic parameters like shoulder width and length are needed, and minor adjustments can be made. Machines can achieve this functionality. Since I handle **small-batch orders**, if today's customer orders a long, loose trench coat but tomorrow needs a cinched waist style, **that's definitely not feasible**. (I6)
		Self-adjust to adapt customers' shift	2	We continuously a**djust ourselves based on customer needs.** (I6)
		Short lead time, small-batch quick turnaround	**5**	Many SMEs face customer groups requiring **small-batch**, **fast-response orders** with very high design demands, making it difficult to meet such needs. (I4)
	Production efficiency and quality control	**Increase work efficiency**	**7**	A cutting machine can handle over 100 complex pieces a day, while manually cutting 10 sets a day is already impressive. This has significantly **improved efficiency**. (I1)
		Tolerance recognition and flexible quality control	2	This means **the machine is too precise**. In reality, some error is acceptable, but AI machines might **eliminate all errors**. Whether we're making fabrics or clothes, achieving **zero error is impossible**. (I3)
		Fabric and trimmings selection	5	For **lining and trimming materials**, every task involves different selections. We need to **choose from** thousands of options based on customer preferences and create combinations. Each clip holds various materials, and each selection has similar underlying issues. (I4)

Augmented human-AI collaboration capability	AI-human co-work	Human precision augmentation and error compensation	2	In practical operations, since **humans are still involved, errors are inevitable** advanced equipment struggles to accomplish due to fabric characteristics, but our workers can achieve it, outperforming the machines. (I2)
		Pattern cutting capabilities replace human beings	4	Typically, a pattern maker takes a full day to finish a set of samples, including revisions. For tailored pieces, it takes at least 4-6 hours after taking measurements. **Automating sample creation** and **pattern cutting significantly speeds up the process.** (I1)
		Complex process engaged with human being	4	The customer categories involve deep-level raw material development, including chemical and structural types, and **require a large number of operators.** (I2)
		Sewing machines need to be operated by human being with automatic machines	**9**	While certain processes can intermittently or **fully automate in mature workflows**, **human supervision** is ultimately still required. (I6)
		Revise patterns for complex garment design	2	For knitting, **many patterns require adjustments** upon arrival at the factory, and further modifications are needed for unreasonable designs. (A2)
	AI-sustainable supply chain management	Outsourcing different suppliers	3	I need to locate **"satellite factories"**, each with its own strengths. (I6)
		Green manufacturing	2	They are now undergoing **green upgrades**, increasingly meeting the needs of customers and end-users. (I7)
		Save labor cost	**5**	In manufacturing, AI **replaces manual labor and reduces costs.** (I3)
	Big data training and analytics	Data analytics	4	The template library contains 100 patterns, which can be used for **machine learning and algorithm**. Once key parameters like shoulder width and waist circumference are input, the angle can be directly cut, and sewing naturally follows. (I6)
		Assist apparel workers understand technical specifications	3	Now, **how to explain** the most cost-intensive areas to them using the simplest and most **understandable language is a challenge.** (I2)

In a global fashion market where customization and rapid responses are essential for competitiveness (Masson et al., 2007), these two mechanisms are closely linked: effective scheduling enables manufacturers to manage resources optimally, supporting the capacity to meet short lead times. Quick turnaround for small-batch orders would be challenging without flexible order scheduling, especially when customer preferences shift frequently. For instance, respondent I8 highlighted the crucial role of predictive AI in flexible scheduling.

"In production, AI can predict my needs, such as how many linings and trimming materials I require and their quantities when orders come in".

This capability allows manufacturers to proactively prepare resources and materials based on anticipated needs, thus setting the stage for faster response times. Additionally, the emphasis on quick turnaround is underscored by another respondent who explained, *"Many SMEs face customer groups requiring small-batch, fast-response orders with very high design demands, making it difficult to meet such needs"* (I4). This statement underscores how vital rapid response is to meet the specific, often complex demands of small-batch orders. Therefore, by enabling predictive scheduling, AI supports the capacity to meet rapid turnaround demands, ensuring manufacturers can fulfill customized orders efficiently, even as customer requirements shift. This dynamic interaction between scheduling and turnaround time forms the foundation for adaptive production in a highly variable apparel market.

Supporting these primary mechanisms are additional, closely related functions, including the nodes of dynamic priority adjustment and flexible response (frequency: 4), precision forecasting and real-time response (frequency: 2), and self-adjustment to adapt to customers' shifts (frequency: 2). Each of these mechanisms further enhances adaptive production by allowing manufacturers to make real-time adjustments as customer needs evolve. For instance, dynamic priority adjustment enables manufacturers to handle varying order specifications, such as respondent I6's scenario where AI systems facilitate flexibility by adjusting garment styles:

"For trench coats or jackets, only basic parameters like shoulder width and length are needed, and minor adjustments can be made… if today's customer orders a long, loose trench coat but tomorrow needs a cinched waist style, that's definitely not feasible without AI".

This flexible response aligns with and supports the primary scheduling and turnaround functions by ensuring that production remains adaptable to last-minute design changes without disrupting workflow.

Another key aspect of adaptive production capability in Chinese apparel manufacturing industry is production efficiency and quality control, where AI plays a pivotal role in optimizing work efficiency, ensuring quality, and managing the complexity of material selection.

The most frequently mentioned need within this capability is increasing work efficiency, which appears with a frequency of seven. This high frequency underscores the industry's prioritization of automation to boost productivity. For example, respondent11 emphasized the impact of AI-driven cutting machines:

"A cutting machine can handle over 100 complex pieces a day, while manually cutting 10 sets a day is already impressive. This has significantly improved efficiency".

This quotation highlights how AI enables manufacturers to significantly enhance output, achieving levels of efficiency that would be impossible with manual labor alone. In an industry where rapid production cycles are essential, AI's contribution to improving work efficiency is fundamental to achieve business performance and maintaining competitiveness (Đorđević, et al., 2024). Complementing efficiency is the need for tolerance recognition and flexible quality control. Although less frequently mentioned (Frequency:2), this mechanism addresses a critical challenge in apparel production in balancing precision with practical flexibility. Respondent 13 explained,

"*This means the machine is too precise. In reality, some error is acceptable, but AI machines might eliminate all errors. Whether we're making fabrics or clothes, achieving zero error is impossible*".

This perspective underscores the importance of flexible quality control systems that can accommodate slight imperfections, as complete elimination of error is neither feasible nor necessary. By providing adjustable quality parameters, AI allows manufacturers to meet quality standards without compromising on efficiency, aligning production outcomes with realistic expectations.

Furthermore, fabric and trimmings selection, cited with a frequency of five, illustrating the complexity of managing materials to meet diverse customer preferences. As respondent I4 noted that,

"For lining and trimming materials, every task involves different selections. We need to choose from thousands of options based on customer preferences and create combinations".

This points to the need for AI systems capable of navigating vast material options, automating the selection process, and recommending combinations based on past preferences or design requirements. The ability to streamline fabric and trimming selection is particularly valuable for small-batch production, where customer-specific customization is paramount.

As the analysis of the first required AI capability shows, Chinese apparel manufacturers expect AI to enable them to streamline production, ensure quality, and manage material complexities in a highly variable and demanding environment. By improving work efficiency, balancing precision with flexibility, and optimizing material selection, AI empowers apparel manufacturers to achieve adaptive, responsive production that aligns with industry demands for speed, quality, and customization.

5.3.2. Augmented Human-AI Collaboration Capability

The augmented human-AI collaboration capability is another key capability demanded in the apparel manufacturing industry, focusing on co-work between AI and human experts, which is the focal point of Industry 5.0. Unlike fully autonomous systems, this capability emphasizes a collaborative model in which AI empowers human workers to improve efficiency, maintain quality, and manage complex processes. This collaboration is essential in the apparel manufacturing industry, where specific tasks still require human supervision, flexibility, and skill, such as pattern cutting and sewing. In this capability, the mechanism for AI humans to work together is fundamental and includes several key requirements. "Automatic sewing machine also needs workers to operate" at the highest frequency, a total of nine times, indicates that automation equipment and human operating experience of this ability is required. This reflects the industry's recognition of the limitations of AI in dealing with complex material properties that require human touch and supervision. For example, respondent 16 stressed, *"While certain processes can intermittently or fully automate in mature workflows, human supervision is still required."* This statement emphasizes that whilst AI can simplify many facets of production, activities including stitching still need people who are independent enough to be able to figure out the variations in the material qualities and examine other details of the product to confirm that it meets the standards of the quality. Looking into this necessity of human assistance indicates that AI is not the one which takes over the occupation of skillful human beings but improves it instead through doing the main operations and leaving the employees with the more sensitive parts of the production process.

The pattern-cutting capabilities to replace human beings also play a significant role, with a frequency of four, underscoring how AI is used to automate pattern-cutting measurement. This automation significantly reduces the time required for tasks traditionally handled by skilled pattern makers. Respondent I1 noted,

"Typically, a pattern maker takes a full day to finish a set of samples, including revisions. For tailored pieces, it takes at least 4-6 hours after taking measurements. Automating sample creation and pattern cutting significantly speeds up the process". By automating this process, AI frees human workers to engage in higher-value tasks that require creative input, creating more efficient and balanced workflows.

Complex process engagement with human involvement, with a frequency of four, further underscores the importance of human oversight in tasks that AI alone cannot manage due to their complexity. This sub-mechanism addresses tasks involving specialized material properties and customization, where human judgment remains indispensable. As one respondent mentioned,

"The customer categories involve deep-level raw material development, including chemical and structural types, and require a large number of operators" (I2). This statement reflects that while AI can automate certain standardized processes, it lacks the adaptability required for tasks that demand a nuanced understanding of materials. This highlights a key limitation of AI and reinforces the role of human-AI collaboration in handling tasks where adaptability and expertise are critical, further proving that AI's role is primarily supportive in such contexts.

Beyond direct production tasks, AI-sustainable supply chain management is another important mechanism within this capability, focusing on AI's role in reducing costs and promoting environmentally sustainable practices in supply chain management. This capability has been reviewed through many studies (Qu and Kim, 2024); however, apparel manufacturing's sustainable supply chain capability has not been fully explored. The node entitled "save labor cost", with a frequency of five, reflects the economic benefits of using AI to handle labor-intensive, repetitive tasks. For example, the respondent I3 stated,

"In manufacturing, AI replaces manual labor and reduces costs", highlighting how AI-driven automation can lower production costs by reducing dependence on manual labor for repetitive tasks. This cost-saving measure is particularly valuable for small and medium-sized enterprises that operates with limited budgets and must optimize resources.

AI also plays a crucial role in supplier sourcing as part of sustainable SCM (Qu &Kim, 2024). The manufacturer can use the AI of the supplier selection tool to optimize the outsourcing strategies through the selection of those suppliers who meet the sustainability criteria and the environmental regulations. For instance, respondent I6 mentioned that "*I need to locate 'satellite factories', each with its own strengths."* AI helps locate "satellite factories", contributing to a more adaptive and resilient supply chain. While supplier sourcing did not emerge as the most frequently coded mechanism, it remains an integral component of AI-powered supply chain optimization, supporting businesses in managing sustainability across production networks. Moreover, green manufacturing, cited with a frequency of two, shows an emerging focus on sustainable practices within the industry. As one participant noted,

"They are now undergoing green upgrades, increasingly meeting the needs of customers and end-users" (I7), suggesting that AI supports sustainable practices by optimizing resource use and reducing waste, aligning production with broader environmental goals.

Lastly, the node "big data training and analytics is a vital mechanism within this capability", enabling data-driven decision-making that enhances production planning and quality control. Data analytics, with a frequency of four, underscores the importance of analyzing large datasets to optimize operations. A respondent illustrated this by stating,

"The template library contains 100 patterns, which can be used for machine learning and computation. Once key parameters like shoulder width and waist circumference are input, the angle can be directly cut, and sewing naturally follows" (I6). By leveraging data analytics, AI helps standardize certain production elements, ensuring consistency across orders and reducing variability. This capability not only guarantees quality control but it properly integrates demand forecasting, allowing the manufacturers to provide and utilize resources more efficiently.

Ultimately, the principle of human-AI cooperation is at the forefront of the apparel manufacturing industry, which is the advantageous implementation of AI in conjunction with human labor, rather than the latter being the target of a replacement. By automating routine tasks, AI enables workers to focus on complex, skill-intensive processes. Furthermore, AI-human co-work and sustainable sustainable SCM ensure that AI supports productivity while maintaining the craftsmanship and adaptability essential to the industry. This capability complements other adaptive capabilities, collectively forming a comprehensive framework that allows manufacturers to leverage AI's strengths while preserving the crucial human elements of the apparel production process.

5.4. Factors Hinder AI Adoption

5.4.1. Industry Factors

Table 5.2 shows that the industry factors present systemic barriers to AI adoption in the apparel manufacturing industry, rooted in the sector's unique characteristics and structural limitations, such as technical, financial, managerial, workforce, customer-related, and market-oriented. The complexity of garment production emerges as a central theme, with technical constraints such as design variability and material diversity posing significant obstacles. With 13 mentions, "complexity of garment design" highlights the rigidity of current AI manufacturing systems, which excel in standardized tasks but struggle with intricate designs requiring creativity and customization. The Respondent I4 posited: *"They are limited to certain categories, such as knitwear, denim, or down jackets. These products are relatively simple and easy to operate"*. This underscores AI's inability to accommodate the demands of high-complexity garments, particularly those requiring layered construction, delicate materials, or unique customers' technological specifications. Such limitations reduce the applicability of AI systems to only a subset of production tasks for simple garment styles and requirements, such as T-shirts or suits and blazers, restricting their broader adoption.

The second axial category is economic constraints that exacerbate these technical challenges. Among these, high costs for MSMEs, mentioned 8 times, stand out as a critical barrier, particularly for micro and small-sized ones that dominate the sector.

As the I3 respondent noted, *"For small businesses like ours, it's difficult to compete because the cost is too high" (I3).* The financial burden of acquiring and maintaining AI systems often outweighs their perceived benefits, especially in an industry where profit margins are narrow. This is compounded by low profitability and uncertain return of invest (ROI), mentioned 3 and 4 times, respectively. As another respondent observed,

"The issue of whether the return on investment can be achieved is real, as most people are unwilling to buy machines like ours, or even a 3D software solution" (I6). This financial uncertainty discourages manufacturers from investing in AI, creating a reinforcing cycle where limited adoption reduces the opportunities to realize AI's potential cost-saving and efficiency benefits (Chen, et al, 2022).

Managerial challenges further impede progress. With 12 mentions, the "unawareness of AI among top managers" highlights a pervasive knowledge gap that delays decision-making and stifles innovation. One participant stated,

"Many of our companies have not reached the management level required; they don't understand how to use AI or even its potential" (I4). This lack of awareness is closely tied to a perception of AI's irrelevance, with managers skeptical of its applicability to their specific operations. Without targeted education and clear demonstrations of AI's benefits, this decision-making lag will persist, particularly in risk-averse organizations.

Table 5.2 Results of Barriers to AI Adoption

Selected coding	**Axial coding**	**Open coding (33 nodes)**	**Frequency**	**Quotations**
Industry Factors	Garment complexity constraints	Material waste risk in quality inspection	2	In fact, artificial intelligence has this capability; it can perform inspections, specifically in terms of quality control. (I3)
		Complexity of garment design	13	They are limited to certain categories, such as knitwear, denim, or down jackets. These products are relatively simple and easy to operate. (I4)
		Complex specifications	2	This is because clothing involves raw materials, designs, and production methods, all of which are highly variable. (I2)
	Insufficient budget	Insufficient economic foundation	7	Currently, the main challenge for small and medium-sized enterprises is a lack of funds. (I4)
		High cost for MSMEs	8	There is also a lot of outsourcing. For example, Hengli Group, a Fortune 500 company, requires many talents and operates across multiple industries. For small businesses like ours, it’s difficult to compete because the cost is too high. (I3)
		Low return of invest for MSMEs	4	The issue of whether the return on investment can be achieved is real, as most people are unwilling to buy machines like ours, or even a 3D software solution.(I6)
		Low profit	3	Currently, profits are low. This year, domestic factories are generally struggling to turn a profit and are cutting expenses. (I4)
		Technological cost	3	If you want to lead them in intelligent upgrades, I think we can provide significant guidance in terms of mindset, but they definitely cannot afford the equipment. (I1)
	Top management decision lag	Unusefulness to adopt AI	2	First, you need to look at whether artificial intelligence involves equipment or software. We must identify where it can be applied. If we find it applicable, we will test it immediately to see if it works for us. If it does, we’ll adopt it right away. (I8)

		Top managers' unawareness of AI	12	Many of our companies have not reached the management level required; they don't understand how to use it. (A2)
	Workforce readiness	Worker faces population ageing	7	With the 70s generation retiring, even fewer from the '80s generation are entering the industry. You must adopt intelligent solutions. (I4)
		Low educational level of apparel workers	6	Due to workers' skill levels and knowledge reserves, memory errors are frequent, and work progress is slow. (I1)
		Psychological factors to adopt AI for innovation	2	Manufacturing needs to address this issue. However, solving it feels extremely difficult and out of reach because our supply chain is very long. (I4)
		Aversion to skilled labor jobs	7	During a meeting, the person in charge asked about issue, and I replied that there was a shortage of workers, which they couldn't solve. Although I didn't ask directly, I wondered in my heart: when government officials or academic investigators conduct research, are they genuinely useful? When I ask if they'd send their own children to technical schools and endure the social gap, they don't dare answer. (I6)
	Self-Involution	Competitive pressure to adopt AI	7	I don't think this can be called a consumer group; it is caused by peer competition. It's all due to intense internal competition. (I4)
		Price competition	3	Taobao has now introduced a price comparison system that offers many similar products at the time of payment. This mechanism disrupts the market; the Red Ocean strategy relies on price competition and somewhat undermines healthy market development. (I4)
		Future AI trend to adopt AI	2	If someone truly wants to follow the path of artificial intelligence, or if the entire industry, society, and all sectors take AI as the driving force and ultimate goal, AI will definitely be indispensable in the future. Only with such confidence can this path be truly pursued. (U4)
		Peer influence to adopt AI	2	For example, we haven't had much exposure to artificial intelligence, but over time, through some friends, like our suppliers and customers who often talk to me about AI, we are gradually able to accept it. (I3)

	Requirements of customer	Customers focus on the quality of garments not the technology they used	5	They don’t care whether your work is produced intelligently or manually; as long as the quality is good, that’s enough. (I11)
		Customer requirements are complexed	2	Customers care about your craftsmanship, sewing details, and whether the patterns fit their body shapes. Even if the 3D modeling is done well, it’s not very applicable to them because they might be B-end customers whose needs haven’t reached that level yet. So, it remains a conceptual tool. (I6)
	Complicated Management	Complex supply chain management	3	We are just one part of the supply chain, which is very long. You should explore further upstream. (I6)
		Management process is too complicated to adopt AI	3	Streamlining the process is indeed very difficult. (I6)
	Market uncertainty	The demand of labor force is increasing	3	As orders continuously expand, the demand for people increases. (I1)
		Market shift	8	Our difficulty lies in the sharp decrease in the number of stores, which leads to fewer customers. Consequently, we produce far fewer products and don’t need to do much. (I7)
University Factors	Lack of disciplinary graduates	University cannot cultivate talents industry required	5	This doesn’t quite align with us because we focus more on specialties. If schools don’t offer these specialties, such as sportswear and performance fabrics, very few students can adapt. (I8)
		Talent requirement	4	The kind of talent you just mentioned is indeed what’s needed. System development and subsequent maintenance require skilled professionals. (A1)

		Students do not have access to intelligent equipment	3	If manufacturing truly transitions to being technology-driven, it will likely attract more scientific and technical talent and expose them to advanced technology and equipment. This could change their mindset and also guide employment trends. (U4)
		Lack of AI talents for the new emerging AI department	9	If AI is introduced, it could also attract highly knowledgeable talent into traditional industries. High-performance equipment can disrupt and transform traditional industries. We don't just need people skilled in making clothes but also engineers, those in industrial engineering, and professionals skilled in software system development. (I3)
		Lack AI talents in fashion specialties	5	These enterprises and schools are still mainly focused on designers and pattern makers, but pattern design is becoming less common and is mostly design-oriented. When it comes to AI, I have had limited exposure to places like Dalian University of Technology. (A1)
		Lack of technological employees	2	In reality, we lack industrial workers rather than technical or managerial talent. While there's a shortage of those as well, with proper training, they can adapt to this level. But the fundamental issue lies in the competitiveness of the industry itself. (A2)
		Lack of disciplinary talents in the fashion manufacturing sectors	2	Natural fabrics with enzymes involve chemical knowledge and even food science. If you're solely trained in fashion, you might know nothing about this. Fabrics are composed of chemical materials, making the field of fashion inherently interdisciplinary. (I2)
	Awareness of talent cultivation	Teachers' educational value	5	Not knowing how to use it is secondary; many students have already started teaching themselves. If students are learning and using it, but as a teacher, you don't know how or don't understand it, then you're really not fit to be a teacher, right (U3)
		The direction of student cultivation does not satisfy AI requirements	8	The knowledge taught in schools is essentially useless for our companies. (I1)

		Knowledge level gaps	15	For industrial transformation, the most important thing is the completeness of university teachers' knowledge frameworks. They need to have a comprehensive understanding of the industry, including in-depth knowledge of tools, to perfectly integrate those tools into different fields of work. This is crucial. (U1)
		Teachers' awareness	3	If university teachers lack foresight and don't believe artificial intelligence will bring changes, they will eventually be eliminated in the teaching process. (U4)
		Constraint knowledge of both educators and students	11	This is especially true for art teachers, who believe that design should focus on students' originality, while technology is secondary. However, with the rapid development of artificial intelligence, we must take it seriously. If not, we'll truly be left behind. (U2)
		Passively accept knowledge in universities	2	He is inherently self-driven, creative, proactive, and dynamic, rather than passive. However, he is constrained by the framework of the talent cultivation system within the school. For instance, the limitations of the curriculum might prevent him from exploring another field he is curious about. There might not be such a program, or as you mentioned earlier, there might not be the faculty resources to teach him what he wants to learn. I feel that, in fact, there isn't any university or educational institution today that can fully cover the most advanced and current developments in the world (I2)
		Lack of meaningful university-industry collaboration	5	The association is also exploring university-enterprise collaboration. From what I know, collaboration in Dalian mainly focuses on product development and lacks technological influence. (A2)
Government Factors	Government support	Regional policy distribution through association sectors	9	They have such associations, but they mostly exist to fulfill policy-related tasks and address very few actual problems. (I5)
		Lack of association support effectiveness	2	Other than informing me about Dalian Fashion Week or asking about exhibition fees, there's practically nothing else. (I7)

		Rely on the government support	5	If the government had supportive policies, many things would become much easier. (A1)
		Limited resource of AI knowledge	3	We serve mass chemical enterprises. For example, 80% of enterprises meet the policy requirements, so we provide services for them. As for niche companies, we rarely interact with them. (A1)
		Geographical disparities	6	Some southern companies are doing quite well in this regard, while in the north, there is relatively less involvement. (U1)
	Neglecting apparel manufacturing MSMEs	The apparel manufacturing is not a key supportive industry	6	Schools seem to approach it from a design perspective, with little official funding support. AI application in art fields is almost non-existent, but there's a clear policy inclination toward engineering and AI-related fields. (U1)
		Governments invest only to large sized firms	4	The government's support in this area is relatively strong, and many Japanese-funded companies enjoy national treatment. For instance, Jian Shan receives government subsidies, but other Chinese small-sized enterprises are excluded due to eligibility thresholds. (A2)
		Priority for large sized firms	6	The company must have scale to avoid waste. For instance, if you only have 30 orders, and I set up an intelligent system for you, once you're done with the work, the system becomes useless. (I1)
		Universities prefer to cooperate with large sized enterprises	2	Some large dyeing factories collaborate with textile colleges, offering internship opportunities. (I3)
		Information gap	3	In 2020, during the pandemic, the deputy district mayor visited us for an inspection and added me on WeChat. He shared a document from the Ministry of Commerce, asking if we had ever participated in overseas exhibitions. It turns out the government offers subsidies for this. I didn't know about it before—I used to pay for these trips myself, which cost a lot. (I7)
		Policy support but no financial support	5	There is some policy support for using AI, but no subsidies for now. (I3)

Another significant concept is self-involution (in Chinese is 内卷), which is a socio-cultural phenomenon characterized by excessive competition and internal focus without yielding significant external gains. It is particularly relevant to understanding barriers to AI adoption in Chinese apparel manufacturing industry. This phenomenon manifests in several interconnected ways, including competitive pressure, price competition, and peer-driven dynamics, all of which contribute to a culture of resistance or misalignment in adopting transformative technologies like AI.

One of the most significant aspects of self-involution is competitive pressure to adopt AI, which is referenced seven times in the dataset. This pressure often leads to reactive and short-term decision-making, unlike constructive competition, which drives innovation. As one respondent noted,

"I don't think this can be called a consumer group; it is caused by peer competition. It's all due to intense internal competition" (I4). This response states that AI is not brought in by firms to enhance operational efficiency or customer satisfaction in a way that is genuine but is in fact instead being used as a defensive posture to catch up to rivals. This competition creates a zero-sum mentality (Kakkar & Sivanathan, 2022), in which firms prefer fragmented and non-sustainable implementations.

Price competition, mentioned three times, is another facet of self-involution that fully undermines the market's capacity to leverage AI's potential. Firms often prioritize cost-cutting strategies over technological investments in a hyper-competitive pricing environment (Lochmann & Steger, 2002). A respondent explained,

"Taobao has now introduced a price comparison system that offers many similar products at the time of payment. This mechanism disrupts the market; the Red Ocean strategy relies on price competition and somewhat undermines healthy market development" (I4). This seeks to show that the industry case concerning price wars prices the AI product lower than the company that focuses on the long-term benefits of process automation and efficiency improvements. Therefore, a company is less likely to use AI technologies because of the possibility of a low-margin, high-volume manufacturing cycle.

The future AI trend to adopt AI reveals an aspirational but constrained perspective within the industry. While some recognize AI as an inevitable force, this awareness is not translated into immediate action. One participant stated,

"If someone truly wants to follow the path of AI, or if the entire industry, society, and all sectors take AI as the driving force and ultimate goal, AI will definitely be indispensable in the future" (U4). This highlights a cultural tension between the long-term acknowledgment of AI's importance and the short-term pressures of competition and survival. This disconnect often leads to procrastination, as firms defer investments until broader systemic changes compel adoption.

Peer influence to adopt AI, also mentioned two times, further illustrates how self-involution drives reactive, rather than proactive, technology adoption. One respondent observed,

"For example, we haven't had much exposure to AI, but over time, through some friends, like our suppliers and customers who often talk to me about AI, we are gradually able to accept it" (I3). This suggests that peer influence often impacts AI adoption (Cao et al., 2021; Talukder & Quazi, 2011). Firms are hesitant to invest in AI until their peers or competitors demonstrate its viability, leading to delaying widespread adoption.

This scenario is deeply rooted in the Chinese cultural phenomenon of "卷" (self-involution) (Ni et al., 2024), where excessive internal competition encourages companies to focus on immediate survival rather than long-term innovation. In this environment, companies are reluctant to take risks, instead prioritizing the benefits and impact of adopting AI with their competitors or peers. This culture not just causes the delay of the AI system; it is also the case in the fact that companies are kept from using the full spectrum of these technologies to attain uniqueness and advancement. Self-involution is also closely tied to other barriers, such as financial constraints and managerial decision lag. For instance, intense competition reduces profit margins, making it harder for firms to justify AI investments. Similarly, the reactive nature of AI adoption driven by peer influence compounds managerial hesitation, as leaders prioritize short-term strategies over long-term technological planning. These interconnections highlight the systemic nature of self-involution as a barrier to AI adoption in the Chinese apparel manufacturing industry.

The systematic management category indicates that many common dilemmas afflicting apparel manufacturers are mainly organizational issues that stand in the way of AI adoption. This theme concerns the problems of controlling complicated supply chains and the proper management of operations, which are the imperative conditions for successfully introducing AI into the business. Sustainable inefficiency in any given decade among these challenges increases the difficulty for organizations in taking full advantage of the scope of activities that AI has.

One prominent issue is complex SCM with the frequency of three. The apparel manufacturing industry is characterized by extensive and fragmented supply chains (Christopher et al., 2004), often involving multiple stakeholders across raw material procurement, production, and distribution. One respondent described this complexity succinctly:

"We are just one part of the supply chain, which is very long. You should explore further upstream" (I6). This indicates that businesses frequently lack understanding and governance over the entire supply chain, hindering their ability to use AI-driven solutions efficiently. For example, the efficiency of AI in the procurement process or logistics begins with the comprehensive collection of real-time information across the supply chain.

Additionally, the complication of management processes, also mentioned three times, further restricts AI adoption. Streamlining operations, a prerequisite for successful AI integration, is perceived as a challenging task. One participant noted,

"Streamlining the process is indeed very difficult" (I6). This reflects the traditional apparel industry's heavy reliance on legacy systems, which hinders applying AI. Without streamlined processes, implementing AI solutions becomes more complex.

The complex interactions between these factors create a difficult cycle: the fragmentation of supply chains contributes to increasing complexity in management, which in turn creates fragmentation in supply chains, further deepening the problem. To illustrate, firms that are characterized by segmented supply chains find it difficult to optimize their internal processes due to having to consider the elements of variability and unpredictability that are brought about by the involvement of external stakeholders. On the other hand, poor internal management practices hinder the coordination of the supply chain partners and this results in a lack of feasibility for the integration of AI technologies in the supply chain.

Workforce readiness adds another layer of complexity. The aging workforce, referenced seven times, reflects the sector's demographic challenges. As one respondent noted,

"With the 70s' generation retiring, even fewer from the '80s generation are entering the industry. You must adopt intelligent solutions" (I4). This highlights the diminishing pool of skilled labor, which AI systems could potentially alleviate, but the low educational level of apparel workers, also cited 6 times, limits their ability to effectively operate advanced AI technologies. A participant remarked, *"Due to workers' skill levels and knowledge reserves, many errors are frequent, and work progress is slow" (I4).* Thus, the lack of technical expertise creates a bottleneck, as the implementation of AI systems often requires skilled operators who can oversee and optimize their performance.

Market uncertainty compounds these barriers, with eight mentions of "market shift" reflecting the volatile nature of consumer demand and retail environments. As respondent I7 complained,

"*Our difficulty lies in the sharp decrease in the number of stores, which leads to fewer customers" (I7)*. This unpredictability discourages manufacturers from making long-term investments in AI, as fluctuating demand reduces the likelihood of achieving consistent returns. Additionally, customer requirements, with five mentions of their focus on quality over technology, reveal another misalignment. One respondent stated,

"They don't care whether your work is produced intelligently or manually; as long as the quality is good, that's enough" (I11). This reduces the perceived value of AI, further limiting its adoption despite its potential to enhance efficiency and precision.

The above interconnectedness of industry challenges suggests that technical limitations in handling garment complexity increase operational risks, which are further amplified by financial constraints and managerial hesitation. Workforce unpreparedness exacerbates these issues, as a lack of skilled operators reduces the efficacy of AI systems, while market volatility and customer expectations limit the perceived benefits of AI adoption. All these systemic barriers require a holistic approach to overcome.

5.4.2. University Factors

University factors highlight the critical gap between educational outputs and the industry's evolving needs in the context of AI integration. The lack of alignment between university programs and industry requirements, combined with insufficient technological exposure, creates a significant talent bottleneck. These limitations impede the apparel manufacturing industry's ability to leverage AI effectively, as the necessary skills and knowledge have not been either unavailable or inadequately developed yet.

A recurring theme within university factors is the inability of universities to cultivate talents required by the industry, with five mentions underscoring this challenge. The lack of specialized programs tailored to emerging areas, such as AI applications in apparel manufacturing, is a significant concern. One respondent remarked,

"This doesn't quite align with us because we focus more on specialties. If schools don't offer these specialties, such as sportswear and performance fabrics, very few students can adapt" (I8). This reflects

a disconnect between academia and industry, where universities continue to emphasize traditional design-oriented training at the expense of integrating advanced technologies. Consequently, graduates often lack the technical proficiency needed to operate, maintain, or innovate within AI-enabled systems.

Relatedly, talent requirements for system development and maintenance were cited four times as a critical gap. AI implementation requires not just theoretical knowledge but also practical skills in software development, engineering, and industrial systems. As one participant noted,

"The kind of talent you just mentioned is indeed what's needed. System development and subsequent maintenance require skilled professionals" (A1). This highlights the industry's demand for multidisciplinary knowledge that combines apparel knowledge with engineering and data science. However, current educational programs are failing to meet.

Another barrier is that students lack access to intelligent equipment, mentioned three times. Without hands-on experience with AI technologies, students are ill-prepared to address the practical challenges of integrating and operating such systems in real-world manufacturing environments. A participant stated,

"If manufacturing truly transitions to being technology-driven, it will likely attract more scientific and technical talent and expose them to advanced technology and equipment" (U4). This suggests that exposure to cutting-edge tools during education could not only enhance skill development but also shift employment trends, attracting more talent to technologically advanced industries.

The lack of AI talents for emerging AI departments emerged as the most frequently mentioned challenge in this category, with nine occurrences. Respondents pointed out that AI adoption is not limited to creating new opportunities within the industry but also requires the transformation of traditional roles. One respondent remarked,

"If AI is introduced, it could also attract highly knowledgeable talent into traditional industries. We don't just need people skilled in making clothes but also engineers, those in industrial engineering, and professionals skilled in software system development" (I3). This highlights the transformational potential of AI, provided universities can adapt their curricula to include these emerging roles. The gap, however, is significant, as most institutions have not yet developed comprehensive AI-focused programs that align with the interdisciplinary demands of the industry in China.

Compounding these challenges is the lack of AI talent in fashion specialties, with five mentions indicating the difficulty of integrating AI into design and pattern-making processes. One participant noted,

"These enterprises and schools are still mainly focused on designers and pattern design, but pattern design is becoming less common and is mostly design-oriented. When it comes to AI, I have had limited exposure to places like Dalian University of Technology" (A1). This underscores the limited scope of AI applications in fashion, which remain confined to isolated academic or experimental contexts rather than being incorporated into mainstream curricula.

A notable sub-theme within the broader university factors is the lack of interdisciplinary talents in the fashion manufacturing sectors, mentioned 2 times. This issue reflects the increasing complexity of modern fashion manufacturing, which demands expertise that transcends traditional design and production skills. As respondent I2 highlighted, *"Natural fabrics with enzymes involve chemical knowledge and even food science. If you're solely trained in fashion, you might know nothing about this. Fabrics are composed of chemical materials, making the field of fashion inherently interdisciplinary" (I2).* This statement underscores the multifaceted nature of the challenges facing the industry, where the integration of advanced materials, sustainability, and AI technologies requires knowledge spanning multiple disciplines.

Nowadays, apparel manufacturing is not limited to the aesthetic part of design and tailoring. Thanks to innovations in fabric technology, integrative bio-based materials, enzyme treatments, etc. (Rahman et al., 2022) drive talents to acquire knowledge of chemistry, material science, and biology. However, the current academic frameworks held by many universities are still centered on one discipline, with fashion programs purely being the place of artistic and design-oriented curriculums. This gap leaves graduates with a dilemma in fulfilling the demands of new technology and science in the contemporary production of clothes, and it is a major difficulty in the incorporation of AI.

The consequences of this multidisciplinary gap are twofold. First, it is the barrier to progress in the industry's use of state-of-the-art technologies in fabric and material sciences, owing to workers lacking the essential skills to adopt and leverage innovations. Second, it is worsening the obstacles to AI adoption in the industry, where the successful integration of AI usually involves the partnership of technologists, material scientists, and designers. The underlying reason for this is that it is almost always impossible to apply the AI technology of material selection, performance testing, and production optimization without staff who are the ones linking these sectors.

This interdisciplinary challenge is closely tied to the broader educational gaps highlighted earlier. Universities' failure to incorporate diverse fields into fashion-related programs not only reduces the industry's access to skilled talent but also perpetuates a culture of specialization that is increasingly misaligned with industry needs. Furthermore, this gap interacts with workforce readiness challenges, as existing employees lack the opportunity to reskill in areas outside their original training.

Thus, the concept of "lack of technological employees", mentioned 2 times, reflects broader workforce challenges. Even with proper training, the absence of a strong base of technically proficient workers limits the industry's ability to scale AI solutions. As one respondent explained,

"While there's a shortage of those as well, with proper training, they can adapt to this level. But the fundamental issue lies in the competitiveness of the industry itself" (A2). This statement points to the structural nature of this barrier, where educational gaps are compounded by industry-wide competitiveness challenges that further deter investment in skill development.

The awareness of talent cultivation as a key axis in university factors reveals how gaps in recognizing the importance of AI-related talent development hinder the apparel manufacturing industry's AI adoption. This challenge is rooted in the misalignment of educational priorities, a lack of forward-thinking strategies among educators, and insufficient emphasis on preparing students for the demands of AI-driven industries.

One significant aspect of this axis is the teachers' educational value, cited 5 times, which highlights the limitations in how educators contribute to talent cultivation. The issue lies not only in the content being taught but also in the educators' ability to understand and teach emerging technologies effectively. Respondent U3 observed,

"Not knowing how to use it is secondary; many students have already started teaching themselves. If students are learning and using it, but as a teacher, you don't know or don't understand it, then you're really not fit to be a teacher, right?". This statement underscores a fundamental issue: the lag in educators' technical competence undermines their role in preparing students for technology-centric roles. When students are forced to self-teach critical skills, the formal education system fails to fulfill its role as a primary knowledge source.

Another major issue is the direction of student cultivation, mentioned eight times, which reflects a broader misalignment between university curricula and the skillsets required by AI-driven industries. I1 respondent remarked,

"The knowledge taught in schools is essentially useless for our companies". This illustrates how the existing education system focuses on traditional and generalized knowledge areas, which are no longer adequate for meeting the demands of advanced manufacturing environments. Programs often lack the specificity needed to train students in interdisciplinary fields like AI for apparel manufacturing, leaving graduates ill-equipped for modern industry challenges.

The disconnect between universities and the industry further exacerbates this problem, as educators and administrators fail to adjust their strategies to meet the rapidly evolving technological landscape. Instead, curricula remain focused on conventional disciplines, leaving critical gaps in areas such as software systems, engineering, and AI applications in apparel manufacturing.

This lack of awareness and focus on cultivating relevant talent is deeply interwoven with other university factors, particularly knowledge level gaps and constraint knowledge in educators and students. When educators themselves are not equipped to understand or value AI's role in transforming the industry, they are less likely to prioritize its integration into their teaching. As one respondent noted,

"If university teachers lack foresight and don't believe AI will bring changes, they will eventually be eliminated in the teaching process" (U4). This resistance to change perpetuates a cycle where students are denied exposure to the skills and technologies needed for future industry demands.

The emphasis on maintaining traditional teaching methods and subject areas also reflects a cultural resistance to change within universities. This cultural inertia stems from a lack of accountability for aligning education with industry outcomes and a broader skepticism toward AI's role in reshaping the apparel manufacturing sector. Such resistance limits the proactive development of innovative programs that could bridge the gap between education and industry, further delaying progress.

In addition to the previously discussed gaps in talent cultivation, passively accepted knowledge in universities and the lack of impactful university-industry collaborations further hinder the alignment of academic outputs with the needs of AI-driven industries. These problems are mainly related to the structural and cultural limitations of the education system, which prevent students from freely exploring interdisciplinary fields and prevent collaboration between academia and industry. As mentioned twice before, the passive acceptance of knowledge in universities exposes a key problem in the traditional education system. Although students themselves are creative and motivated to learn, the reality is that they are often trapped in a fixed curriculum framework, unable to really try something beyond the established subject. One interviewee said,

"He is inherently self-driven, creative, proactive, and dynamic, rather than passive. However, he is constrained by the framework of the talent cultivation system within the school. For instance, the limitations of the curriculum might prevent him from exploring another field he is curious about. There might not be such a program, or as you mentioned earlier, there might not be the faculty resources to teach him what he wants to learn" (I2). This illustrates how the inflexible nature of the education system stifles innovation and makes it difficult for students to engage with emerging fields like AI that require interdisciplinary understanding. The structural rigidity is not just a constraint on individual students, it also creates a mindset in the entire academic environment that knowledge is fixed rather than something that needs to be constantly developed. As the respondent further stated, *"In fact, there isn't any university or educational institution today that can fully cover the most advanced and current developments in the world" (I2)*. This disconnect between the academic curriculum and the real world is symptomatic of a larger problem: universities often fail to keep pace in the face of a rapidly changing technological landscape. Moreover, the lack of valuable collaboration between universities and industry, which has been mentioned five times, also makes talent development more difficult. While there are some collaborations between universities and companies, they are usually narrow in focus and often revolve around clothing design rather than technological innovation. One interviewee mentioned,

"The association is also exploring university-enterprise collaboration. From what I know, collaboration in Dalian mainly focuses on garment design and lacks technological influence" (A2). This indicates that these collaborations fail to integrate cutting-edge AI technologies into the manufacturing processes, limiting their impact on both student training and industry outcomes.

The lack of a truly effective cooperation mechanism between universities and enterprises makes it difficult for students to be exposed to the practical application of AI technology, and enterprises cannot find talent that truly meets their needs. As a result, the disconnect between academia and industry becomes more and more serious, and eventually becomes a cycle - students are not ready, companies are not able to use the new technology, and innovation is difficult to achieve.

5.4.3. Government Factors

Under China's governance system, government factors play a central role in promoting the application of AI in the garment manufacturing industry. Although the government's top-down approach to policymaking has ambitious goals and hopes to promote innovation, in practice, the results are often uneven because of regional differences and uneven allocation of resources. Coupled with institutional inefficiencies, a lack of localized support, and a more decentralized governance structure, these issues make it more difficult for AI to land in the garment manufacturing industry. These phenomena, in essence, are the result of China's political and economic environment.

The Chinese government frequently relies on intermediary organizations, such as industry associations, to implement policies and distribute support. With nine mentions, this reliance is a key mechanism for policy dissemination, yet it often lacks efficacy. One respondent observed, *"They have such associations, but they mostly exist to fulfill policy-related tasks and address very few actual problems" (I5)*. This reflects a systemic problem in China's decentralized policy enforcement model, in which local associations place more emphasis on administrative compliance than on providing real on-the-ground support. This problem is particularly pronounced in some regions with limited technical capacity and resources, making it difficult for these associations to effectively guide manufacturers in the application of AI. Although the policy encourages the integration of AI, the lack of specific localization guidance makes it difficult for enterprises to start in actual operation, and it is difficult to convert macro goals into executable strategies. The mismatch between the goals of national policies and local implementation has also greatly reduced the actual effect of the government's promotion of AI applications.

The lack of effectiveness of association support, mentioned two times, further illustrates the shortcomings of this institutional model. In China, industry associations are often tasked with peripheral activities, such as organizing events or reporting compliance metrics, rather than providing substantive support to manufacturers. One respondent from MSMEs brand manager remarked,

"Other than informing me about Dalian Fashion Week or asking about exhibition fees, there's practically nothing else" (I7). This suggests that apparel associations are underutilized as channels for delivering meaningful support, such as training programs, funding assistance, or technical expertise related to AI. Administrative reforms in China have also had an impact on cross-regional investment (Shi et al., 2021). But from the perspective of the larger policy environment, many intermediaries still prefer to handle administrative matters rather than focus on driving innovation. As a result, manufacturers lack the necessary support when applying AI, and can only explore their own solutions to technical, financial and operational problems.

The previous factors further lead to a strong reliance of MSMEs on government support. This reliance, cited five times, underscores the industry's dependence on government-led initiatives to drive technological advancements. One respondent stated,

"If the government had supportive policies, many things would become much easier" (A1). This reflects a common phenomenon in China's manufacturing sector, where government policy is often the main driver of innovation because private companies invest relatively little in research and development. But this reliance also creates problems, as many manufacturers struggle to have the funding or autonomy to drive AI adoption without government subsidies or incentives. For example, many MSMEs in China have narrow profit margins themselves, and government subsidies mainly support technology upgrades. However, these subsidies are often allocated based on macroeconomic objectives, rather than precise support for specific industries or technologies, which also undermines their effectiveness in truly solving real problems in AI applications.

China's regional economic and industrial disparities further complicate the effectiveness of government policies in fostering AI adoption. With six mentions, geographical disparities emerged as a critical barrier, reflecting uneven access to resources and support across different regions. One respondent (U1) noted, *“Some southern companies are doing quite well in this regard, while in the north, there is relatively less involvement”* (U1). This situation illustrates the development gap between different regions of China, such as the Yangtze River Delta, the Pearl River Delta and other economically developed regions, manufacturers can enjoy more government investment, better infrastructure, and more technical talent. In contrast, enterprises in some less developed areas in the north are not so lucky, with limited capital, insufficient technical support, and the implementation of policies is not satisfied. This regional gap makes it easier for enterprises that already have advantages to apply AI technology and occupy market opportunities, while enterprises with fewer resources can only be left behind. In fact, this also reflects China’s “dual-track” economic development model (Wu & Zhou, 2024), different local governments can mobilize different resources and autonomy, and ultimately affect the actual effect of AI-related policies in different places.

Another critical barrier is the limited resource of AI knowledge, cited three times, which reflects a gap in the Chinese government’s approach to fostering technological applications in apparel manufacturing. While policies may emphasize AI adoption, they often fail to address the knowledge and expertise required to implement these technologies effectively. One respondent noted,

“We serve large-sized enterprises. For example, 80% of enterprises meet the policy requirements, so we provide services for them. As for small and medium sized companies, we rarely interact with them” (A1). This suggests that policies tend to favor larger, better-founded companies, while MSMEs have much less access to AI-related technical knowledge and training. This reflects a general problem in Chinese top-down policymaking, which often ignores the real needs of smaller, less visible players in the industry. Without targeted support programs to help manufacturers improve AI-related capabilities, the potential benefits of government policies will not be fully realized.

Another issue of the government factor is the neglect of MSMEs in the apparel manufacturing industry. When the Chinese government promotes the application of AI, it is often more inclined to support large enterprises, because these enterprises have more resources and scale, and can bring more significant returns. But this practice has implicitly marginalized the MSMEs that make up the majority of the industry. This neglect is reflected in many aspects, such as the tilt of financial support, the uneven distribution of cooperative resources, and the asymmetry of industry information.

In addition, the apparel manufacturing industry is not regarded as a key support industry, which was mentioned six times by respondents, and further illustrates the marginalization of the industry in the policy system. One interviewee mentioned,

“Schools seem to approach it from a design perspective, with little official funding support. AI application in art fields is almost non-existent, but there’s a clear policy inclination toward engineering and AI-related fields” (U1). This highlights the government’s focus on high-tech sectors, such as engineering and advanced manufacturing, at the expense of traditional industries like apparel. As a result, apparel manufacturers face challenges in securing the financial and technical support needed for AI adoption, even though the sector has significant potential for transformation through automation and smart technologies. This policy bias is indicative of broader trends in China’s economic development strategy, which prioritizes industries perceived as more technologically advanced or strategically

important. However, this approach overlooks the opportunity to modernize traditional sectors like apparel manufacturing, which remain labor-intensive and ripe for efficiency gains through AI.

Government policies also exhibit a clear priority for large-sized firms, mentioned 6 times, and a tendency to invest only in large enterprises, cited four times. One participant explained,

"The company must have scale to avoid waste. For instance, if you only have 30 orders, and I set up an intelligent system for you, once you're done with the work, the system becomes useless" (I1). This reflects a common perception that smaller firms lack the scale necessary to justify investments in AI systems, leading policymakers to concentrate resources on larger companies that are seen as more capable of implementing and benefiting from such technologies. However, this focuses on large enterprises neglects the unique challenges and opportunities within MSMEs. Smaller firms often face more acute resource constraints, making them prime candidates for targeted support that could enable them to adopt cost-effective AI solutions. Moreover, the exclusion of MSMEs from government support limits the overall impact of AI adoption on the industry, as these firms collectively represent a substantial share of production capacity and employment. This bias extends to university-industry collaborations, which also favor large enterprises. With two mentions, respondents noted that partnerships with educational institutions primarily benefit larger firms. One participant remarked,

"Some large dyeing factories collaborate with textile colleges, offering internship opportunities" (I3). This reflects how MSMEs are often excluded from such collaborations, further restricting their access to the knowledge and talent needed to integrate AI technologies.

The presence of information gaps, cited three times, further exacerbates the challenges faced by MSMEs. One respondent recounted,

"In 2020, during the pandemic, the deputy district mayor visited us for an inspection and added me on WeChat. He shared a document from the Ministry of Commerce, asking if we had ever participated in overseas exhibitions. It turns out the government offers subsidies for this. I didn't know about it before—I used to pay for these trips myself, which cost a lot" (I7).

This further illustrates the lack of communication between government agencies and enterprises, resulting in many enterprises simply not knowing what subsidies, grants or other support policies are available. This information gap is particularly acute for MSMEs, as they often do not have sufficient internal resources or industry connections to navigate complex policy environments. If the channel to obtain policy information is not clear and convenient, these enterprises will easily miss the opportunity to take advantage of government support, so that the gap between large and small enterprises in AI application is getting wider and wider.

In addition, the lack of corresponding funding for policy support, which was mentioned five times, also reflects the disconnect between policy objectives and actual implementation. Although the government encourages AI applications, without direct financial incentives, it is difficult for MSMEs to truly implement these policies. One interviewee mentioned,

"There is some policy support for using AI, but no subsidies for now" (I3). This reflects a broader trend where policies often emphasize long-term goals without addressing the immediate financial barriers faced by smaller firms. This lack of financial backing is particularly challenging in the context of MSMEs,

which operate on thin profit margins and cannot afford the upfront costs associated with AI implementation. Without subsidies or low-interest loans, these firms are unlikely to invest in the technologies needed to remain competitive, perpetuating a cycle of underinvestment.

In summary, the neglect of MSMEs in government policies reflects deeper structural and cultural biases within China's economic development strategy. By prioritizing large enterprises and high-tech industries, policymakers inadvertently marginalize MSMEs that play a critical role in the fashion industry. This approach also limits the broader impact of AI adoption, as the exclusion of MSMEs reduces the potential for widespread transformation across the industry. Furthermore, the reliance on information dissemination through informal channels, such as personal connections or localized networks, highlights inefficiencies in policy communication. These gaps reflect a broader need for more inclusive and transparent governance mechanisms that ensure all industry players, regardless of size, have equal access to resources and support.

5.5. Summary of Chapter

This chapter presents the results of the semi-structured interviews and grounded the emerging main conceptual categories using qualitative grounded theory (process) to theorize what required AI capabilities in Chinese apparel manufacturing sectors, and categorized the industry, universities, and government factors hinder them to adopt AI technologies in manufacturing and production processes (product). The two layers of findings will be further discussed in the next chapter, and theorize the AI-enabled innovation ecosystem. Combining with the analysis of ***Study 1*** and ***Study 2***, ***Chapter 6*** will also discuss these theoretical contributions and managerial implications in detail.

6. Discussions and Contributions

6.1. Introduction

This chapter discusses the results from ***Chapter 4*** and ***Chapter 5***, analyzing data from Chinese apparel manufacturing sectors to evaluate the determinants of AI-integrated technology adoption driving MSMEs' open innovation. It also develops a theoretical AI-enabled innovation ecosystem framework with proposed mechanisms. Section 6.2 addresses the SRQs of ***Study 1***, focusing on AI adoption, open innovation, KACAP mediation, and the hypothesized relationships. Section 6.3 discusses the grounded results, focusing on the SRQs of ***Study 2***. This is followed by Section 6.4, which achieves the MRO by developing an AI-enabled innovation ecosystem framework. Section 6.5 highlights the theoretical contributions and managerial implications, while Section 6.6 provides a synthesis discussion and conclusion summary of the chapter. Section 6.7 summarizes the chapter. The sequence of sections is illustrated in **Figure 6.1**.

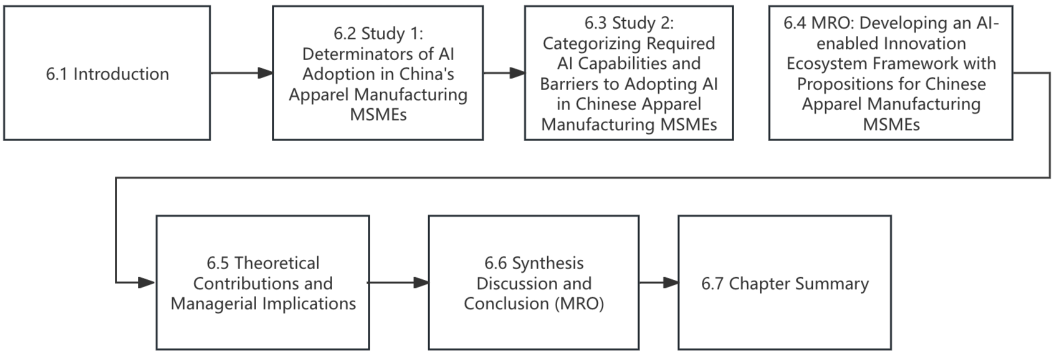

Figure 6.1 Flow Chart of Chapter 6

6.2. *Study1*: Determinators of AI Adoption in Chinese Apparel Manufacturing MSMEs

Study 1 consists of two ***SRQs***: 1) What factors affect AI adoption, KACAP, and open innovation in Chinese apparel manufacturing? 2) What is the role of KACAP in the linkage between AI adoption and organizational open innovation? This section primarily focuses on discussing these two issues. Thus, to discuss the results of ***SRQs***, this section follows the previous analysis phases by first inferences of preliminary analysis and then the hypothesized relationships.

6.2.1. Inferences of Preliminary Analysis

Data collected from Chinese apparel manufacturing MSMEs underwent screening for missing values, unengaged responses, outliers, normality, and common method bias. This preliminary analysis (Section 5.3) was conducted to prepare for descriptive statistics (Section 5.4) and PLS-SEM analysis (Section 5.5). The descriptive statistics provided insights into demographic characteristics, such as firm size, age, business types, and industry clusters.

The analysis revealed that most responses were collected through a third-party agency, ensuring complete data without unengaged responses. To maintain generalizability and minimize data modifications, outliers were retained based on established criteria (Tabachnick & Fidell, 2019). The dataset was also tested for normality using the Kolmogorov-Smirnov test, confirming its suitability for PLS-SEM analysis (Hair et al., 2022).

Common method bias, a potential concern when using third-party data collection services, was addressed through partial correlation analysis, revealing no significant effects on study correlations (Simmering et al., 2015). The structural model was robust, demonstrating high explanatory (R^2) and predictive power ($PLS_{predict}$) within the extended TAM-TOE framework. These findings highlight the reliability and quality of the dataset, supporting its application in this thesis.

6.2.2. Structural Equation Modelling – Hypothesized Relationships (*SRQs 1 and 2*)

This subsection presents the findings from the empirical analysis conducted using the PLS-SEM statistical approach. PLS-SEM involves a dual-stage process to evaluate the research model (Hair et al., 2022). The results begin with assessing the measurement model and confirming its adequacy for further analysis. Following this validation, attention shifts to the structural model, which forms the foundation for the subsequent discussion on the model's contributions. We drew on TAM and TOE to develop the extended TAM-TOE model to understand the antecedents behind AI adoption to influence open innovation. We examined that the 11 hypotheses from technological factors (H1 and H2), organizational factors (H3a and H4a), and environmental factors (H5, H6, H7, and H8) impact AI adoption. Meanwhile, organizational factors (H3b and H4b) directly impact KACAP, and environmental factors (H5b, H6b, H7b, and H8b) directly impact open innovation. Subsequently, the drivers of AI adoption (H9) towards open innovation (H10) through KACAP (H11).

6.2.2.1. Technology Factors

H1: Perceived usefulness will positively influence AI adoption.
H2: Perceived ease of use will positively influence AI adoption.

The study hypothesized that AI adoption would be positively influenced by perceived usefulness (H1) and perceived ease of use (H2); however, based on the results, the path coefficient of perceived ease of use (PEOU -> AIA) is 0.068, with a T-value of 1.033 and a p-value of 0.302, which does not meet the significance level of $p<0.05$. Therefore, it can be concluded that perceived ease of use has no significant impact on AI adoption. This outcome challenges the foundational assumptions of traditional technology adoption frameworks, such as the TAM, which posit perceived ease of use as a key determinant of technology acceptance (Chatterjee et al., 2021; Davis, 1989). In the case of AI, a more nuanced interpretation is required. AI technologies' increasing sophistication and complexity likely necessitate a shift in organizational priorities, where decision-makers emphasize the potential strategic benefits and innovative capabilities AI can unlock rather than its ease of use in short-term. For managers and executives, the perceived value of AI lies more in its capacity to transform business processes and confer competitive advantages than in its ease of use.

Moreover, this diminished role of perceived ease of use in the context of Chinese MSMEs, particularly those operating in OEM firms, may also be attributed to the sector's operational dynamics. These organizations, often resource-constrained, have likely developed a higher tolerance for technological complexity, viewing it as a necessary trade-off for potential gains in operational efficiency and market competitiveness (Dickson et al., 2006). As such, ease of use may no longer serve as a primary consideration when adopting advanced technologies like AI. Instead, perceived usefulness emerges as a more critical factor in driving adoption decisions, as reflected by its significant path coefficient of 0.228 and a statistically significant p-value ($p<0.05$), suggesting that organizations place a premium on the demonstrable benefits AI adoption can bring.

Thus, the limited significance of perceived ease of use in this context underscores a broader shift in technological adoption behavior, where the emphasis is placed on outcome-oriented assessments, focusing on the tangible impacts and strategic advantages offered by AI, rather than on minimizing user effort or system complexity.

6.2.2.2. Organizational Factors

Organizational complexity and ORE are two internal organizational factors hypothesized in this study. Both are proposed to impact AI adoption (H3a and H3b) and directly toward KACAP (H4a and H4b).

H3a: Organizational complexity will negatively influence AI adoption.

H3b: Organizational complexity will positively influence knowledge absorptive capacity.

Although the complexity has been demonstrated, its negative impacts on individuals' intentions to use AI (Chatterjee et al., 2021; Gangwar et al., 2015; Kamble et al., 2021; Tasnim et al., 2023) for adoption by organizations, the results on H3a and H3b reveal that organizational complexity does not exhibit a significant impact on AI adoption. This suggests that, within the context of this study, the structural complexity of organizations does not directly facilitate the adoption of AI technologies. High organizational complexity could impede decision-making processes, reduce information flow efficiency, and consequently, slow the adoption of new technologies.

The results also show that organizational complexity has no significant impacts on KACAP, which is in contrast with prior research that has highlighted the potential of complexity to shape knowledge processes within organizations. For example, complexity in organizational studies, as defined by structural differentiation (Ali et al., 2018; Robbins, 1990, as cited in Ali et al., 2018), has been shown to affect both the extent and intensity of knowledge creation and absorption (Kim, 1980). This perspective is built upon earlier theories, such as Cohen and Levinthal's (1990) work on absorptive capacity, which posits that the structural complexity of an organization facilitates the flow and integration of new knowledge, primarily by leveraging prior knowledge. In light of these findings, the insignificant relationship observed between organizational complexity and KACAP in this study might be explained by several factors. First, the level of organizational complexity in the firms sampled may not have reached the threshold necessary to enhance knowledge flows and foster absorptive capacity. While prior research suggests that increased differentiation can create opportunities for deeper knowledge integration, this may only hold in highly complex organizations with advanced structures. In contrast, the organizations in this study, particularly MSMEs in the apparel manufacturing sector, may exhibit relatively moderate levels of complexity that neither impede nor enhance the absorptive process. Second, the specific type of complexity at play could also be a determining factor. Previous studies, such as those by Winkelbach and Walter (2015), focused on advanced technological complexity, which may directly influence absorptive capacity more than structural complexity alone. It is possible that the type of organizational complexity referring to primarily structural does not sufficiently align with the kind of complexity that facilitates knowledge absorption, as proposed in prior theoretical frameworks. Third, while prior studies have consistently shown that organizational complexity can foster KACAP, the particular context, industry, and characteristics of complexity in this study may not align with the requisite conditions for such benefits to materialize. As a result, the influence of organizational complexity on knowledge absorption is likely context-dependent. Further investigation is required to clarify the circumstances under which complexity functions as an enabler rather than an impediment to knowledge absorption, contributing to a more refined understanding of its multifaceted role.

H4a: Organizational readiness will positively influence AI adoption.
H4b: Organizational readiness will positively influence knowledge absorptive capacity.

Another organizational antecedent is organizational readiness. As Lacovou et al. (1995) articulated, it encompasses the availability of necessary financial and technological resources required to adopt innovations. Several studies, including those by Kuan and Chau (2001), Aboelmaged (2014), and Chatterjee et al. (2021), highlight that larger organizations, due to their abundant resources, exhibit higher readiness and, consequently, a greater likelihood of adopting advanced technologies, such as AI. Financial resources ensure that firms can cover ongoing expenses during the implementation of AI, while technological resources, both tangible (e.g., infrastructure) and intangible (e.g., IT skills), enable effective integration of AI into business processes. The findings from H4a, however, show that organizational readiness does not significantly impact AI adoption despite theoretical support for this relationship in the literature. This discrepancy could be attributed to several factors. While organizational readiness, especially regarding resources, is a critical enabler, the actual decision to adopt AI might depend on other factors such as the organization's strategic alignment, cultural readiness, or the perceived usefulness of AI. For example, despite having adequate resources, firms may lack the managerial support or innovation mindset required to initiate AI adoption (Cao et al., 2021; Hashem & Aboelmaged, 2023). Additionally, industries in emerging economies might face external challenges, such as regulatory barriers or market uncertainty, which can reduce the efficacy of organizational readiness in driving AI adoption (Hossain et al., 2024). These findings suggest that while resources are necessary, they may not be sufficient for AI adoption, particularly if other organizational or contextual factors are not aligned.

On the other hand, the results of H4b show a significant positive relationship between organizational readiness and KACAP. This finding aligns with prior research that emphasizes the role of organizational readiness in enhancing a firm’s ability to assimilate and exploit new knowledge (Van den Bosch et al., 1999, as cited in Vega-Jurado et al., 2008). In this context, organizational readiness, particularly its intangible assets such as technical knowledge, collaboration strategies, and IT development plans, equips firms with the necessary infrastructure and skills to absorb and utilize external knowledge. This capacity is essential for organizations aiming to stay competitive in a rapidly evolving technological landscape, especially in sectors driven by AI and digital transformation. As Machado et al. (2021) noted, readiness is not just about resource availability but also about the organization's ability to adjust to digital transformation. Lokuge et al. (2019) further highlight that the readiness for adopting and exploiting digital technologies plays a critical role in shaping an organization's KACAP. The findings from H4b suggest that organizations with higher readiness levels are better positioned to acquire, integrate, and exploit new knowledge, thus fostering ACAP, which is crucial for leveraging AI-integrated technologies.

Thus, while ORE may not directly lead to AI adoption (as evidenced by H4a), it plays a significant role in building the foundational capacities necessary for knowledge absorption (as supported by H4b). This distinction highlights the multifaceted nature of organizational readiness, which may not always guarantee immediate adoption of advanced technologies like AI but provides the critical infrastructure and capabilities that underpin long-term organizational learning and innovation.

6.2.2.3. Environmental Factors

There are four antecedents behind AI adoption (H5a, H6a, H7a, and H8a) to drive open innovation, and four direct hypotheses of H5b, H6b, H7b, and H8b between the antecedents of AI adoption and open innovation.

H5a: Competitive pressure will positively impact AI adoption.
H6b: Competitive pressure will positively impact open innovation.

In the context of Chinese manufacturing MSMEs, competitive pressure emerges as a pivotal driver of AI adoption, aligning with existing literature findings. Competitive pressure, defined as the degree of pressure felt by firms from their competitors within the industry (Oliveira & Martins, 2010), has been recognized as a key factor influencing the adoption of innovative technologies, particularly in resource-constrained environments like SMEs (Dickson et al., 2006; Ghobakhloo, 2019). In Chinese apparel MSMEs, which operate in a highly competitive and fast-paced market, this pressure is further amplified by the challenges posed by globalization and digital transformation. Also, it is intensified by the need to adapt to Industry 4.0 and 5.0, respond to shifting market demands, and compete with other larger OEMs, ODMs, and OBMs. The results from H5a show a significant positive relationship between competitive pressure and AI adoption, which is in line with Ghobakhloo (2019) and Sayginer & Ercan (2020) studies that adopting AI is crucial to maintaining their competitiveness in a market where technological advancements are becoming essential for survival. These firms face constant threats such as suppliers' unsatisfying and unsustainable performance, market share loss, and customer disloyalty, which AI adoption helps mitigate by enabling faster production cycles, improving quality control, and enhancing customer responsiveness. However, unlike larger firms, apparel manufacturing MSMEs often lack the resources to develop or deploy advanced technologies internally. This forces them to adopt AI strategically, focusing on applications that deliver immediate efficiency gains or customer value, such as automating labor-intensive production processes or optimizing supply chain management. Therefore, competitive pressure in this context does not merely drive AI adoption as a reactive measure but also pushes MSMEs to innovate in cost-effective and targeted ways that align with their limited resource base, such as talent, equipment, knowledge, etc.

The findings from H5b indicate a significant positive relationship between competitive pressure and open innovation, which is particularly relevant for Chinese apparel MSMEs. Due to their limited internal capacities, these firms often rely on open innovation to compensate for their resource constraints, a notion supported by prior research (Aboelmaged, 2014; Z. Yang et al., 2015). Competitive pressure compels these firms to engage in external collaborations, leveraging partnerships with suppliers, research institutions, and technology providers to access new knowledge and innovations they cannot generate in-house. In the highly competitive Chinese apparel sector, MSMEs are constantly pressured to innovate quickly in response to fast-evolving market trends and customer expectations. This competitive pressure fosters a reliance on open innovation to enhance their technological capabilities, particularly in the context of AI adoption. Collaborating and drawing on external expertise allows these firms to adopt AI and tailor its applications to their specific production needs. For instance, partnerships with technology firms can help MSMEs develop AI-driven solutions for optimizing fabric usage or enhancing design customization, both of which are critical for maintaining competitiveness in a customer-driven market, especially for companies with design initiatives and proposals such as ODMs and OBMs.

H6a: Supplier involvement will positively influence AI adoption.
H6b: Supplier involvement will positively influence open innovation.

As previously noted, supplier involvement refers to suppliers engaging with downstream organizations to create competitive advantages, particularly in collaborative supply chain processes (Jöhnk, 2021; Oliveira & Martins, 2011). However, the results of H6a indicate that supplier involvement does not have a significant impact on AI adoption, suggesting that the role of suppliers in this context may be limited or indirect.

In Chinese apparel MSMEs, the supply chain is often complex, involving multiple stakeholders from raw material suppliers and their suppliers to brand customers or customers' customers. This finding can be explained by several industry-specific characteristics. First, the supply chain in this sector is often highly fragmented and hierarchical, involving multiple tiers of suppliers, from raw material providers to finished product distributors (Horani et al., 2023). This fragmentation reduces the influence of any single supplier in driving technological advancements like AI adoption. Many suppliers focus on fulfilling operational tasks rather than contributing to strategic innovations, such as implementing AI technologies. Second, Chinese apparel MSMEs typically prioritize cost efficiency and production volume over technological collaboration with suppliers. While larger enterprises in other industries might engage suppliers in AI-driven process improvements, MSMEs in apparel manufacturing may lack the resources or incentives to leverage supplier involvement for such purposes. Consequently, suppliers often play a more transactional role rather than a transformative one. Third, the adoption of AI in Chinese apparel industry often faces resource constraints and low digital maturity, further limiting the potential for supplier-driven AI implementation. Suppliers in this sector may themselves lack the technical expertise or capacity to support AI adoption effectively.

The positive relationship between supplier involvement and open innovaiton in H6b is supported by existing literature and reflects the realities of Chinese apparel MSMEs. Open innovation, as defined by Gassmann and Enkel (2004), emphasizes the importance of external collaborations, including partnerships with suppliers, to facilitate the flow of valuable knowledge and co-create innovative solutions. In Chinese apparel industry, MSMEs often rely on external partners, such as suppliers, to access new technologies and knowledge that they cannot generate internally. This aligns with findings from studies by Guan et al. (2023), which indicate that supplier partnerships (*guanxi*) are crucial for advancing innovations in sectors such as AI-integrated blockchain technologies.

For Chinese MSMEs, engaging in open innovation with suppliers is not merely a reactive response to market pressures but a proactive strategy to enhance their innovation capacity. Equipment suppliers are often at the forefront of technological advancements, providing access to the latest AI-based systems and solutions. By integrating suppliers early in the innovation process, MSMEs can tap into external knowledge, which accelerates internal innovation and improves their ability to compete in a rapidly changing industry (Hagedoorn, 1993; 2002). This collaboration with suppliers is essential for fostering open innovation, as it allows firms to co-develop AI applications tailored to their specific needs, whether in production optimization, supply chain transparency, or customer engagement. This supports the view of open innovation as a framework that leverages both internal and external knowledge to drive innovation performance, as noted by Chatterjee et al. (2021) and Lokuge et al. (2019).

H7a: Market uncertainty will positively influence AI adoption.
H7b: Market uncertainty will positively influence open innovation.

Tracing back to market uncertainty, adapted from the concept of environmental uncertainty, refers to the lack of information and predictability regarding changes in the external business environment, which can impact organizational decision-making (Duncan, 1972; López-Gamero et al., 2011). This unpredictability arises from various factors, including evolving technologies, fluctuating market conditions, and unforeseen events such as the COVID-19 pandemic, which disrupted global supply chains and increased uncertainty in production and operations (X. Lu et al., 2022). In the case of Chinese apparel MSMEs, which operate in a highly competitive and dynamic environment, market uncertainty can have a profound impact on their decision to adopt AI technologies.

As noted in previous literature, AI plays an important role in mitigating the effects of market uncertainty through its advanced data processing, forecasting, and decision-making capabilities (Bai & Li, 2020; Cannas et al., 2023). In apparel manufacturing sectors, AI enables firms to predict market trends, analyze customer demand, and control potential disruptions caused by supply chain instability

(Brau et al., 2023; Dey et al., 2023). For China's MSMEs, which often struggle with unpredictable customer demand and volatile market conditions, adopting AI can provide a strategic advantage by reducing the uncertainty associated with future market developments. This is particularly relevant given the resource constraints typical of MSMEs, where the ability to make informed decisions about production, inventory, and distribution can significantly improve operational efficiency and competitiveness. The data supporting H7a may reveal a significant positive relationship between market uncertainty and AI adoption. This would indicate that as market uncertainty increases, MSMEs are more likely to adopt AI technologies to cope with unpredictability. AI provides firms with the tools to reduce the risks associated with volatile market conditions, enabling them to make informed decisions and improve operational efficiency.

H7b explores the relationship between market uncertainty and open innovation. Open innovation involves leveraging external knowledge and collaborations with partners, suppliers, and other stakeholders to drive innovation within the firm (Gassmann & Enkel, 2004). In the face of high market uncertainty, firms often seek external expertise and resources to navigate unpredictable changes and maintain their competitive edge. Engaging in open innovation becomes a critical strategy for managing market uncertainty for Chinese apparel MSMEs, which may lack extensive internal R&D capabilities. Collaborating with external partners—such as suppliers, AI technology vendors, or research institutions—enables these firms to access cutting-edge knowledge and resources they cannot develop in-house, which is aligned with the RBV and KBV. This is particularly important in the apparel sector, where rapid changes in market demand and consumer preferences can quickly render existing products or processes obsolete. The results for H7b might indicate a significant positive relationship between market uncertainty and open innovation, suggesting that firms are more likely to engage in open innovation activities as market uncertainty increases. In response to unpredictable market conditions, Chinese apparel MSMEs may form partnerships with suppliers and other external stakeholders to co-develop new AI-driven solutions that improve their ability to forecast demand and adjust to market shifts (Horani et al., 2023). This collaborative approach helps these firms not only to manage risks but also to seize competitive opportunities that arise from market volatility.

H8a: Government support and policy will positively influence AI adoption.
H8b: Government support and policy will positively influence open innovation.

H8a explores the relationship between government support and policy and AI adoption. Government support refers to the facilitation provided to organizations, such as financial incentives, pilot programs, training, and scientific resources, and policy releases to encourage the adoption of new technologies (Badghish & Soomro, 2024). In the context of Chinese apparel MSMEs, government policies and incentives play a crucial role in promoting AI adoption, particularly given the limited resources and technical expertise that many MSMEs face. Previous studies have consistently shown that government support is a key driver in adopting AI technologies (Badghish and Soomro, 2024; Jun et al., 2019). In China, government-led policies that foster Industry 4.0 and digital transformation further accelerate the adoption of AI by offering subsidies, tax breaks, and innovation grants to MSMEs in manufacturing sectors, including apparel. These policies provide financial and technical support for MSMEs to overcome barriers to AI adoption, such as high implementation costs and a lack of skilled labor.

The results of H8a reveal a significant positive relationship between government support and policy and AI adoption, underscoring the importance of governmental facilitation in technology diffusion within MSMEs. For Chinese apparel MSMEs, which often struggle with limited resources, government support is critical for enabling AI adoption by lowering the financial and operational risks associated with integrating new technologies. Furthermore, government policies create a favorable environment for MSMEs to adopt AI, not only by offering direct support but also by fostering an ecosystem where digital technologies are increasingly essential for maintaining competitiveness in both domestic and global markets.

H8b examines the influence of government support and policy on open innovation in Chinese apparel MSMEs. Open innovation involves leveraging external and internal knowledge sources, often through collaborations with suppliers, customers, and other partners, to drive innovation (Gassmann & Enkel, 2004). Government support and policy are often assumed to facilitate these collaborative efforts by promoting knowledge-sharing initiatives, funding collaborative R&D projects, and establishing innovation ecosystems. However, the results of H8b reveal that government support and policy does not have a significant impact on open innovation in Chinese apparel MSMEs, contrasting with prior research emphasizing the enabling role of government policies in fostering innovation practices (Akbari & Hopkins, 2022; Tang et al., 2023). This nonsignificant relationship can be attributed to the following aspects. First, government policies promoting innovation are often designed with high-tech or large-scale industries in mind, leaving traditional sectors like apparel manufacturing, especially MSMEs, underserved. Many of these policies may lack alignment with the practical needs of apparel MSMEs, which often prioritize cost efficiency and operational stability over collaborative innovation. As a result, policies aimed at fostering open innovation may not resonate with the operational realities of smaller apparel firms. Second, limited absorptive capacity among MSMEs in Chinese apparel industry further diminishes the impact of government support. Effective participation in open innovation initiatives often requires a certain level of internal technical expertise, R&D capability, and managerial capacity to integrate external resources. Many MSMEs in this sector operate with constrained resources and lack the capacity to leverage government-provided grants, innovation platforms, or collaborative opportunities, reducing the effectiveness of government support and policy in driving open innovation practices.

6.2.2.4. AI Adoption, KACAP, and Open Innovation

H9 explores the relationship between AI adoption and KACAP, grounded in the ACAP framework introduced by Cohen and Levinthal (1990). ACAP refers to a firm's ability to acquire, assimilate, transform, and apply external knowledge to achieve innovation and maintain competitiveness (Zahra & George, 2002). In the context of Chinese apparel MSMEs, the adoption of AI represents a critical knowledge-based resource that can significantly enhance a firm's ACAP. AI technologies, with their capabilities in data processing, knowledge management, and predictive analysis, enable firms to absorb external information better and integrate it into their internal processes, thus increasing their innovation potential (Kinkel et al., 2022).

The significant positive relationship in H9 indicates that AI adoption enhances KACAP in Chinese apparel MSMEs. This result aligns with previous literature, such as the work of Adamides and Karacapilidis (2020) and Kastelli et al. (2024), demonstrating that AI is a catalyst for improving a firm's ability to recognize and exploit valuable external knowledge. In apparel manufacturing, AI helps MSMEs better manage and integrate external knowledge, such as tacit knowledge, experience, culture, and explicit knowledge, such as customers' data, garment technique specification, etc., into their production processes, enhancing absorptive capacity. Therefore, the results demonstrate the roles of AI-integrated technologies in apparel production and manufacturing processes for tacit and explicit knowledge ACAP.

H10 examines the impact of KACAP on open innovation. KACAP enables firms to utilize external knowledge effectively, which is a critical component of open innovation. The open innovation theory posits that firms intentionally manage knowledge flows across organizational boundaries to drive internal and external innovation (Chesbrough & Bogers, 2014). In the case of Chinese apparel MSMEs, KACAP provides the foundation for integrating external knowledge, which means acquired from suppliers, customers, and other stakeholders, into internal processes, enabling these firms to engage more effectively in open innovation.

The significant positive result for H10 suggests that KACAP plays a critical role in facilitating open innovation in Chinese apparel MSMEs. This finding aligns with prior studies, which highlight the importance of ACAP in leveraging external knowledge for innovation (Moilanen et al., 2014). For Chinese MSMEs operating in a highly competitive and dynamic industry, open innovation is essential for maintaining competitiveness. KACAP enables these firms to effectively absorb external knowledge and collaborate with external partners, leading to improved innovation outcomes. This relationship is significant in apparel manufacturing, where rapid consumer preferences and market trends require firms to innovate continuously through collaboration with external stakeholders.

Hypothesis H11 tests the direct relationship between AI adoption and open innovation. Previous research suggests that AI capabilities can enable open innovation by facilitating knowledge sharing and collaboration across organizational boundaries (Mariani et al., 2023). However, the results of H11 indicate that AI adoption does not significantly impact open innovation in Chinese apparel MSMEs. This non-significant result suggests that while AI adoption may enhance a firm's technological capabilities, it does not directly lead to open innovation without the presence of the mediating factor of KACAP. The lack of a direct relationship could be due to the complexity of managing external collaborations and knowledge flows, which require firms to have absorptive solid capacities to effectively leverage AI technologies for open innovation. In other words, AI adoption alone may not be sufficient to drive open innovation unless firms can also absorb, integrate, and apply external knowledge effectively (Kastelli et al., 2024). This finding emphasizes the importance of KACAP as a mediating effect between AI adoption and open innovation, suggesting that AI adoption alone is insufficient to facilitate the complex, boundary-spanning knowledge flows required for open innovation. Using AI in isolation may enhance internal efficiencies or provide better decision-making tools. Still, the firm's capacity to engage in open innovation remains limited without the ability to collaborate with external partners and integrate diverse knowledge streams effectively. In this context, KACAP acts as the critical mediating factor that transforms AI-driven insights into actionable innovations by enabling the firm to engage meaningfully with external partners and co-develop new solutions.

6.3. *Study 2*: Categorizing Required AI Capabilities and Barriers to Adopting AI in Chinese Apparel Manufacturing MSMEs

The objective of ***Study 2*** is to ground the required AI capabilities and barriers to adopting AI in Chinese apparel manufacturers. By integrating the previous analysis and contextualizing it within China's unique manufacturing landscape, this section has addressed the study's findings by structuring the discussion around two key research questions following the ***SRQs*** of ***Study 2***: 1) What are the emerging concepts of AI capabilities that Chinese manufacturing firms need? 2) What are the emerging concepts of challenges hinder AI adoption in China's manufacturing sector?

6.3.1. Layer 1- Required AI Capabilities in Innovation Ecosystem Framework (SRQ3)

As our informants indicated, AI is urgently required to enhance adaptive and human-centered capabilities in apparel manufacturing MSMEs' production processes. These firms, which lag behind larger sectors, struggle to cope with uncertain market shifts, a lack of skilled talent, and financial constraints. They also face neglect from local governments and apparel associations. Thus, the first layer of the framework focuses on AI capabilities, particularly adaptive production capability and augmented human-AI collaboration capability. These capabilities are directly derived from the specific needs identified in earlier analyses of the apparel manufacturing sector, where agility, precision, responsiveness, and sustainability are paramount.

This ability to adapt and be human-centered emphasizes the flexibility to respond to customers' demands for low-volume, high-quality production in a short period of time. According to previous coding analysis, many MSMEs struggle with tight delivery cycles and frequent design changes. Some respondents mentioned that when dealing with custom orders, such as switching from making loose trench coats to waist models, the production process must often be adjusted quickly. This ability can help garment manufacturers coordinate resources and production schedules more efficiently and maintain an edge in a competitive market.

Although AI has made breakthroughs in many industries, human-machine collaboration remains indispensable due to the peculiarities of the garment manufacturing industry. Unlike highly automated industries, garment production relies heavily on human experience in fabric handling, creative decision-making, and real-time quality assessment. AI performs well when performing structured tasks, but still requires human intervention in the face of unpredictable fabric properties, complex sewing processes, and rapidly changing design requirements. As a result, augmented human-machine collaboration has become a major feature of the industry, which uses AI technology to make up for skills shortages and improve productivity.

From previous coding analysis, AI has played an important role in processes such as cutting and fabric selection, tasks that are error-prone and time-consuming under traditional manual operations. Some respondents pointed out that while human labor remains the core of production, AI compensates for human limitations by reducing errors in complex processes. This capability is especially important for MSMEs, as they often lack enough skilled workers. Compared to large enterprises that can afford full automation, MSMEs need AI to complement manpower rather than completely replace it. The need for this hybrid model is also driven by market demands for high customization, shorter production cycles, and sustainable production, challenges that AI alone cannot yet fully address.

However, these capabilities are not standalone but deeply interconnected. For example, real-time production adjustments (adaptive capability) often rely on AI-enabled tools that are part of human-AI collaboration. Without human adaptability, AI would be limited in addressing last-minute order changes, ensuring material compatibility, or responding to unexpected production challenges. Together, these capabilities form the operational foundation of the innovation ecosystem, driving its ability to deliver value to external stakeholders in Layer 3.

6.3.2. Layer 2 – Factors that Hinder AI Adoptions (*SRQ4*)

Layer 2 contextualizes the systemic barriers that impede the development and deployment of Layer 1 capabilities, which are categorized into industry factors, university factors, and government factors, highlight the complex interplay between organizational, technical, and policy-level challenges.

Industry factors represent intrinsic constraints, such as high costs, technical complexity, and unclear ROI. For instance, as noted in the earlier analysis, many SMEs lack the financial resources to implement AI solutions, and even when resources are available, the perceived risks often deter investments. The absence of standardized AI solutions tailored to apparel manufacturing further complicates adoption, requiring firms to navigate technical challenges independently. These barriers directly limit the development of adaptive production capabilities, as firms are unable to invest in the required technologies or expertise.

University factors underscore the persistent talent gap that hinders the sector's ability to leverage AI. Earlier coding revealed that university curricula remain misaligned with industry needs, focusing more on design than on the technical skills required for AI integration. A respondent pointed out that even when students are trained in fashion-related fields, their knowledge of AI applications is minimal, leaving a gap in technical expertise that enterprises struggle to fill. This shortfall in talent impacts not only human-AI collaboration but also the ability to implement adaptive production systems, as firms lack access to professionals capable of managing these transitions.

Government factors involve both enablers and constraints. While central government policies provide strategic support, regional "uneven policy implementation' (Schubert & Alpermann, 2019, p. 203) often leave partial SMEs without sufficient resources or guidance. Previous coding analysis revealed that local governments frequently prioritize large apparel enterprises, with SMEs receiving little direct support. For example, subsidies for AI adoption are often inaccessible to smaller firms due to eligibility thresholds, creating a structural barrier that perpetuates inequalities within the ecosystem.

These barriers interact dynamically, compounding the challenges faced by apparel manufacturers. For instance, the lack of talent (university factor) exacerbates the technical complexity (industry factor), while limited financial support (government factor) leaves firms unable to address either issue effectively.

6.4. MRO: Developing an AI-enabled Innovation Ecosystem Framework with Propositions for Chinese Apparel Manufacturing MSMEs (MRQ)

The ***MRQ*** of the research is how to develop an AI-enabled innovation ecosystem to explain the mechanisms through which enterprises, universities, associations, and government enhance collaboration in the Chinese's manufacturing sectors. To enhance the academic context, this section incorporates previous literature on innovation ecosystems and open innovation**,** providing a comprehensive view of how AI technologies shape collaborative processes within this framework.

AI plays a key role in facilitating collaboration among businesses, universities, industry associations, and governments (Arenal et al., 2020; Kim et al., 2024). This mechanism of cooperation aligns with the principle of an innovation ecosystem where multiple actors interact to drive technological progress and economic growth (Rabelo Neto et al., 2024). As Chesbrough (2003) noted in his open innovation framework, collaboration between external and internal stakeholders is essential for enhancing innovation, and AI provides the technological infrastructure to enable such interactions in this context. As we decided to adopt Granstrand and Holgersson (2020. p3) defined innovation ecosystems as our grounded theory of AI-enabled innovation ecosystem framework' theoretical foundations, which is aligned with Chesbrough (2003)'s open innovation definitions, the grounded layer 3 explains the collaborative mechanisms around 13 propositions through internal organizational and external university actors and government actors in collaborated activities in the China's government support.

An innovation ecosystem comprising "…actors, activities, artifacts, and the institutions and relations." Artifacts here include *"products and services, tangible and intangible resources, technological and non-technological resources, and other types of system inputs and outputs, including innovations."*

Thus, in the context of AI adoption in the Chinese apparel manufacturing sector, as shown in **Figure 6.2**, the **Layer 3** serves as the collaborative framework that underpins the innovation ecosystem. This layer emphasizes the systemic and inter-organizational dynamics through which government, universities, and enterprises coordinate efforts to address barriers to the adoption of AI (Layer 2) and enable the development of AI capabilities (Layer 1). Layer 3 functions as the central engine of the ecosystem, orchestrating resource allocation, fostering knowledge exchange, and ensuring policy alignment to create an environment conducive to innovation. As the integrative mechanism of the framework, Layer 3 directly tackles the challenges outlined in Layer 2 based on the results of grounded data, such as high adoption costs, skill shortages, and data-sharing constraints, by facilitating multi-stakeholder collaboration. At the same time, it strengthens enterprises' KACAP, enabling them to internalize and utilize external AI-related knowledge, which supports the development of required AI capabilities, such as adaptive production and human-AI collaboration.

This foundational understanding of Layer 3 as the driving engine of the innovation ecosystem sets the stage for the subsequent sub-sections. These sections delve into the mechanisms by which government policies, university contributions, and industry dynamics synergize to operationalize this framework. This discussion highlights how these collaborative efforts can foster collaboration, overcome barriers, and create the necessary conditions for the effective application and integration of AI technology in China's apparel manufacturing industry.

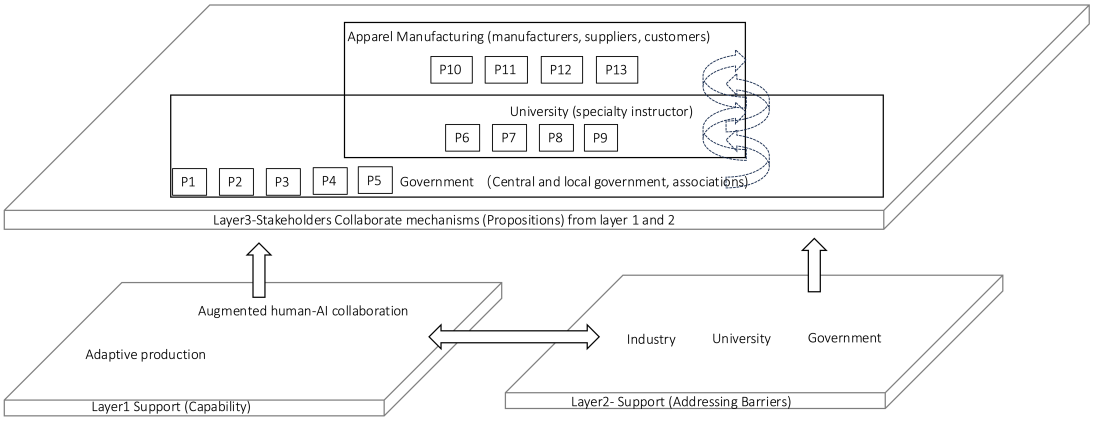

Figure 6.2 AI-enabled Triple-Layer Innovation Ecosystem Framework

6.4.1. Mechanism 1of Layer 3: Government Policies as Enablers for Collaboration

A critical mechanism within Layer 3 lies in the evolving role of government policies in fostering AI adoption. Governing in China involves both steering through state power and cooperating with corporate, collective, and individual actors within a highly complex institutional setting (Schubert & Alpermann, 2019). However, the top-down policy implementation has traditionally emphasized national-level frameworks and prioritized large-scale enterprises. While these strategies have driven technological advancements in advanced regions, they have often overlooked the needs of MSMEs and exacerbated geographic disparities in AI adoption. To address these systemic challenges, a shift in government policies is essential, which is from acting as a centralized policy setter to becoming a collaborative enabler within the innovation ecosystem. This transition requires a more nuanced approach that emphasizes decentralized implementation, tailored financial support, and ecosystem-wide collaboration. As previously indicates by our informants, regional disparities are one of the key barriers limiting the equitable diffusion of AI capabilities, revealing that southern regions, with advanced infrastructure and strong industrial clusters, have a significant advantage, while northern and less-developed regions face challenges in accessing financial and technical resources (Frequency: 6, U1). In the apparel industry, geographic disparities are also pronounced. Southern regions typically benefit from well-developed infrastructure and robust industrial clusters, whereas northern and underdeveloped areas face significant resource constraints (Wang, 2013). Establishing regional innovation hubs is crucial for apparel MSMEs as it provides centralized access to funding, technology, and expertise, thereby reducing regional inequalities and enhancing overall competitiveness within the sector. These disparities create bottlenecks for the development of Layer 1 capabilities, as firms in underdeveloped areas are unable to access the tools and knowledge needed to build adaptive production systems or augmented human-AI collaboration.

Governments, therefore, need to establish regional AI innovation hubs that act as centralized resource centers, providing access to funding, technology, and expertise. Such hubs would also facilitate cross-regional knowledge-sharing, enabling less-developed regions to benefit from the experiences and successes of advanced areas.

In addition to addressing geographic disparities, tailored funding mechanisms are critical to supporting MSMEs. The prioritization of large-scale enterprises in policy frameworks (Frequency: 6, I1) has left MSMEs struggling to compete. High costs (Frequency: 8, I3) and limited access to subsidies (Frequency: 5, I3) prevent these smaller firms from investing in AI, despite their critical role in supply chain operations. Without targeted interventions, MSMEs risk being excluded from the broader ecosystem. In the apparel industry, the rapid evolution of trends and consumer preferences necessitates continuous adaptation (Trieu, 2024). Unlike sectors characterized by longer product cycles, the apparel market operates at an accelerated pace, where fashion trends can shift within weeks or even days. This dynamic environment compels apparel MSMEs to make frequent and incremental investments in sourcing materials, production processes, and technological advancements to maintain competitiveness. The need for agility in responding to market shifts underscores the importance of flexible supply chain strategies and adaptive business models in the apparel sector (Irfan et al., 2019). Therefore, decentralized funding mechanisms, such as microgrants and low-interest loans, can lower the entry barriers for MSMEs in such case. By incentivizing AI experimentation and pilot programs, governments can empower smaller firms to explore AI applications without bearing the financial risks associated with large-scale implementation. Furthermore, local governments are uniquely positioned to act as facilitators of collaboration within the ecosystem. By connecting enterprises, universities, and industry associations, local governments can create platforms for knowledge exchange and joint problem-solving. However, current government-related associations are often ineffective in fostering innovation, focusing primarily on policy dissemination rather than enabling collaboration (Frequency: 2, I7). The fast-paced nature of downstream customers' fashion trends necessitates a rapid response from upstream suppliers' constant adaptions in the complex supply chain processes, which many apparel MSMEs cannot generate independently. In this context, governments should promote public-private partnerships that align the objectives of diverse actors. For instance, local governments could host workshops, innovation challenges, or AI demonstration projects encouraging cross-sectoral collaboration and providing real-world applications for university research. In addition, the apparel industry in China is undergoing a significant transformation as firms shift from traditional OEM/ODM models to OBM strategies that emphasize branding and market differentiation. This transition is not solely a technological upgrade but also a comprehensive strategic repositioning that demands enhanced capabilities in design, marketing, and consumer engagement. Government-led public-private partnerships play an important role in this transformation, bringing together a variety of resources and expertise from the public and private sectors. By sharing the risks and costs of research and development and market adjustment, this collaborative model offers MSMEs the opportunity to experiment with innovation without overburdening them financially. Therefore, this collaborative model has become an important support to promote the successful transformation of OBM and promote the overall development of the industry.

At the same time, the apparel industry association acts as a bridge between enterprises and government policies, university research, and technical resources. While they could have played a greater role, the current focus is on policy communication rather than actually driving innovation (Frequency: 2). If they can further expand their functions, such as organizing training and building knowledge-sharing platforms, they can play a more critical role in the application of AI, especially for MSMEs that have difficulty accessing advanced technologies.

In Layer 3, the role of government has changed, which has profound implications for the entire innovation ecosystem. By narrowing regional gaps, supporting SMEs, and promoting cross-industry cooperation, government policies can not only help enterprises and universities enhance Layer 1 core competencies but also break through Layer 2 barriers. This shows that the government is not only a policy maker but also an enabler in promoting ecological innovation as a whole. Therefore, based on the above discussion, we propose the following propositions:

P1: Regional innovation hubs should be established to reduce geographic disparities in AI adoption.

P2: Tailored funding mechanisms targeting MSMEs will increase their capacity to experiment with and adopt AI technologies.

P3: Governments should prioritize public-private partnerships that align the goals of enterprises, universities, and associations.

P4: Local governments must act as facilitators of cross-sectoral collaboration, promoting platforms for joint innovation.

P5: Industry associations must expand their role to include capacity-building initiatives and knowledge-sharing platforms.

6.4.2. Mechanism 2 of Layer 3: Universities as Knowledge Hubs in Addressing Talent and Knowledge Gaps

Another critical mechanism within Layer 3 is the role of universities as knowledge hubs in fostering AI adoption in the apparel manufacturing sector. Universities are uniquely positioned to address the talent and knowledge gaps that impede the industry's ability to fully integrate AI technologies. However, their potential remains underutilized due to misalignments between academic outputs and industry needs. For instance, university programs predominantly focus on traditional disciplines like design and pattern-making, while the industry increasingly demands expertise in AI engineering, software development, and data analytics (Frequency: 9, I3). Additionally, the limited access to advanced manufacturing technologies in educational settings further delays graduates' readiness to contribute effectively to AI adoption (Frequency: 3, U4).

To bridge these gaps, universities must reform their curricula to integrate AI-specific modules that cater to the interdisciplinary demands of the industry. Programs combining AI-driven production systems with practical training on intelligent equipment can better prepare students for workforce challenges. Partnerships with enterprises can also provide students with hands-on experience, ensuring the development of skills needed to transition seamlessly into the workforce. However, the current state of collaboration between universities and enterprises often focuses on short-term product development rather than long-term technological innovation (Frequency: 5, A2). This narrow focus prevents universities from addressing systemic industry challenges such as garment complexity or workforce readiness, which are critical barriers in Layer 2. To align academic research with industry needs, universities should participate in government-funded joint R&D programs that prioritize the co-development of AI tools tailored to specific challenges. These programs would leverage academic expertise and industry insights to create innovations like predictive analytics for supply chains or automated quality control systems. Moreover, universities need institutional support to foster interdisciplinary innovation. Current frameworks often lack the resources and infrastructure necessary to integrate expertise from computer science, engineering, and fashion (Frequency: 2, I2). Thus, establishing interdisciplinary AI innovation centers within universities would enable collaborative research while providing shared access to advanced equipment for experimentation.

The transformation of universities into active contributors to the innovation ecosystem holds profound implications for AI adoption in the apparel manufacturing sector. By addressing the talent gap, enhancing research collaboration, and institutionalizing interdisciplinary innovation, universities can overcome barriers while building the capabilities needed in Layer 1. Therefore, we propose the following propositions:

P6: Universities must reform curricula to integrate interdisciplinary AI modules that address the needs of the apparel industry.

P7: Joint R&D programs between universities and enterprises should prioritize the co-development of AI solutions for industry-specific challenges.

P8: Establishing interdisciplinary AI innovation centers will enable universities to serve as collaborative hubs for research and training.

P9: Partnerships between universities and enterprises should focus on providing hands-on experience to students, fostering workforce readiness for AI adoption.

6.4.3. Mechanism 3 of Layer 3: Collaboration and Competition as Drivers of AI Adoption for Apparel Industry

Layer 3 focuses on the dynamics of industry actors and their roles in shaping AI adoption as the third critical mechanism. Participants in the apparel manufacturing industry are in a complex network of cooperation and competition. As the previous coding analysis, the apparel industry is often involved in collaborative efforts through supply chain interactions and industry associations. The integration of AI tools in apparel supply chain is very complicated (Frequency:3). However, if companies along the supply chain can share data through a collaborative platform, seamless integration of AI systems can be achieved. For example, a unified data standard can help suppliers and manufacturers better synchronize production schedules, reduce inefficiencies, and increase production speed.

In contrast to collaboration, competitive pressures also drive AI adoption within the industry. Firms that lead in adopting AI technologies often create a demonstration effect, setting benchmarks that other enterprises emulate (Frequency: 2). This dynamic encourages the diffusion of AI but can exacerbate inequalities, as smaller firms struggle to meet the resource-intensive requirements of AI systems.

Moreover, intense competition within the sector often manifests as price wars (Frequency: 3, I4), which limit firms' ability to invest in innovation due to low profit margins. Thus, balancing competitive pressures with support mechanisms directly impacts maintaining robust enterprise-customer relationships within the innovation ecosystem. This outcome reinforces the importance of maintaining equitable support structures for enterprises to sustain strong customer engagement in the ecosystem.

The interplay between collaboration and competition highlights the need for systemic interventions to balance these forces. Apparel industry associations can play a crucial role in mitigating disparities by facilitating access to shared AI resources and promoting best practices. Similarly, firms that succeed in AI adoption should be encouraged to mentor smaller enterprises, fostering a culture of knowledge-sharing and mutual growth.

Layer 3's industry dynamics further emphasize that innovation across the entire ecosystem can only be truly fostered by promoting collaboration while maintaining a level playing field. Therefore, we propose the following propositions:

P10: Supply chain partners should adopt standardized data-sharing protocols to enhance interoperability and support AI integration.

P11: Firms leading in AI adoption should mentor smaller enterprises to promote equitable technology diffusion.

P12: Collaborative platforms should focus on aligning supply chain operations with AI-enabled tools to optimize efficiency.

P13: Competitive pressures should be balanced with support mechanisms to prevent marginalization of smaller firms in the ecosystem.

6.4.4. ACAP as the Outcome of Layer 3 Interactions

The three mechanisms of government policies as enablers, universities as knowledge hubs, and industry dynamics of collaboration and competition lay the foundation for the fourth mechanism, which is ACAP. In the previous literature defined absorptive capacity as a firm's ability to recognize the value of external knowledge, assimilate it, and apply it to create innovation (Cohen & Levinthal, 1990; Grant, 1996), emerges as a systemic outcome of Layer 3 interactions. As we proposed, the Chinese government policies play a pivotal role by reducing structural barriers, such as geographic disparities and financial constraints, through regional AI innovation hubs and tailored subsidies for MSMEs. Hence, these initiatives provide firms with access to external resources and technologies, creating opportunities for experimentation and engagement with AI solutions. Universities, as knowledge providers, bridge the gap between theoretical research and practical applications, equipping firms with the specialized skills and technical expertise required for AI adoption through joint R&D programs and interdisciplinary innovation centers. Meanwhile, industry dynamics foster KACAP by creating environments for shared learning and competitive benchmarking. Collaborative supply chain platforms and industry associations facilitate knowledge sharing, while competitive pressures incentivize firms to adopt and adapt AI innovations to maintain market relevance. Together, these mechanisms enable firms to recognize, assimilate, and apply external knowledge, transforming barriers into adaptive capabilities. Thus, KACAP becomes both a product of Layer 3 interactions and a driver for sustained innovation within the ecosystem, reinforcing the recursive and dynamic nature of the innovation framework.

6.5. Theoretical Contributions and Managerial Implications

The findings of this research offer substantial contributions to understanding how AI facilitates open innovation and enhances collaboration across industries, universities, associations, and government, particularly within the context of Chinese apparel manufacturing sector. This section outlines the key theoretical contributions and managerial implications of the two studies presented in this thesis. ***Study 1*** utilized PLS-SEM to empirically validate the factors influencing AI adoption and its mediating role in organizational open innovation (***SRO 1*** was addressed). ***Study 2*** applied grounded theory to develop a comprehensive framework, yielding 13 propositions describing the collaboration mechanisms between enterprises, universities, and government (***SRO 2*** was addressed). These two complementary approaches offer substantial theoretical insights into the AI-enabled innovation ecosystem and provide practical guidelines for industry and policymakers (***MRO*** was addressed). The following sub-sections discuss these theoretical contributions and managerial implications for Chinese apparel manufacturing sector.

6.5.1. Theoretical Contributions

The thesis aims to build an AI-enabled innovation ecosystem for Chinese apparel manufacturing, and thus, to achieve it, ***Study 1*** provides a preliminary statistical analysis of AI adoption of MSMEs toward open innovation based on the TOE-TAM model. It contributes to the existing literature by empirically validating the relationships between technology, organizational, and environmental factors and AI adoption within Chinese apparel manufacturing sector, using PLS-SEM. The extended TAM-TOE model developed in this study integrates multiple theoretical perspectives, including the TAM, the TOE framework, and the ACAP theory. Several key theoretical contributions emerge from the empirical findings. First, the study advances the TAM-TOE model by introducing KACAP as a mediating construct between AI adoption and open innovation. Second, while the traditional TAM posits that perceived ease of use is critical for technology adoption, the findings challenge this assumption in the context of AI. Specifically, perceived ease of use does not significantly influence AI adoption in China's MSMEs, reflecting a shift towards more outcome-oriented evaluations, where the perceived usefulness of AI and its potential to drive competitive advantage play a more pivotal role. Therefore, the diminished impact of perceived ease of use on AI adoption suggests a need to reconsider the emphasis placed on use ease when adopting highly complex technologies like AI. Unlike conventional IT systems, AI's sophistication and transformative potential outweigh operational ease concerns, highlighting the importance of long-term strategic benefits over immediate usability. Third, the study introduces new insights into the relationship between organizational readiness and KACAP. While organizational readiness does not directly influence AI adoption, it significantly impacts a firm's ability to absorb and exploit external knowledge, highlighting its indirect importance in driving AI-enabled open innovation. Fourth, ***Study 1*** reveals that competitive pressure is critical environmental factor facilitating AI adoption. The results suggest that China's MSMEs are driven to adopt AI to maintain competitiveness and meet evolving market demands. Simultaneously, suppliers play an essential role in providing the necessary resources and expertise for AI integration, which highlights the interdependence of firms within the supply chain and the critical role of external actors in fostering innovation. Lastly, as stated, knowledge is a crucial input and a significant source of value in manufacturing (Chatterjee et al., 2021; Legesse et al., 2024; Tasnim et al., 2023), and open innovation is the process based on intentional management of knowledge flows across organizational boundaries (Chesbrough & Bogers, 2014, as cited in Arias-Pérez & Huynh, 2023), which provides a framework for utilizing external and internal knowledge, technology, and resources to accelerate internal and external innovation. Thus, KACAP would leverage purposive inflows and outflows of knowledge to achieve innovative performance. Overall, this thesis contributes to the empirical investigation of KACAP's mediating effect on AI adoption toward open innovation, an area where no research currently exists.

To achieve ***SRO 2***, ***Study 2*** extends the theoretical foundation laid by ***Study 1*** by developing the framework, grounded in empirical findings from the Chinese apparel manufacturing sector. This framework builds on the grounded theory approach to propose 13 key propositions that describe the mechanisms through which AI facilitates collaboration across industries, universities, associations, and government, thereby constructing the AI-enabled innovation ecosystem framework. The grounded innovation ecosystem framework developed through qualitative interviews offers significant theoretical contributions by advancing our understanding of how innovation ecosystems operate in emerging economies and traditional industries like apparel manufacturing. While much of the existing literature on innovation ecosystems focuses on high-tech industries in developed economies, this framework broadens the scope by contextualizing the adoption of AI within a sector traditionally considered low-tech, emphasizing the unique pathways through which such industries can transform. A central contribution lies in its layered structure, which integrates requried capabilities (Layer 1), barriers to adopting (Layer 2), and external collaborative mechanisms (Layer 3), offering a dynamic, multi-level perspective on how ecosystems evolve. This layered approach highlights the interplay between internal capabilities, such as adaptive production, and external systemic factors, such as workforce readiness and policy constraints, while also revealing the mechanisms by which external collaborations mitigate these challenges and enable knowledge absorption. Moreover, the framework reconceptualizes the role of governments in emerging economies, shifting from a top-down policy enforcement perspective to one that emphasizes enabling bottom-up initiatives and supporting decentralized innovation, especially for MSMEs. It also underscores the critical importance of interdisciplinary knowledge integration, revealing how ecosystems thrive by bridging disciplinary silos across fashion design, AI engineering, and supply chain management, facilitated by universities as key knowledge hubs. Furthermore, the framework positions KACAP not as a standalone firm-level construct but as a systemic outcome of collaborative mechanisms in Layer 3, illustrating how government policies, university contributions, and industry dynamics interact to enhance firms' ability to assimilate and apply external knowledge. By contextualizing these interactions within China's institutional environment, characterized by a blend of top-down state influence and market-driven dynamics, the framework provides a culturally specific lens that deepens theoretical insights into how ecosystems adapt in complex governance settings. Additionally, the framework enriches the understanding of the dual forces of collaboration and competition, showing how cooperation fosters shared learning and resource pooling while competition drives innovation and benchmarking, achieving a balance that propels systemic innovation. Taken together, the framework not only extends the theoretical boundaries of innovation ecosystem studies but also offers a robust, context-sensitive model for examining the transformation of traditional industries in emerging economies.

Overall, this thesis combines the findings of ***Study1***'s PLS-SEM analysis with the grounded theory propositions from ***Study 2*** to offer an integrated understanding of AI's role in fostering open innovation in Chinese apparel manufacturing sector. The integration of findings from the PLS-SEM analysis (***Study 1***) and the grounded theory- innovation ecosystem framework (***Study 2***) provides a comprehensive, multi-layered understanding of AI adoption in Chinese apparel manufacturing sector by connecting quantitative determinants with qualitative insights into systemic collaboration. The PLS-SEM analysis identifies key constructs that influence AI adoption and open innovation. These constructs, when contextualized within the innovation ecosystem developed in ***Study 2***, reveal the roles and interactions in Layer 3. For instance, perceived usefulness aligns with Layer 1's emphasis on adaptive and collaborative AI capabilities, while government support and policy and supplier involvement highlight Layer 3's mechanisms of resource mobilization and knowledge exchange. This integrated framework advances theoretical discussions by showing how firm-level determinants operate within a broader ecosystem structure. Furthermore, the SEM finding that organizational readiness positively influences KACAP (H4b) reinforces qualitative insights that firms' ability to assimilate external knowledge is critical, bridging internal readiness with the external dynamics of Layer 3. The interaction between competitive pressure, market uncertainty, and open innovation, as evidenced by ***Study 1***'s findings (e.g., H5b and H7b), aligns with ***Study 2***'s focus on industry dynamics in Layer 3, illustrating how competitive benchmarking and uncertainty stimulate collaborative problem-solving across supply chains. Overall, these findings contribute to the literature by demonstrating how external pressures, rather than solely acting as barriers, serve as catalysts for innovation within a coordinated ecosystem.

6.5.2. Managerial Implications

The thesis's findings have offered valuable managerial implications that can be developed to guide the future development of AI technology acceptance intentions in organizations. ***Study 1*** focuses on identifying the determinants of AI adoption in Chinese apparel manufacturing MSMEs through the TAM-TOE and KACAP frameworks. The managerial implications of these findings highlight the importance of strategic decision-making in the adoption and integration of AI-integrated technologies in the apparel manufacturing sectors.

First, for apparel manufacturing managers, the findings of the diminished role of perceived ease of use in AI adoption (H2) imply that managers suggest that focusing on the strategic value of AI, rather than its operational simplicity in use, is critical for driving adoption. Managers should prioritize AI-integrated technologies and tools that deliver long-term competitive advantages, such as improved production efficiency and enhanced decision-making capabilities, even if the technology is initially complex. Second, the findings underscore the critical role of organizational readiness in KACAP (H4b). Thus, managers must ensure their firms are prepared for AI knowledge absorption and integration by securing the necessary financial, technological, and human resources for readiness. This includes not only investing in infrastructure but also facilitating open innovation that is adaptable to technological resources (knowledge) and strengthening their ACAP. Organizational readiness should be seen as a multi-faceted concept, encompassing IT infrastructure, financial capacity, and the development of a skilled workforce capable of interacting with AI-integrated technologies and fostering a culture of collaboration that embraces external knowledge sources. Third, the external factors of competitive pressure and close collaboration with suppliers are crucial drivers of AI adoption and open innovation (H5a, H5b, and H6b). As a result, managers should prioritize the strategic importance of adopting AI more quickly than their competitors. This proactive approach will boost the confidence of forego users (e.g., technicians and pattern cutters using AI after its adoption), helping them recognize that integrating AI tools can make the organization more productive than others (Chatterjee et al., 2021). Managers, also, must ensure employees understand how AI technology contributes to the organization's competitive advantage. These advantages of AI tools in production and manufacturing processes would benefit all stakeholders in complete apparel supply chains. The benefits of AI tools in production and manufacturing processes extend to all stakeholders across apparel supply chains. Therefore, managers should actively seek partnerships with suppliers and external experts to facilitate the integration of AI technologies and ensure that their firm remains competitive in a rapidly evolving industry. Fourth, firms need to enhance their dynamic capacity since market uncertainty significantly positively affects AI adoption and open innovation, as ascertained from our study (H7a and H7b) and prior studies (Arifin & Frmanzah, 2015; Graham & Moore, 2021). It has been discovered that increasingly uncertain external circumstances bring internal agile management. Consequently, organizations must enhance learning and adaptation through continuous training and knowledge-sharing activities to promote and foster an organizational culture of innovation with AI's challenges to traditional industries (e.g., apparel manufacturing). To sustain their competitive advantages, managers leverage their agile management capabilities to improve, refresh, and reconfigure the stock of resources and adapt AI tools. Furthermore, leadership, outsourcing capability, and governance can ensure that AI initiatives are aligned with all stakeholders and employees in the organizations' innovation ecosystems. This, as such, is the prerequisite of AI adoption in organizations. Fifth, precisely because AI adoption is intricately linked to a firm's ability to absorb and utilize external knowledge (H9), it has been discovered that increasingly uncertain external circumstances bring internal agile management. Thus, managers should focus on enhancing their firms' KACAP by encouraging continuous learning, establishing channels for knowledge exchange, and promoting cross-departmental collaboration based on the results of H10 and H11. Investing in training programs that help employees understand and utilize AI technologies can significantly improve the firm ability to innovate and compete in a technology-driven marketplace. Last, as ascertained in H8a and H8b, policymakers should release favorable concrete AI policies in collaboration with higher education and apparel manufacturing, focusing on reducing regional disparities in AI adoption by providing targeted subsidies, improving access to technological infrastructure, and encouraging cooperation between inland and coastal apparel clusters. Addressing these imbalances is essential for ensuring that all firms, regardless of geographical location, can benefit from AI-enabled innovation.

Building on the empirical analysis of ***Study 1***, which examined the antecedents of AI adoption, thus driving open innovation in Chinese apparel manufacturing sector, ***Study 2*** shifts the focus toward a theoretical exploration of how AI facilitates collaboration across industries, universities, associations, and government policy within the broader innovation ecosystem. The grounded theory approach in ***Study 2*** provides a set of propositions that emphasize the mechanisms through which these stakeholders interact to foster open innovation driven by AI. This section will elaborate on how each actor (enterprises, universities, associations, and government) can work together to establish collaborative pathways in AI integration, drawing on the 13 activities' propositions from the grounded study.

The grounded innovation ecosystem framework developed in ***Study 2*** offers several key managerial contributions for stakeholders in Chinese apparel manufacturing sector. First, it provides actionable insights into how firms can leverage interorganizational collaboration to overcome barriers to AI adoption. For managers, the framework highlights the importance of engaging with external actor, such as universities, suppliers, and government bodies, not only to access resources and knowledge but also to build long-term partnerships that enhance adaptive and collaborative AI capabilities. By understanding the roles and mechanisms outlined in Layer 3, firms can strategically position themselves within the ecosystem, proactively aligning their internal capabilities with external opportunities. Second, the framework underscores the need for managers to cultivate KACAP within their organizations. By fostering a culture of learning and openness, firms can better assimilate external knowledge and innovations, enabling more effective integration of AI technologies into their operations. Additionally, the emphasis on decentralized, bottom-up policy engagement suggests that managers should not passively rely on government support but should actively advocate for their needs and participate in shaping supportive policies, particularly for MSMEs that often lack direct access to resources. Finally, the framework highlights the role of competitive benchmarking and collaborative experimentation in driving open innovation. Managers are encouraged to balance competitive pressures with opportunities for shared learning within supply chains and industry networks, fostering a culture where collaboration and competition coexist to accelerate innovation. By operationalizing these insights, managers can enhance their firms' resilience and adaptability, ensuring sustainable growth in an increasingly AI-driven industrial landscape.

6.6. Synthesis of Discussion and Conclusion (MRO)

To achieve the ***MRO*** of developing an AI-enabled innovation ecosystem for Chinese apparel manufacturing sector, this thesis employs a systematic, dual-phase approach, combining quantitative and qualitative methods. In the first phase, ***Study 1*** (to achieve ***SRO1***) quantitatively investigates the relationship between AI adoption and open innovation in Chinese apparel manufacturing MSMEs. Using the TAM-TOE framework, ***Study 1*** identifies key drivers of AI adoption, with a focus on Knowledge Absorptive Capacity (KACAP) as a critical mediating factor that converts AI adoption into actionable innovation. By quantitatively establishing these foundational elements, ***Study 1*** creates an organizational basis for AI readiness, highlighting KACAP's essential role in bridging technology adoption and innovative outcomes.

Building on these findings, the second phase, ***Study 2*** (addressing ***SRO 2***), utilizes an inductive grounded theory approach to identify the essential AI capabilities needed by firms and the barriers hindering AI adoption. Through qualitative analysis, ***Study 2*** explores how universities, industry associations, and government entities can collaborate with apparel firms to promote open innovation. The results clarify the roles and interactions of these stakeholders, providing theoretical support for developing an AI-enabled innovation ecosystem framework and propositions (***MRO***).

Therefore, the combined insights from both studies effectively fulfill the ***MRO,*** developing a comprehensive, empirically supported ecosystem framework that addresses both internal organizational readiness and external collaborative dynamics. By synthesizing quantitative and qualitative data, the triple-layer framework offers actionable guidance, ensuring MSMEs leverage both absorptive capacities and external partnerships to sustainably drive AI-enabled open innovation in the Chinese apparel manufacturing sector. This holistic, evidence-based approach bridges an essential gap in AI ecosystem development, contributing valuable strategic insights for policymakers, industry stakeholders, educators, and academic partners (see **Figure 6. 3**).

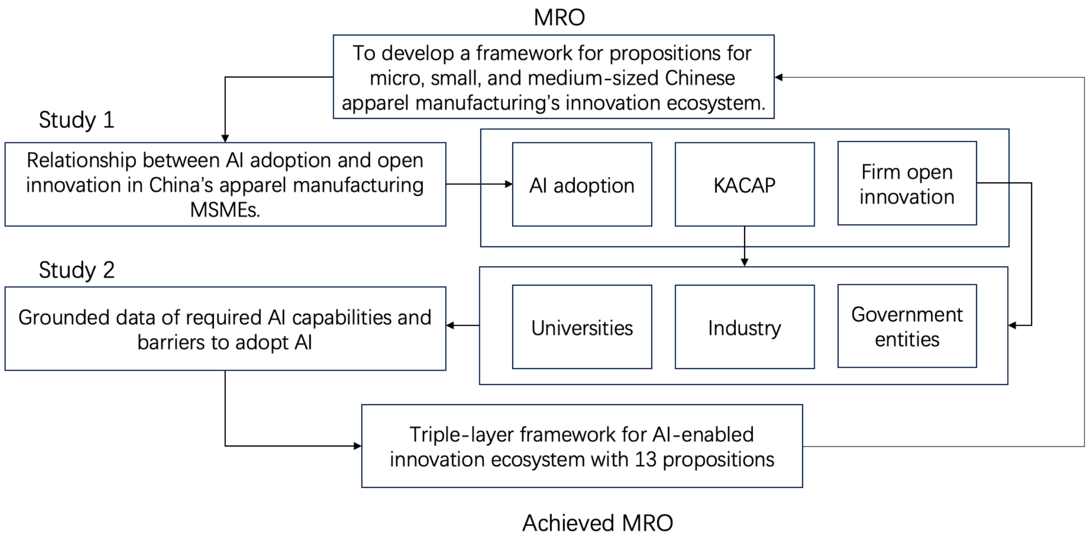

Figure 6.3 The Relationship of the Findings of *MRO*, *SRO 1* and *SRO 2*

6.7. Chapter Summary

This chapter discusses and reflects upon the results reported in *Chapter 4* (***Study1***) and *Chapter 6 (**Study 2**)* to construct a comprehensive framework for understanding AI adoption within Chinese apparel manufacturing sector. ***Study 1*** employed PLS-SEM to identify key determinants of AI adoption. These quantitative insights provided a foundational understanding of the factors directly influencing firms' AI adoption and open innovation. Complementing this, ***Study 2*** utilized qualitative methods to grounded the AI capabilities essential for apparel firms and the barriers preventing AI adoption for developing an innovation ecosystem framework with 13 propositions (***MRO***). While ***Study 1*** highlighted firm-level dynamics, ***Study 2*** expanded the perspective by exploring the multi-layered mechanisms driving collaboration, resource flow, and KACAP across the ecosystem. Overall, these studies highlight the interplay between micro-level adoption determinants and macro-level systemic enablers and barriers, providing both theoretical insights and practical implications for fostering AI-driven innovation in the apparel manufacturing sector.

7. Conclusion, Limitations and Future Research, and Highlights

7.1. Introduction

This chapter serves as the conclusion of this thesis research. Section 7.2 provides an overview of the key findings from each chapter. Section 7.3 discusses the limitations and offers recommendations for future research. Finally, Section 7.4 presents highlights. The chapter flowchart is illustrated in **Figure 7.1**.

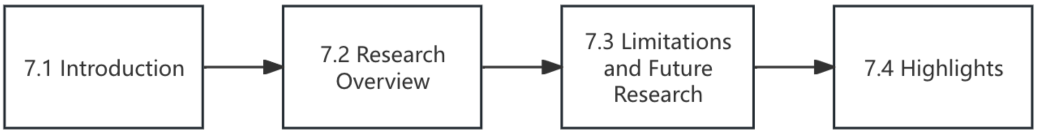

Figure 7.1 Flow Chart of Chapter 7

7.2. Research Overview

Chapter 1 presented the research context of AI evolution, its disruption in China's traditional apparel manufacturing in Industry 4.0, and the extent to which Chinese AI policies foster an innovative environment. This presented an overview of AI adoption drives innovation and updating in this domain. Furthermore, the theoretical background provided the rationale and gaps for researchers aware of the rare research on specific industry with the current technology adoption theories, and promoted organizations to understand holistically the antecedents driving AI adoption. Thus, the ***MRO*** and ***SROs*** were identified, and the research approach was also briefly described, and the research approaches and boundaries were determined. The research significance was introduced from theoretical and practical aspects, and the policy-related significance was briefed, thereby crystallizing the research idea to conduct the literature review further.

Chapter 2 reviewed the theoretical background associated with AI's capabilities toward innovation and AI adoption, documenting their influence on open innovation. This provided the foundations of AI adoption, enabling roles in innovation, and arrival to present these AI-integrated technologies adoption, together with the factors driving their adoption, influencing the MSMEs' open innovation in exchange. Among the reviewed studies, the TAM-TOE framework is widely recognized in technology adoption studies as a robust analytical tool (Dobre, 2022). It enables an in-depth examination of technological and organizational factors within the broader context of the business environment. Thus, this study has been conducted with the underpinning of the TOE-TAM for exploring AI-integrated technologies adoption research from firm level. To further expand the driver of technology adoption toward open innovation, several studies mentioned RBV has been applied in a significant number of the studies reviewed for this thesis. Therefore, the research applied KBV that is derived from RBV for exploring the mediator roles of KACAP between AI adoption and open innovation in the present status of China's traditional apparel manufacturing transformation. Using the integrated and extended TAM-TOE framework, the integrated and extended TAM-TOE framework was used to develop a conceptual model that simplifies complex concepts by incorporating antecedents, intermediates, and consequences derived from established technology adoption models. In ***Study 1***, the model integrates and extends the TAM-TOE framework by introducing the new concept of KACAP, which acts as a mediator between AI adoption and open innovation within the organizational component of the TOE framework. The TAM model's dimensions of perceived usefulness and perceived ease of use align with the technological factors in the TOE framework, while the organizational dimension includes organizational complexity and readiness. Additionally, the external environment is defined by competitive pressure, supplier involvement, market uncertainty, and government support and policies. The study formulates hypotheses regarding the effects of technological, organizational, and environmental factors on AI adoption, KACAP, and open innovation. By introducing KACAP as a key mediator, the study expands the traditional TAM-TOE framework, which fills a research gap by providing a structured approach to understanding the relationship between AI adoption and open innovation. From the KBV perspective, this research offers a comprehensive framework for assessing how AI technologies can enhance open innovation within firms, thus contributing to academic knowledge and practical applications in strategic management in Chinese apparel manufacturing MSMEs.

Furthermore, this ***Chapter*** reviewed the literature of innovation ecosystem and revisited AI capabilities in open innovation to define innovation ecosystem in the AI age for ***Study 2***. This thesis employs the definition of innovation ecosystem by Granstrand and Holgersson's (2020) in that this definition aligned with Chesbrough (2003)'s open innovation theory, highlighting the importance of external knowledge flows, where firms leverage ideas and technologies from outside sources to enhance their internal innovation capabilities with the collaboration with stakeholders. As we hypothesized that AI adoption drives open innovation in ***Study 1***, the understanding of how firms leverage AI to build an innovation ecosystem from open innovation perspectives is crucial. It is a significant theoretical base for the grounded AI-enabled innovation ecosystem theory in ***Study 2***. As this definition emphasizes the importance of collaboration of different stakeholders within the manufacturing ecosystem, the theory of TH model (Etzkowitz & Leydesdorff, 1995) was employed to further clarify the roles of universities, industry, and the China's central government, providing the theoretical context for building the grounded theory for ***Study 2***. The literature review has been synthesized for the relationships between ***Study 1*** and ***Study 2***, which suggests a theoretical direction for achieving the ***MRO***.

Chapter 3 was to proceed with the research framework, consisting of two different research approaches in ***Study 1*** and ***Study 2***, respectively. First, the research paradigms and corresponding methodological approaches based on Saunders et al. (2015, p.164) "research onion" were provided together with the rationale for the research philosophy of this thesis. Then, the research design, including methodology choices, strategies, and time horizons, was presented, followed by a description of the data collection and procedure of ***Study 1*** and ***Study 2***, respectively. In terms of ***Study 1***, it adopts an ontological objectivist perspective combined with an epistemological positivist approach, utilizing a deductive methodology. A quantitative method was implemented, employing a web-based survey as the primary data collection tool. The measurement scale was designed using items validated in prior research. For sampling, a quota-based approach was applied to ensure representativeness. It was employed to select specific manufacturers, and a simple random sampling technique was then applied to ensure representativeness among apparel manufacturing companies in China, identified through research of apparel association databases. The data collection started in June 2024 and lasted until August 2024. The minimum sample size was set for 155 observations, with 269 responses that were received and usable for the survey. ***Study 2*** was identified as an ontological constructivist perspective with epistemological interpretivism. It was an inductive qualitative study using grounded theory, a theory-constructing procedure by open, axial, and selected coding framework. It conducted a semi-structured interview using purposive sampling research with theoretical sampling and snowball sampling. The contents of these subsequent documents were analyzed using the constant comparison method. No new concepts emerged after examining the theoretical saturation, and existing categories were fully developed. As a result, 15 semi-structured interviews with 5 for data saturation were conducted in ***Study 2***.

To satisfy the ethical requirements, the ethical research protocol approval of the thesis was obtained prior to data collection. The survey questionnaire and interviews were provisioned with a comprehensive Participant Information Sheet and an Informed Consent. A cover letter has also been provided to third agency to ensure that the participants to whom they are distributed are aware of the research content, including detailed research purposes, researchers, and corresponding academic information.

Chapter 4 and ***Chapter 5*** presented the data results and analysis of the thesis. ***Chapter 4*** **(*****Study 1)*** conducted an analysis using the PLS-SEM technique. It presented the preliminary data analysis results, including the pilot and main studies. The pilot study has been found appropriate for further testing through the construct reliability and validity results. Outliers and normality were analyzed in the preliminary data assessment, and all items were retained for subsequent evaluation. Further, the descriptive statistics offered valuable insights into the demographics of MSMEs, including their size, age, business type, and industry clusters. The chapter then focused on MSEM analysis, detailing the outcomes of both the measurement and structural models for the full sample. The analysis of the proposed model revealed critical findings, highlighting the significant impact of the AI construct on MSMEs' open innovation mediated by KACAP. AI adoption was significantly influenced by one technological factor (perceived usefulness), not by perceived ease of use. Both two organizational antecedents were found to have insignificant impacts on AI adoption. Except for the supplier involvement factor, all external environmental factors (Competitive pressure, supplier involvement, market uncertainty, government support and policy) significantly impact AI adoption (excluding supplier involvement) and open innovation (excluding government support and policy).

Chapter 5 (Study 2) presents the findings from ***Study 2***, which employed qualitative methods to explore the dynamics of AI adoption in Chinese apparel manufacturing sector. Drawing on semi-structured interviews with key stakeholders from industry, government, and universities, the analysis identified critical AI capabilities, such as adaptive production and human-AI collaboration, as well as systemic barriers, including insufficient resources, talent shortages, and policy mismatches. These findings provide rich, grounded insights into the challenges and opportunities associated with AI adoption, emphasizing the interconnected roles of stakeholders across the sector.

Chapter 6 revisited the results reported in ***Chapter 4*** and the findings from ***Chapter 5***, aligning them with the five research questions. The preliminary data analysis initially confirmed that the research model was robust and that the data set was high quality. Regarding the structural TAM-TOE model, the review and analysis of results followed a clear and systematic approach, accurately assessing the model's explanatory power using the R^2 coefficient of determination. The predictive power was also evaluated through $PLS_{predict}$, which effectively demonstrated the models' explanatory solid and predictive capabilities. Then, the first and second research questions have been discussed, especially in the aspects of the contributions of the KACAP concept in examining the determinators of AI-integrated technologies adoption toward MSMEs' open innovation. The third and fourth research questions were addressed from the coding analysis based on the grounded data, and then the fifth research question was addressed through an AI-enabled triple-layer innovation ecosystem framework.

It also discussed the theoretical contributions and managerial implications. KACAP served as a mediator, contributing to the KBV and RBV literature on strategic management by bridging AI and business alignment, fostering both AI adoption and open innovation. The theoretical contributions of this research also include advancing innovation ecosystem theory by bridging micro-level adoption determinants and macro-level systemic mechanisms. The framework was developed to demonstrate how external collaborations, such as university-industry partnerships and supply chain integrations, enable firms to overcome barriers and build knowledge absorptive capacity. Additionally, the study reconceptualized the role of government, highlighting the transition from top-down directives to facilitating collaborative innovation.

From a managerial perspective, the findings underscore the importance of developing internal capabilities while leveraging external resources. Managers are encouraged to foster interdisciplinary teams and actively engage in ecosystem-wide collaborations. Policymakers should focus on creating regional innovation hubs, tailored funding mechanisms, and programs that address talent shortages and resource inequities. By aligning organizational efforts with ecosystem dynamics, stakeholders can accelerate AI adoption and foster sustainable innovation.

7.3. Limitations and Future Research

7.3.1. Limitations and Future Research of *Study 1*

The study has contributed comprehensive theoretical lenses and managerial implications; however, it has several limitations, which could provide room for future research. The first limitation arises from the study's cross-sectional nature. This research has conducted a cross-sectional analysis in which the data was gathered at only one point. Thus, future studies could collect longitudinal data to see how the model performs, using data collected from the same responses over a certain period (Chatterjee et al., 2021).

Second, although it covers China's typical apparel clusters, given that geographic variance is associated with local culture and subjective norms (Dziembowska-Kowalska & Funck, 2000; Tomczak & Stachowiak, 2015), the antecedent of culture or *Guanxi* may influence managers' attitudes toward AI adoption (W. Guan et al., 2023). This is the second limitation of geographical culture in China. Thus, future studies might revisit cultural factors in the proposed model. Third, the proposed model suggests that the two indicators of organizational complexity may not fully capture the construct's complexity, affecting the measurement model's ability to adequately reflect the underlying concept and potentially impacting the construct validity of organizational complexity in the analysis. Therefore, future studies should consider incorporating more latent indicators for a construct to ensure its robustness and better capture its complexity.

Last, the study has identified the factors influencing AI adoption in Chinese apparel manufacturing sector, driving open innovation through KACAP. However, the gap in educational levels across apparel manufacturing is significant, and different types of apparel manufacturing reflect distinct business models. The study did not differentiate between various types of managers based on the types of products they manufacture. For example, companies specializing in producing single product types, such as suits and shirts, tend to have a greater need for AI technologies, while companies with a more diverse range of products are currently less confident in the ability of AI to handle the complexity of more intricate designs. Therefore, future research should differentiate the study sample by categorizing company owners based on product types to compare the effects of the same model across different types of apparel manufacturers. In addition, MSMEs' trust in AI technologies should also be incorporated as a factor in adoption models, as it might significantly influence AI adoption.

7.3.2. Limitations and Future Research of *Study 2*

One of the primary limitations of this grounded theory study is the extensive time required for data collection and analysis, as these processes must coincide with constant comparison. This study conducted the interviews in two rounds, and theoretical saturation was tested after the second coding round. However, whether theoretical saturation was achieved largely depends on the researcher's coding experience and subjective judgment. Future research should emphasize continuously comparing grounded data and increasing the number of coding rounds to ensure that theoretical saturation and validity are adequately achieved.

A second limitation relates to the sample size in the first round of interviews, which consisted of 15 participants representing key roles in the innovation ecosystem. Due to the wide variation in participants' educational backgrounds and experiences, some interviewees struggled to engage deeply with the questions, occasionally leading to biased responses. Additionally, the relatively small number of interviews with association leaders stemmed from difficulties in securing interviews, as many declined participations due to the technical or policy-related nature of the discussions. These challenges posed significant barriers to the research process. The researcher relied on personal connections within China (Guanxi) (Guan et al., 2023) to establish contact with apparel associations and secure company interviews, which inevitably limited the diversity and range of participants. To address these limitations, future studies should consider diversifying the interview methods, such as incorporating focus groups. Given that grounded theory can draw from various data sources, future research could also include policy text analysis and, where copyright permits, content from apparel-related video platforms as additional data, and industry panel data for grounded theory analysis. These alternative data sources could enrich the findings and provide a broader perspective on AI adoption and open innovation within the apparel industry.

The third limitation is the lack of validation for the identified barriers to AI adoption through structural equation modelling. Thus, future research should focus on empirically validating the identified barriers to AI adoption using structural equation modeling or other quantitative methods. This would allow for a more robust understanding of the relationships between these barriers and their impact on AI adoption within the innovation ecosystem.

Fourth, the model of AI-enabled innovation ecosystems in Chinese apparel manufacturing sector has not yet been applied to an apparel firm to validate its practical effectiveness, which highlights a key agenda for future research. Therefore, this theoretical model should be implemented in a specific project to examine how these barriers evolve over time and interact with dynamic changes in policy, market conditions, and technological advancements, ideally through a longitudinal case study.

Fifth, Propositions (P1, P2, and P3) are rooted in the specific challenges and opportunities of the Chinese apparel manufacturing sector, they hold potential applicability for other industries facing similar issues of regional disparity, financial constraint, and the need for collaborative innovation. However, their broader implementation requires careful contextual adaptation, considering industry-specific market dynamics, funding cycles, and institutional environments. Future research should aim to empirically test and refine these propositions in diverse industrial settings to better delineate their scope and optimize their effectiveness beyond the apparel sector.

Last but not least, while the findings provide valuable insights into AI adoption in emerging markets, they may not directly apply to developed economies, such as the U.S., without further validation. The dynamics of manufacturing in Western countries, particularly in terms of technological infrastructure, labor markets, and policy environments, differ significantly from those in China. For instance, Western manufacturers may face different drivers and barriers to AI adoption, such as higher levels of AI readiness and stricter regulatory frameworks. Future research could extend this study by examining how the conceptual framework and findings apply in developed economies, adapting for context-specific variables. A comparative study between Chinese and Western manufacturers could also provide a more comprehensive understanding of AI adoption patterns globally, enriching both theoretical and practical implications. In addition, this study has not yet tested the framework in other developing economies that share similar characteristics with China, such as Vietnam, India, Indonesia, or Bangladesh. These countries also have large MSME sectors, government-driven industrial policies, and growing AI adoption initiatives, making them potential candidates for future validation of this framework. Therefore, Future research should conduct comparative studies across these developing economies to determine whether the identified AI adoption challenges, policy influences, and innovation ecosystem dynamics hold true in different national contexts. Such research would help refine the framework, allowing for potential adaptations that account for regional variations in government support, industrial maturity, and digital transformation strategies.

7.4. Highlight of Conclusion

To conclude, this chapter offers an overview of the entire research conducted in this study, highlighting the key points and main insights from each chapter. The **MRO** and **SROs** of the thesis have been achieved, providing a comprehensive understanding of the evolutionary nature of AI adoption in Chinese apparel manufacturing MSMEs. The study presents preliminary findings on the factors influencing open innovation within the context of current AI development, applied to the traditional industry under Industry 4.0 and Industry 5.0. Evidence from the Chinese apparel manufacturing sector supports these conclusions. The results of ***Study 1*** indicated that technological, organizational, and environmental factors significantly influence AI adoption, KACAP, and open innovation. Notably, this study emphasized that AI adoption must be mediated by KACAP to drive open innovation, suggesting that a traditional apparel MSME's ability to absorb new technologies is pivotal in determining the extent of its open innovation. However, firms do not exist in isolation within the innovation ecosystem; they must continuously adapt to external environmental uncertainty and leverage external resources (knowledge) to address the challenges posed by technology-driven transformations in traditional industries.

Building on this premise, ***Study 2*** employed a grounded theory approach to qualitatively analyze interviews with representatives from enterprises, universities, and government entities. Through systematic coding and analysis, the study identified critical required AI capabilities, adoption barriers, and collaborative mechanisms, which informed the development of a triple-layered innovation ecosystem framework. This framework illustrates the dynamic interplay between external knowledge absorption and internal innovation capacity within firms, highlighting the roles of various stakeholders in enabling AI adoption and fostering open innovation. By addressing barriers and aligning multi-actor collaborations, the framework contributes to achieving the ***MRO*** of this thesis, providing a theoretical foundation for understanding and advancing AI-driven innovation in the apparel manufacturing sector.

In conclusion, this doctoral thesis presents a comprehensive exploration of AI adoption and open innovation in Chinese apparel manufacturing industry, integrating the concepts of KACAP and collaboration among enterprises, universities, and government bodies. Theoretically, the research develops a novel framework that connects AI adoption with open innovation, filling gaps in the existing literature by highlighting the mediating role of KACAP. Empirically, ***Study 1*** employs PLS-SEM to quantify the relationships between AI adoption, KACAP, and open innovation, while ***Study 2*** applies grounded theory to uncover the layered roles and interactions of stakeholders in the innovation ecosystem. The study provides practical insights for manufacturers seeking to integrate AI into innovation processes and improve competitiveness. Moreover, the findings offer policymakers guidance on promoting AI-enabled collaboration across industries and institutions, contributing to sustainable economic development in Chinese apparel manufacturing sector. This research serves as a foundational framework for future studies and provides valuable direction for stakeholders to co-create value through AI-enabled innovation ecosystems.

Publication

Journal Paper

[1] Qu, Chen & Kim, Eunyoung. Reviewing the Roles of AI-Integrated Technologies in Sustainable Supply Chain Management: Research Propositions and a Framework for Future Directions. *Sustainability*, 16(14), 6186. pp. 1-26. 2024 https://doi.org/10.3390/su16146186

[2] Qu, Chen & Kim, Eunyoung. Investigating AI Adoption, Knowledge Absorptive Capacity, and Open Innovation in Chinese Apparel MSMEs: An Extended TAM-TOE Model with PLS-SEM Analysis. *Sustainability*, *17*(5), 1873. https://doi.org/10.3390/su17051873

Conference Proceedings and Presentations

[1] Qu, Chen; Kim, Eunyoung; Gokon, Hideomi; Ding, Wei. The Characteristics of Chinese Artificial Intelligence Policies for Innovations in Industry: Policy Distribution and Inclination. The 4th Kyoto Conference on Arts, Media & Culture, Kyoto, Japan, 10-13 Oct. 2023, 22 pages.

[2] Qu, Chen & Kim, Eunyoung. Artificial Intelligence-Enabled in Clothing Supply Chains: Research Context and Motivation Perspectives. The 4th IAFOR International Conference on Arts & Humanities, Hawaii, USA, 03-07 Jan. 2024. 15 pages.

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Appendices

Appendix A(a) The Core National Stakeholders of China's AI Policies (2017-2022)

Stakeholders	Acronym	Total Issues
Ministry of Science and Technology	MOST	26
Ministry of Industry and Information Technology	MOIIT	9
Ministry of Education	MOE	8
National Radio and Television Administration	NRTA	6
National Development and Reform Commission	NDRC	5
Office of the Central Cyberspace Affairs Commission	OOTCCAC	3
China Machinery Industry Federation	CMIF	2
Standardization Administration	SA	2
Ministry of Human Resources and Social Security	MOHRSS	2
Department of Science and Technology, Ministry of Transport	DOSTMOT	2
Ministry of Human Resources and Social Security General	MOHRSSGO	1
Ministry of Civil Affairs	MOCA	1
New Generation AI Governance Expert Committee	NGAGEC	1
Ministry of Transport	MOT	1
China National Intellectual Property Administration	CNIPA	1
Chinese Association for Artificial Intelligence	CAFAI	1
China National Intellectual Property Administration	CNIPA	1
Cyberspace Administration	CA	1
Ministry of Finance	MOF	1
State Administration for Market Regulation	SAFMR	1
National Information Security Standardization Technical	NISSTC	1
National Bureau of Statistics	NBOS	1
State Council	SC	1

Appendix A(b)The Core Regional Stakeholders of China's AI Policies (2017-2022)

The Regional Stakeholders	Acronym	Total
Guangzhou Municipal Science and Technology Bureau	GMSTB	11
Shanghai Municipal Commission of Economy and Informatization	SMCOEI	8
Wuhan Municipal Science and Technology Bureau	WMSTB	7
Guangzhou Municipal Industry and Information Technology Bureau	GMIITB	6
Hefei Municipal People's Government	HMPG	6
Xiamen Municipal Industry and Information Technology Bureau	XMIITB	6
Hefei Municipal Science and Technology Bureau	HMSTB	5
Department of Economy and Information Technology of Hubei Province	DOEITOHP	5
Jinan Municipal Industry and Information Technology Bureau	JMIITB	5
Tianjin Municipal Industry and Information Technology Bureau	TMIITB	5
Tianjin Municipal Science and Technology Bureau	TJMSTB	5
Chengdu Municipal People's Government	CDMPG	4
Hangzhou Municipal People's Government	HZMPG	4
Department of Industry and Information Technology of Hunan	DOIITHNP	4
Jinan Municipal Commission of Economy and Informatization	JNMCOEI	4
Shenzhen Municipal Industry and Information Technology Bureau	SZMIITB	
Changsha Municipal Science and Technology Bureau	CSMSTB	4
Changsha Municipal Science and Technology Bureau	CSMSTB	4
Chengdu Municipal Bureau of Economic and Information Technology	CDMBOEIT	3
Chengdu New Economic Development Commission	CDNEDC	3
The People's Government of Gansu Province	PGOGSP	3
Big Data Development Bureau of Guangxi Zhuang Autonomous Region	BDDBOGX ZAR	3
Hefei Municipal Development and Reform Commission	HFMDRC	3
Nanning Municipal Industry and Information Technology Bureau	NNMIITB	3
Shanghai Municipal People's Government	SHMPG	3
Shanghai Xuhui District People's Government	SHXDPG	3
Science, Technology and Innovation Commission of Shenzhen Municipality	STICSM	3
Shenyang Municipal Science and Technology Bureau	SYMSTB	3
Chongqing Municipal Science and Technology Bureau	CQMSTB	3

Appendix B. Survey Questionnaires of *Study 1*

Please read the informed consent, and if you agree, please complete the following questions.

Please confirm that you would like to participate and click "Next".

Section 1. Descriptive questions (Demographics)

Q01. How many years did you own your company?

☐ <5years ☐ 6-10years ☐ 11-15years ☐ >15years

Q02. How many employees are there in your company?

☐ 1-10 ☐ 11-50 ☐ 51-200 ☐ 201-500 ☐ >500

Q03. What are your company's annual sales (unit: thousand)?

☐ <1,000 ☐ 1,001-5,000 ☐ 5,001-10,000 ☐ >10,000

Q04. What is your production capacity for export (unit: piece per month)?

☐ <1,000 ☐ 1,000-5,000 ☐ 5,001-10,000 ☐10,000-20,000 ☐>20,000

Q05. What is the business type of your company/manufacturing (Multiple choice)?

☐ for OEM ☐ for ODM ☐ for OBM

Q06. What is your main exported country or region (multiple choice)?

☐ Asia- Japan, Korean ☐ Asia-Singapore ☐ Europe ☐North America- Canada ☐ North America- the U.S.☐ Domestic

Section 2. Likert-scale questions

Please circle a number that best reflects your perspectives on AI technology adoption in the manufacturing and production processes. (1= 'strongly disagree', 2 = 'disagree', 3 = 'neutral', 4= 'agree', 5 = 'strongly agree')

Q7_About perceived usefulness

Q7_1. Using AI-based manufacturing and production systems can enhance work efficiency.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q7_2. Using AI-based manufacturing and production systems can improve the quality of task.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q7_3. Using AI-based manufacturing and production systems can increase productivity.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q7_4. Using AI-based manufacturing and production systems can save a significant amount of time.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q7_5. AI can provide valuable decision support for manufacturing and production.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q8_About perceived ease of use

Q8_1. The AI operation process is easy to understand.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q8_2. The time required to learn AI is reasonable.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q8_3. Our employees can easily operate an AI-based manufacturing and production system.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q8_4. Our employees can quickly learn about the usage of AI in their work processes.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q9_About organizational complexity

Q9_1. Integrating AI technology with the existing legacy system is difficult for our organization.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q9_2. Resistance to change is high regarding migrating from the legacy system to an AI-based manufacturing and production system.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q10About Organizational Readiness

Q10_1. Our company has the complete infrastructure to develop AI in manufacturing and production processes.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q10_2. Our employees have the necessary skills and knowledge to use the AI-based system.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q10_3. Our management has a high level of support for AI in manufacturing and production systems.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q11_About competitive pressure

Q11_1. A few of our competitors are implementing an AI-based manufacturing and production system.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q11_2. Using an AI-based manufacturing and production system will bring a competitive advantage to my firm.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q11_3. The apparel industry has increasingly applied an AI-based manufacturing and production system.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q12_About supplier involvement

Q12_1. Our suppliers provide satisfying products and services.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q12_2. Our suppliers respond quickly to our demands.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q12_3. We have close relationships with our suppliers.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q13_About market uncertainty

Q13_1. Our market demand frequently experiences significant changes.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q13_2. Our customers' needs are variable and unpredictable.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q13_3. The pace of technological development in our industry is very fast.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q13_4. The emergence of new technologies has an unpredictable impact on our industry.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q14_About government support and policy

Q14_1. I knew about government policies and regulations regarding the application of AI technology in apparel manufacturing and production.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q14_2. The government provides adequate financial support for developing and applying AI-integrated technology to our company.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q14_3. The government's support and help are very important when applying AI technologies.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q15_About AI adoption

Q15_1. We need to adopt AI technology for manufacturing and production.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q15_2. We need to adopt AI technology to solve problems in supply chain management.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q15_3. We need to adopt AI technology to reduce risks in our manufacturing and production processes.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q15_4. We need to adopt AI technology to be agile in an uncertain environment.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q16_About knowledge absorptive capacity

Q16_1. Our company can effectively identify and acquire important new knowledge and information within and outside the industry to support the application of AI technology.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q16_2. We actively acquire knowledge from external sources and integrate it with internal knowledge.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q16_3. Our company can understand and analyze the acquired knowledge and information within and outside the industry, ensuring compatibility with existing knowledge.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q16_4. We provide sufficient technical training for our employees to help them absorb and understand AI technology.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q17_About open innovation

Q17_1. Our company culture encourages knowledge sharing.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q17_2. Our company extends sources with our customers.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q17_3. Our company extends sources with our suppliers.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q17_4. Our company extends its resources to institutions and universities.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q17_5. Our collaboration with external partners helps us better adopt new technologies.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Survey Link:

https://www.yibiaoda.com/r/82e30

Appendix C. Informed consent of survey questionnaires.

Dear Participant,

Thank you for taking the time to participate in this research study. The aim of this survey is to explore managers' attitudes toward the use of artificial intelligence (AI) in manufacturing and production processes, examine the impact of AI on organizational innovation, and identify the factors hindering AI adoption in China's manufacturing industry. All the information you provide will be used solely for academic research purposes and will be strictly confidential in accordance with legal requirements. This study is conducted by Chen QU and Eunyoung KIM at the Graduate School of Advanced Science and Technology, Japan Advanced Institute of Science and Technology (JAIST). The research findings will be presented in a doctoral thesis, and your personal and corporate names will not appear in any reports. Your participation is crucial to the success of this research.

Survey Information

Eligibility: The survey is intended for managers working in the Chinese apparel manufacturing industry.

Survey Content: The questionnaire will gather insights into your company's practices and perspectives on AI implementation, innovation management, and knowledge absorption. Completing the survey will take approximately 10-15 minutes.

Confidentiality: The survey is conducted anonymously. All responses will be kept confidential and used solely for aggregate statistical analysis. The data will not be disclosed to any third party or used for commercial purposes.

Voluntary Participation: Participation is entirely voluntary. You may withdraw from the survey at any time, and if you choose to do so, your responses will not be included in the analysis.

Consent

By clicking "Next" and completing the questionnaire, you acknowledge that you have read and understood the above information, and you consent to participate in this study.

If you have any questions or require further information regarding this research, please contact the investigator QU Chen via email: s2120407@jaist.ac.jp.

Thank you very much for your participation!

[Japan Advanced Institute of Science and Technology]

Date: June 2024

Appendix D. Informed consent of semi-structured interview.

Dear Participant (from apparel manufacturing firms),

Thank you for agreeing to participate in this research interview. The purpose of this interview is to explore the mechanisms that hinder AI adoption among decision-makers or managers in apparel manufacturers and how enterprises' roles are involved with universities, associations, and government for a collaborative innovation ecosystem.

This study is conducted by Chen QU and Eunyoung KIM at the Graduate School of Advanced Science and Technology, Japan Advanced Institute of Science and Technology (JAIST). The information you provide will be used exclusively for academic research, and all personal data will be kept strictly confidential. Your name or identifying information will not appear in any reports or publications.

The interview will take approximately 30-60 minutes, and with your permission, we would like to record the conversation for accurate transcription and analysis. Your participation is entirely voluntary, and you can withdraw from the interview at any time without any negative consequences. If you choose to cancel, any data you have provided will not be used in the research.

If you have any questions about the research, please contact the principal investigator Chen QU via email: s2120407@jaist.ac.jp.

Please read and sign below to confirm that you understand the above information and agree to participate in this study.

Participant's Signature: ________________

Date: ________________

Before conducting the interview, we first explained the definitions of innovation ecosystems. Then, we explained what AI-integrated technologies are used in apparel manufacturing, such as AI sewing machine robots, Decision support systems, Blockchain, IoT, Big data, etc.

Q1. Please introduce your company (company size, industry, main business, etc.).

Q2. What is the current state of the company's technology infrastructure?

Q3. Please describe the specific application domains and current application scenarios in apparel manufacturing.

Q4. What do you think are the main uses of AI in apparel manufacturing and production? (e.g., demand forecasting, optimizing operations, customer service, supply chain management, etc.)?

Q5. Has your company adopted AI?

If yes, please tell me the performance that AI brings to your company. (to Q6, Q7, andQ9)

If not, please tell me why your company has not decided to adopt AI. And what is your concern?

Q6. If your company adopts AI technology, what are the main challenges your company faces (e.g., technical difficulties, funding issues, talent shortages, etc.)?

Q7. If your company does not adopt AI technology, what barriers may your company face (e.g., technical difficulties, funding issues, talent shortages, etc.)?

Q8. What do you think is the impact of AI technology adoption on your company? (e.g., improving efficiency, reducing costs, increasing revenue, etc.)

Q9. Are there specific performance indicators that show AI improving company performance?

To achieve the second purpose, we designed the following interview questions.

Q10. What key elements should be included in an effective AI innovation ecosystem (such as technical support, policies and regulations, talent training, partnerships, etc.)?

Q11. Does your company work with external institutions (such as universities, research institutes, and other businesses) in AI? If yes, describe the impact of these collaborations on the company's performance. If not, do you plan to, or are you willing to work with external institutions?

Q12. What role should government or industry associations play in building an AI innovation ecosystem?

Q13. What else do you think or suggest about the impact of the AI innovation ecosystem?

Thank you for participating!

Dear Participant (from universities),

Thank you for agreeing to participate in this research interview. The purpose of this interview is to explore the direction of cultivating fashion talents in the AI age, the challenges of current teaching faculty, and how universities' roles are involved with industries, associations, and government for a collaborative innovation ecosystem.

This study is conducted by Chen QU and Eunyoung KIM at the Graduate School of Advanced Science and Technology, Japan Advanced Institute of Science and Technology (JAIST). The information you provide will be used exclusively for academic research, and all personal data will be kept strictly confidential. Your name or identifying information will not appear in any reports or publications.

The interview will take approximately 30-60 minutes, and with your permission, we would like to record the conversation for accurate transcription and analysis. Your participation is entirely voluntary, and you can withdraw from the interview at any time without any negative consequences. If you choose to cancel, any data you have provided will not be used in the research.

If you have any questions about the research, please contact the investigator QU Chen via email: s2120407@jaist.ac.jp.

Please read and sign below to confirm that you understand the above information and agree to participate in this study.

Participant's Signature: ________________

Date: ________________

Before conducting the interview, we first explained the definitions of open innovation and innovation ecosystems.

Q1. What is your position/role in university?

Q2. What is the primary academic discipline of your institution?

Q3. In your opinion, what is the necessity of offering AI programs at art institutions?

Q4. What types of collaborative projects related to AI has your university engaged in with apparel companies or organizations? (Please explain the type of collaboration, how the cooperation is carried out, and the goals and outcomes of the collaboration.)

Q5. What challenges has your institution faced in promoting university-industry collaboration in the field of AI? (e.g., technical challenges, resource integration, policy support)

Q6. How do you think AI technology contributes to promoting open innovation? (e.g., collaborative projects, talent cultivation, knowledge flow, technology transfer)

Q7. How does your institution utilize innovation and entrepreneurship centers or other platforms to promote open innovation in the field of AI?

Q8. What contributions do you think your institution has made in promoting intelligent manufacturing and industrial upgrading and transformation?

Q9. In the era of AI, how should companies and schools build an innovation ecosystem? What is the role of AI in this innovation ecosystem?

Dear Participant (from associations),

Thank you for agreeing to participate in this research interview. The purpose of this interview is to explore the direction of working direction in the AI age and how universities' roles are involved with industries, universities, and government for a collaborative innovation ecosystem.

This study is conducted by Chen QU and Eunyoung KIM at the Graduate School of Advanced Science and Technology, Japan Advanced Institute of Science and Technology (JAIST). The information you provide will be used exclusively for academic research, and all personal data will be kept strictly confidential. Your name or identifying information will not appear in any reports or publications.

The interview will take approximately 30-60 minutes, and with your permission, we would like to record the conversation for accurate transcription and analysis. Your participation is entirely voluntary, and you can withdraw from the interview at any time without any negative consequences. If you choose to cancel, any data you have provided will not be used in the research.

If you have any questions about the research, please contact the investigator QU Chen via email: s2120407@jaist.ac.jp.

Please read and sign below to confirm that you understand the above information and agree to participate in this study.

Participant's Signature: ________________

Date: ________________

Before conducting the interview, we first explained the definitions of innovation ecosystems.

To achieve the first purpose, we designed the following interview questions:

Q1. What are the most challenging problems in current AI research in fashion?

Q2. Has the association already had AI-related training or curriculums?

If so, please tell me the curriculum's specific content.

If not, please tell me why there are no related training or curriculums.

To achieve the second purpose, we designed the following interview questions:

Q3. Has the association collaborated with industries, enterprises, government, or other academic institutions?

If yes, please describe some specific cooperation cases in detail and explain how these collaborative projects help advance AI research and applications.

If not, please tell me what the reasons are.

Q4. Has the association received resources from the government or industries?

If yes, how does this support help research and teaching? If not, what do you think of the issues or barriers?

Q5. What additional resources or support are needed to advance AI research and applications?

Q6. What are your suggestions for the government to support the AI innovation ecosystem?

Thank you for participating!

Appendix E. Cover Letter

Dear Beijing Fengling Digital Intelligence Information Technology Co., LTD,

My name is QU Chen, and I am a doctoral student at the Japan Institute of Science and Technology. My supervisor is Kim Eunyoung. We are conducting a survey for the PhD thesis in artificial intelligence (AI) adoption and open innovation in the micro, small and medium-sized Chinese apparel manufacturing firms.

We are reaching out to request your assistance in distributing a survey as part of this doctoral thesis focusing on the adoption of AI in the Chinese apparel manufacturing industry. The survey aims to gather insights into top managers' attitudes toward AI technologies being implemented in this sector, their potential impact on operational efficiency, and their role in driving innovation.

AI in this research pertains to intelligent apparel manufacturing equipment applications, such as automated fabric spreading machines, data-driven pattern generation systems, process instruction readers, automated layout and cutting systems, and sewing robots. These technologies transform traditional manufacturing processes by optimizing efficiency, improving product quality, and enabling companies to respond more effectively to market dynamics. Also, AI is integrating with emerging technologies such as the Internet of Things, blockchain, and cloud computing, which can be applied in the supply chain management.

The survey was designed to capture feedback from top managers and owners in the apparel manufacturing industry, especially OEM, ODM, and OBM companies. Your support in distributing this questionnaire to relevant respondents will be invaluable. We are particularly interested in reaching organizations directly involved in manufacturing operations, decision-making, or innovation processes in the apparel sector.

Key details about the survey:

Estimated Completion Time: 10-15 minutes

Confidentiality: All responses will remain anonymous and used solely for academic purposes.

Survey Link: https://www.yibiaoda.com/r/82e30

We kindly ask your assistance in forwarding this survey invitation to your network of relevant participants. Your support will contribute significantly to the success of this research, helping to advance understanding in this critical area of technological development.

If you require further information about the survey or the research project, please do not hesitate to contact me at s2120407@jaist.ac.jp.

Thank you very much for your collaboration and support in this endeavor.

Sincerely,

QU Chen

2120407@jaist.ac.jp.

Japan Advanced Institute of Science and Technology

Date: July 3, 2024