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Thesis for the Degree of Doctor of Philosophy

The Effect of AI Capability on Novelty and Efficiency: The Moderating Roles of Customer Integration and Supplier Integration

by

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Department of Business Administration

The Graduate School

Pukyong National University

August, 2025

The Effect of AI Capability on Novelty and Efficiency: The Moderating Roles of Customer Integration and Supplier Integration

(인공지능 역량이 참신성과 효율성에 미치는 영향: 고객 통합과 공급자 통합의 조절 효과)

by

DeYu Zhong

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August, 2025

The Effect of AI Capability on Novelty and Efficiency: The Moderating Roles of Customer Integration and Supplier Integration

A dissertation

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August 22, 2025

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The Effect of AI Capability on Novelty and Efficiency: The Moderating Roles of Customer Integration and Supplier Integration

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Abstract

In the context of globalization, artificial intelligence (AI) has emerged as a critical driver of economic growth and corporate innovation, significantly influencing novelty, efficiency, and supply chain integration. This study focuses on the role of AI capability in novelty and efficiency, examining the moderating effects of supplier integration and customer integration in this process. Through theoretical exploration and empirical analysis, the study elucidates the mechanisms by which AI enhances firms' innovation capabilities and operational efficiency in dynamic competitive environments.

The primary objective of this research is to clarify the core role of AI capability in novelty and efficiency, to systematically investigate the moderating effects of supply chain integration. Specifically, the study aims to achieve three objectives:

1) Validate the effectiveness of AI capability in enhancing novelty and efficiency.

2) Explore how customer integration strengthens the positive impact of AI capability on novelty innovation by improving market trend analysis and consumer behavior prediction.

3) Analyze how supplier integration enhances the positive impact of AI capability on efficiency optimization through resource optimization and increased transparency.

This study adopts a rigorous theoretical framework and quantitative research methods, employing the resource-based view (RBV) and dynamic capabilities theory (DCT) to construct the research model. Data were collected through professional organizations, yielding 490 valid responses, and hypotheses were tested using hierarchical regression analysis. To ensure the reliability of the findings, the study controlled for non-response bias and common method bias. Measurement instruments

included variables assessed with a seven-point Likert scale, and construct validity and reliability were thoroughly evaluated.

The study systematically examines AI capability, novelty, efficiency, and supply chain integration from multiple dimensions. First, it identifies the definition of AI capability and its critical roles in resource optimization, collaboration enhancement, and knowledge generation, particularly in novelty and efficiency. Second, it highlights the moderating effect of customer integration on the relationship between AI capability and novelty innovation, emphasizing how customer collaboration enhances market responsiveness and innovation capabilities. Third, it delves into the moderating mechanism of supplier integration on the relationship between AI capability and efficiency optimization, particularly through supply chain resource integration, real-time data sharing, and improved transparency. Finally, empirical analysis validates the theoretical hypotheses and summarizes the compound effects of supply chain integration on AI capability, novelty, and efficiency.

The study's innovation lies in its first attempt to construct an extended research model from the multi-theoretical perspectives of RBV and DCT, systematically analyzing the moderating effects of supply chain integration on the relationship between AI capability, novelty, and efficiency. By combining theoretical exploration with empirical analysis, the research reveals the internal logic of achieving supply chain collaboration and innovation in the context of digital transformation.

The findings of this study are as follows:

1) AI capability has a significant positive impact on both novelty and efficiency, indicating that AI can simultaneously enhance innovation capabilities and operational efficiency.

2) Customer integration significantly enhances the effect of AI capability on novelty innovation by strengthening deep collaboration and information sharing between firms and customers.

3) Supplier integration enhances the effect of AI capability on efficiency optimization by improving resource optimization and transparency.

(4) The interaction between customer integration and AI capability has no significant effect on efficiency, and the interaction between supplier integration and AI capability has no significant effect on novelty.

These findings provide new theoretical perspectives and practical guidance for firms to leverage AI technologies in achieving novelty, efficiency, and supply chain collaboration. Theoretical contributions include deepening the understanding of the relationship between AI capability, novelty, and efficiency, and extending the

applicability of RBV and DCT. Practically, the study offers valuable insights for firms aiming to optimize supply chain collaboration and enhance competitiveness in the context of digital transformation. Specifically, firms can unlock the potential of AI in innovation and efficiency enhancement through customer and supplier integration. Furthermore, the study offers policy recommendations for promoting AI adoption, enhancing supply chain resilience, and optimizing resource allocation. By advancing the widespread application of AI technologies and deepening supply chain integration practices, firms can better address challenges in dynamic market environments, achieving sustained growth and innovation.

Keywords : AI Capability, Supply Chain Integration, Novelty and Efficiency, Resource-Based View, Dynamic Capabilities Theory

PUKYONG NATIONAL UNIVERSITY
국립부경대학교

인공지능 역량이 참신성과 효율성에 미치는 영향: 고객 통합과 공급자 통합의 조절 효과

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요 약

글로벌화 맥락에서 인공지능(AI)은 경제 성장과 기업 혁신의 핵심 동력으로 부상하였으며, 참신성, 효율성 및 공급망 통합에 상당한 영향을 미치고 있다. 본 연구는 AI 역량이 참신성과 효율성에 미치는 역할을 중심으로, 공급자 통합 및 고객 통합의 조절 효과를 검토한다. 이론적 탐색과 실증 분석을 통해, 본 연구는 AI가 역동적인 경쟁 환경에서 기업의 혁신 역량과 운영 효율성을 향상시키는 메커니즘을 규명한다.

본 연구의 주요 목적은 AI 역량이 참신성과 효율성에 미치는 핵심 역할을 명확히 하고, 공급망 통합의 조절 효과를 체계적으로 탐구하는 데 있다. 구체적으로, 본 연구는 다음 세 가지 목표를 달성하고자 한다:

1) AI 역량이 참신성과 효율성 향상에 효과적임을 검증한다.

2) 고객 통합이 시장 동향 분석 및 소비자 행동 예측을 개선함으로써 AI 역량이 참신성 혁신에 미치는 긍정적 영향을 강화하는 방식을 탐구한다.

3) 공급자 통합이 자원 최적화와 투명성 향상을 통해 AI 역량이 효율성 최적화에 미치는 긍정적 영향을 강화하는 방법을 분석한다.

본 연구는 자원 기반 관점(Resource-Based View, RBV)과 동적 역량 이론(Dynamic Capabilities Theory, DCT)을 기반으로 이론적 프레임워크를 구축하고, 정량적 연구 방법을 채택하였다. 전문 기관을 통해 수집한 데이터를 기반으로 490개의 유효 응답을 확보하였으며, 위계적 회귀분석(hierarchical regression analysis)을

통해 가설을 검증하였다. 연구 결과의 신뢰성을 확보하기 위하여 비응답 편향(non-response bias) 및 공통 방법 편향(common method bias)을 통제하였다. 측정 도구는 7점 리커트 척도(Likert scale)를 사용하여 변수들을 평가하였고, 구성타당성과 신뢰성을 철저히 검토하였다.

본 연구는 AI 역량, 참신성, 효율성 및 공급망 통합을 다차원적으로 체계적으로 검토한다. 첫째, AI 역량의 정의와 자원 최적화, 협업 강화 및 지식 생성에서의 핵심적 역할을 규명하고, 특히 참신성과 효율성 측면에서 그 역할을 강조한다. 둘째, 고객 통합이 AI 역량과 참신성 혁신 간 관계에 미치는 조절 효과를 강조하며, 고객 협업이 시장 대응력과 혁신 역량을 강화하는 방식을 조명한다. 셋째, 공급자 통합이 AI 역량과 효율성 최적화 간 관계에 미치는 조절 메커니즘을 심층적으로 탐구하며, 공급망 자원 통합, 실시간 데이터 공유 및 투명성 향상 측면에서 그 효과를 분석한다. 마지막으로, 실증 분석을 통해 이론적 가설을 검증하고, 공급망 통합이 AI 역량 및 참신성과 효율성에 미치는 복합적 효과를 종합한다.

본 연구의 혁신성은 RBV와 DCT라는 다중 이론적 관점에서 확장된 연구 모델을 최초로 구축하고, 공급망 통합이 AI 역량과 참신성 및 효율성 간 관계에 미치는 조절 효과를 체계적으로 분석한 데에 있다. 이론적 탐색과 실증 분석을 결합하여, 디지털 전환 맥락에서 공급망 협력과 혁신을 달성하는 내부 논리를 규명한다. 본 연구의 주요 발견은 다음과 같다:

1) AI 역량은 참신성과 효율성 모두에 대해 유의한 긍정적 영향을 미치며, 이는 AI가 혁신 역량과 운영 효율성을 동시에 향상시킬 수 있음을 나타낸다.

2) 고객 통합은 AI 역량이 참신성 혁신에 미치는 효과를 강화하며, 이는 기업과 고객 간의 심층 협력 및 정보 공유를 통해 가능해진다.

3) 공급자 통합은 AI 역량이 효율성 최적화에 미치는 효과를 강화하며, 이는 자원 최적화 및 투명성 향상을 통해 실현된다.

4) 고객 통합과 AI 역량 간의 상호작용은 효율성에 대해 유의한 효과가 없으며, 공급자 통합과 AI 역량 간의 상호작용은 참신성에 대해 유의한 효과가 없다.

이러한 연구 결과는 기업이 AI 기술을 활용하여 참신성과 효율성 및 공급망 협력을 달성하는 데 있어 새로운 이론적 관점과 실천적 지침을 제공한다. 이론적 기여로는 AI 역량과 참신성 및 효율성 간

관계에 대한 이해를 심화하고, RBV와 DCT의 적용 가능성을 확장하였다. 실천적으로는 디지털 전환 맥락에서 공급망 협력을 최적화하고 경쟁력을 강화하려는 기업들에게 유용한 시사점을 제공한다. 특히, 고객 및 공급자 통합을 통해 혁신과 효율성 향상을 위한 AI의 잠재력을 극대화할 수 있음을 시사한다. 또한, 본 연구는 AI 채택 촉진, 공급망 회복탄력성 강화, 자원 배분 최적화를 위한 정책 제언을 제공한다. AI 기술의 보편적 활용을 촉진하고 공급망 통합 실천을 심화함으로써, 기업들은 역동적인 시장 환경 속에서 지속 가능한 성장과 혁신을 달성할 수 있을 것으로 기대한다.

키워드: AI 역량, 공급망 통합, 참신성과 효율성, 자원기반 이론, 동적 역량 이론

Summary of Findings

This study investigates the impact of AI capability on novelty and efficiency, emphasizing the moderating effects of customer integration and supplier integration. The empirical results derived from hierarchical regression analysis offer several key findings.

First, AI capability exhibits a significant positive effect on both novelty and efficiency. This indicates that firms equipped with stronger AI capability are more likely to achieve innovative outcomes and streamline operational processes simultaneously.

Second, customer integration significantly strengthens the positive relationship between AI capability and novelty. This finding suggests that firms can enhance their innovative outcomes by deeply involving customers in product development, demand forecasting, and feedback mechanisms, which facilitate personalized and market-responsive innovation.

Third, supplier integration significantly enhances the positive effect of AI capability on efficiency. The results highlight the importance of real-time data exchange, resource optimization, and transparency in supplier collaboration, which contribute to improved operational efficiency.

Fourth, the moderating effects are domain-specific. The interaction between AI capability and customer integration does not have a significant effect on efficiency, and similarly, the interaction between AI capability and supplier integration does not have a notable impact on novelty. These asymmetrical results suggest that the benefits of integration depend on alignment with the specific performance logic—customer integration is more conducive to innovation, while supplier integration is more conducive to operational efficiency. Therefore, the research model has been structured accordingly to reflect these domain-specific moderating effects.

These findings not only validate the proposed research model but also underscore the necessity of aligning external integration strategies with the specific objectives of AI deployment. The study contributes to theory by extending the applicability of the resource-based view (RBV) and dynamic capabilities theory (DCT) and provides managerial guidance for firms striving to enhance innovation and efficiency in the digital transformation era.

1. Introduction

1.1 Research Background

In the context of globalization, artificial intelligence (AI) has emerged as a key driver of economic growth and corporate innovation. The integration of AI technologies into business operations has not only revolutionized operational efficiency and customer service but has also driven the evolution of novelty and efficiency (Wu et al., 2024, Dong et al., 2024). With the rapid development and widespread application of AI technologies, their significant position in global news and data underscores their impact across industries. However, integrating AI technology into actual business practices presents substantial challenges, particularly in terms of integrating suppliers and customers (Li et al., 2025). According to IBM's 2023 Global AI Adoption Index, businesses in emerging markets like India and the UAE have demonstrated a high enthusiasm for integrating AI technologies, significantly enhancing their technological competitiveness globally. This extensive adoption highlights the critical role of AI in driving business innovation and operational efficiency across various industries. The integration of AI in business processes is not merely a matter of technological implementation; it also involves strategic alignment with suppliers and customers to enhance overall efficiency and innovation. In an increasingly uncertain global economic environment, marked by events such as trade wars and global pandemic outbreaks, the stability and efficiency of global supply chains have been severely impacted. According to a report by the International Trade Centre (ITC), disruptions in the global supply chain in 2020 affected over 50% of businesses, adding to the uncertainty of business operations and forcing companies to reconsider their supply chain design and management. The application of AI technology is viewed as an effective means to enhance the resilience of supply chains, capable of optimizing decision-making processes and enhancing transparency to meet the ever-changing market demands (Wang et al., 2025b, Abu Huson et al., 2024). The rapid development of AI technology has become a hot topic, especially with breakthroughs in areas like deep learning, machine learning, and natural language processing, which have greatly expanded the scope of AI applications (Sullivan and Wamba, 2024). For instance, Google's BERT model has made significant progress in language understanding, advancing the commercial application of natural language processing technologies. Additionally, AI applications in image recognition and autonomous driving are beginning to change the operational models of traditional industries. However, the integration of AI technology is not merely a matter of technological application but also a challenge of how to effectively integrate this technology within organizational structures and business processes. Concurrently, under the impetus of AI technology, novelty and efficiency are undergoing fundamental changes. Transitioning from product-based novelty and efficiency to service and outcome-oriented models, businesses need to not only focus on product innovation but also on the personalization of services and the optimization of customer experiences. For example, Amazon has improved customer shopping experiences through its intelligent recommendation system, and its AI-based logistics optimization system has significantly enhanced delivery efficiency. These transformations not only enhance customer loyalty but also support Amazon's leadership in the competitive e-commerce market. Therefore, the widespread application and rapid development of AI technology have had significant impacts on business operation models and global supply chain management (Sullivan and Wamba, 2024, Wong et al., 2024, Belhadi et al., 2024). The next section will introduce the theoretical background of AI technology in the fields of operations and supply chain management, to further explore the mechanisms through which it functions.

1.2 Theoretical Background

This section builds on the insights provided by the research background to further delve into the theoretical framework of integrating artificial intelligence (AI) capabilities into novelty and efficiency, with a particular emphasis on the moderating role of supplier and customer integration. This study primarily draws on the resource-based view (RBV) and dynamic capabilities theory (DCT), through which we explore how the strategic deployment of AI capability impacts the innovation and efficiency of novelty and efficiency.

The resource-based view (RBV), as one of the core theories in strategic management, emphasizes the critical role of firms' heterogeneous resources in building sustainable competitive advantage (Zhong and Um, 2024). Barney (1991) introduced the VRIN framework, which identifies resources as sources of sustained competitive advantage if they are valuable, rare, inimitable, and non-substitutable. Artificial intelligence (AI) technology, with its unique algorithmic complexity, data-driven nature, and self-learning capability, aligns well with the VRIN criteria, serving as a novel strategic resource for firms in the era of digital transformation (Sullivan and Wamba, 2024). From the RBV perspective, AI capability empowers firms through three key dimensions: the intelligent restructuring of operational processes, the innovative development of products and services, and the precision management of customer relationships, thereby forming a competitive advantage that is difficult to replicate (Armenia et al., 2024, Babina et al., 2024).

In the context of this study, the RBV provides a critical theoretical foundation for analyzing the impact of AI capability on novelty and efficiency. AI technology, with its superior performance in big data processing, pattern recognition, and predictive analytics, significantly enhances firms' market insights and depth of customer understanding. This capability enables firms to capture market dynamics in real time and accurately forecast demand fluctuations, thereby designing more market-adaptive and innovative novelty and efficiency. The dynamic capabilities theory (Teece, 2023b) extends the theoretical boundaries of RBV by emphasizing the importance of integrating, building, and reconfiguring internal and external capabilities in rapidly changing environments. In the context of AI applications, this theory holds particular explanatory power: AI is not merely a static strategic resource but also a dynamic capability-building platform. Through continuous optimization of machine learning algorithms and iterative upgrades of deep learning models, firms can achieve self-improving business processes and dynamically adjust their novelty and efficiency.

A particularly noteworthy aspect is AI’s unique value-creation potential in supplier and customer integration (Rashid et al., 2024a, Belhadi et al., 2024). In terms of supplier integration, AI-driven intelligent supply chain systems leverage real-time data exchange, precise demand forecasting, and inventory optimization to significantly enhance supply chain coordination efficiency and responsiveness (Li et al., 2025). In terms of customer integration, AI-powered customer relationship management systems utilize behavioral analysis, preference prediction, and personalized recommendations to achieve deeper customer value exploration and targeted engagement (Zhong and Um, 2025). This bidirectional integration effect not only optimizes firms' value creation processes but also reshapes traditional business ecosystems (Fosso Wamba et al., 2024, Shahzadi et al., 2024).

By constructing an analytical framework grounded in RBV and dynamic capabilities theory, this study provides a solid theoretical foundation for exploring the mechanisms through which AI capability, supplier-customer integration, and novelty and efficiency interact. This theoretical perspective not only deepens the understanding of AI-enabled business innovation but also offers new insights for corporate strategy research in the digital transformation era. Future research will build upon this framework to further investigate the specific pathways and boundary conditions through which AI capability influences novelty and efficiency, uncovering new sources of competitive advantage in the digital age.

1.3 Research Gap

Although research on the application of artificial intelligence (AI) technology in operations and supply chain management has been increasing, significant research gaps remain in the existing literature, primarily in four dimensions:

First, in terms of research domain, compared to the extensive studies on AI applications in other management disciplines (e.g., marketing, financial management), research on AI in operations and supply chain management remains relatively underdeveloped (Cannas et al., 2024, Fosso Wamba et al., 2024). In particular, empirical studies examining the impact mechanisms of AI capability on novelty and efficiency are scarce, limiting our systematic understanding of how AI technology reshapes novelty and efficiency. Existing literature predominantly focuses on the technical characteristics of AI, with limited exploration of its role as a strategic capability driving novelty and efficiency.

Second, from the research perspective, while traditional novelty and efficiency have been widely discussed, the impact of AI as a disruptive technology on novelty and efficiency has yet to be fully articulated. Existing studies often confine their analyses to a single dimension, such as efficiency improvement or cost reduction, lacking a systematic investigation into the dual impact of AI capability on novelty and efficiency. This theoretical gap restricts a comprehensive understanding of how AI fosters competitive advantage through novelty and efficiency.

Third, concerning contextual factors, the current literature has paid insufficient attention to the moderating role of supplier and customer integration in the relationship between AI capability and novelty, and efficiency. Particularly in dynamic competitive environments, how the integration of key stakeholders influences the value transformation mechanism of AI capability remains underexplored. This research gap hinders an accurate assessment of the boundary conditions and effectiveness of AI capability across different business contexts.

Based on the identified research gaps, this study makes several theoretical contributions:

(1) It develops a theoretical framework for understanding the impact of AI capability on novelty and efficiency, elucidating the dual mechanisms through which AI enhances novelty and efficiency.

(2) It introduces supplier and customer integration as key moderating variables to clarify their boundary effects in the value transformation process of AI capability.

(3) Through empirical analysis in the manufacturing sector, it provides practical insights into AI-driven novelty and efficiency, enriching research on AI applications in operations and supply chain management.

Fourth, although prior literature has acknowledged that the core of novelty and efficiency lies in the creation of value, it remains underexplored how such value manifests through two distinct yet interrelated logics: novelty and efficiency. The novelty logic emphasizes differentiation, experimentation, and first-mover advantages, while the efficiency logic focuses on cost reduction, process optimization, and transactional simplicity. Recent studies have tended to examine these two logics in isolation, overlooking their potential synergistic coexistence in AI-enabled novelty and efficiency.

Furthermore, while AI capability is recognized as a transformative enabler of business innovation, the mechanisms through which AI integrates with existing organizational resources—specifically customer integration and supplier integration, to create synergistic value have not been sufficiently theorized or empirically examined. In practical contexts, AI does not function independently; rather, it interacts with customer-facing processes and supplier coordination mechanisms to generate compounded effects on novelty and efficiency. For instance, AI-powered analytics may enhance customer integration by personalizing service offerings while simultaneously improving supplier integration by facilitating real-time data exchange and predictive logistics. These synergistic interactions can blur the boundaries between novelty and efficiency, enabling firms to achieve innovation and operational excellence concurrently. Yet, the conditions under which such synergy emerges, and the extent to which it enhances novelty and efficiency performance, remain poorly understood. This gap underscores the need for a more integrative research framework that accounts for the complementary roles of AI capability and supply chain integration in value creation across multiple novelty and efficiency logics.

By addressing these theoretical gaps, this study deepens the understanding of the mechanisms through which AI capability drives novelty, efficiency and offers theoretical guidance and practical implications for enterprises deploying AI technology in dynamic competitive environments.

1.4 Research Question, Purpose, and Dissertation Structure

By addressing theoretical gaps and responding to the growing strategic importance of artificial intelligence (AI) in the era of digital transformation, this study aims to investigate how AI capability influences firms' novelty and efficiency and how this relationship is moderated by customer integration and supplier integration. The central research questions are as follows: (1) How does AI capability affect firms' novelty and efficiency? (2) How does customer integration moderate the relationship between AI capability and novelty? (3) How does supplier integration moderate the relationship between AI capability and efficiency? To address these questions, the study sets out three primary objectives: (1) to validate the positive effect of AI capability on enhancing both novelty and efficiency; (2) to explore how customer integration strengthens the impact of AI capability on novelty by enhancing market responsiveness and innovation potential; and (3) to analyze how supplier integration reinforces the effect of AI capability on efficiency through improved resource optimization and transparency. By building on the resource-based view (RBV) and dynamic capabilities theory (DCT), the study develops a comprehensive theoretical framework and employs hierarchical regression analysis based on empirical data from the manufacturing sector.

This dissertation is organized into seven chapters. Chapter 1 introduces the study, laying the foundation by discussing the rapid advancement of AI technologies in business environments and their profound impact on global supply chains and novelty, and efficiency. This chapter also defines the theoretical framework and core research questions, namely how AI capability, mediated through supplier and customer integration, affects novelty and efficiency.

Chapter 2 provides a comprehensive literature review, systematically examining theories and prior research relevant to the study. This includes the historical development of AI capability, their application in supply chain and operations management, and the challenges in their practical implementation. The review also delves into the two critical dimensions of novelty and efficiency—novelty-oriented and efficiency-oriented designs—and their dynamic interplay. Additionally, it analyzes supplier and customer integration within supply chains, highlighting their significant role in enhancing firms' innovation capabilities and optimizing operational efficiency.

Chapter 3 focuses on hypothesis development, building on the theoretical framework and insights from the literature review to construct a hypothesized model of the relationship between AI capability and novelty, and efficiency. Drawing on the resource-based view (RBV) and dynamic capabilities theory (DCT), the chapter explores how AI capability drives novelty-oriented and efficiency-oriented designs and examines the moderating roles of customer and supplier integration in these processes.

Chapter 4 outlines the research methodology, detailing data collection and measurement methods and describing the construction and validity testing of research variables. To ensure the reliability of data analysis, specific measures for addressing non-response bias and common method bias are introduced.

Chapter 5 discusses the findings, highlighting the unique role of AI capability in fostering innovation within novelty, efficiency, and analyzing the moderating effects of customer and supplier integration under different conditions. The chapter also presents theoretical and managerial implications, summarizes the study's contributions, and suggests limitations and directions for future research.

Chapter 6 discusses the findings, highlighting the unique role of AI capability in fostering innovation within novelty, efficiency, and analyzing the moderating effects of customer and supplier integration under different conditions. The chapter also presents theoretical and managerial implications, summarizes the study's contributions, and suggests limitations and directions for future research.

Chapter 7 concludes the study, reiterating its main contributions and practical significance, particularly regarding the potential value of AI capability for enhancing competitive advantage in the context of digital transformation and supply chain collaboration.

The last one chapter includes detailed references and appendices, providing support for the theoretical and empirical components of the research.

2. Literature Review

This chapter is structured into three primary sections, providing a comprehensive literature review and in-depth discussion of all variables in this study. The first section elaborately discusses various aspects of artificial intelligence capabilities, including the historical development of AI, its applications in operations and supply chain management, and challenges encountered during its implementation. Moreover, this section explores how AI capability can be a key resource for competitive advantage within the framework of the resource-based view and dynamic capabilities theory. The second section analyzes two types: the firm's novelty and efficiency. It discusses how these designs impact firm performance and explores how to balance innovation and efficiency within novelty and efficiency to sustain and enhance competitive advantage. The third section provides a detailed description of external integration in supply chain integration, focusing on customer and supplier integration. The customer integration segment elucidates the importance of directly incorporating customer needs, feedback, and processes into corporate operations and decision-making, highlighting how this strategy can enhance service quality, increase customer satisfaction, and foster innovation. The supplier integration part discusses the significance of establishing strategic cooperative relationships with suppliers. This integration encompasses not only strategic and operational collaboration but also the sharing of information, resources, and practices, aimed at enhancing the efficiency and performance of the entire supply chain through such high levels of collaboration.

2.1 Artificial Intelligence Capability

2.1.1 Development of Artificial Intelligence

Artificial intelligence (AI) is a transformative technology that perceives problems, stores information, autonomously learns, and interprets and evaluates data to solve real-world challenges (Ferràs-Hernández et al., 2017, Mariani et al., 2023). It has the capacity to mimic, augment, and, in some cases, replace human efficiency and performance within business processes (Jarrahi, 2018). The roots of artificial intelligence research can be traced back to the 1950s, highlighted by seminal contributions such as Alan Turing's introduction of the Turing Test in 1950 and John McCarthy's coinage of the term "artificial intelligence" at the Dartmouth Conference in 1956 (Uhr, 1969). During its inception, AI was defined as a branch of computer science aimed at aiding humans in designing, building, and executing fundamental tasks (Uhr, 1969). In subsequent years, Brewka (1996) emphasized the significance of AI's cognitive attributes and its ability to emulate human behavior. Since the beginning of the 21st century, AI has experienced significant advancements and broad adoption across diverse domains, including speech recognition and visual object recognition, target detection, natural language processing, and automation, among other cutting-edge technologies (LeCun et al., 2015, Mithas et al., 2022). According to IBM's 2023 Global AI Adoption Index report, there are significant disparities in the adoption of artificial intelligence (AI) technology across firms in different countries. Businesses in India (59%), the UAE (58%), Singapore (53%), and China (50%) exhibit higher enthusiasm for AI adoption, whereas those in Spain (28%), Australia (29%), and France (26%) appear more conservative (IBM, 2023). These data suggest that emerging markets' proactive approach to AI adoption may contribute to enhancing their technological competitiveness. Globally, the rate of AI adoption by firms has increased from 20% in 2017 to 50% in 2022, with the information technology sector leading adoption at 18.1%, while traditional industries such as construction and agriculture report significantly lower adoption rates, at only 1.4% (News, 2024a). In China, AI applications are predominantly concentrated in areas such as smart cities (12.16%), firm intelligent management (12.10%), and smart manufacturing (8.89%), playing a dominant role in the tertiary sector (Tencent, 2022). In the United States, regional differences are evident, with Colorado and Washington, D.C., showing the highest AI adoption rates at 7.4% and 7.2%, respectively (News, 2024a). Overall, while AI applications are rapidly expanding in fields such as information technology and smart cities, adoption in some traditional industries remains in its nascent stages (News, 2024a, McKinsey, 2022).

The rapid development of Artificial Intelligence (AI) can be attributed to two primary factors: (1) The reprogrammable characteristics of AI, coupled with the advent of no-code artificial intelligence (NCAI), have solidified its role as a general-purpose technology, fostering adaptability and facilitating broad implementation across various fields (Haenlein and Kaplan, 2019, Xu et al., 2021). For instance, Sivarajah et al. (2017)

highlighted that AI's information representation mechanisms significantly assist users in solving real-world problems (Hassabis et al., 2017). (2) Academic discussions on AI have recently transitioned from technical to non-technical topics (Glikson and Woolley, 2020), focusing on its autonomous learning and decision-making capabilities (Balasubramanian et al., 2023). By employing various algorithms, AI analyzes internal and external environmental data to complete tasks, interact with humans, and facilitate decision-making (Brewer et al., 2024, Gupta et al., 2023a, Yu et al., 2024). This evolution has led scholars to conceptualize and categorize AI. For example, Iansiti and Lakhani (2020) differentiated between "weak AI," which performs routine tasks and automated analyses such as virtual assistants (e.g., Siri) and autonomous vehicles, and "strong AI," which demonstrates intelligence comparable to or exceeding human capabilities, enabling complex decision-making and innovative problem-solving (Garbuio and Lin, 2021, Yan et al., 2024). Weak AI lacks general learning abilities and self-updating capabilities (Huang and Rust, 2018), whereas strong AI offers transformative potential. From a technological perspective, AI is classified into categories such as machine learning (ML), deep learning (DL), generative AI, reinforcement learning (RL), and hybrid AI. Together, these technologies facilitate the gathering, processing, and analysis of large datasets, which in turn improve the automation of decision-making processes (Drydakis, 2021). This transformative potential has drawn considerable attention from management scholars, who argue that AI is redefining the sources of competitive advantage for businesses (Wilson and Daugherty, 2018). The scope of this study focuses on examining the impact of AI capability on novelty and efficiency within the context of operations and supply chain management. The subsequent section will explore the various applications of artificial intelligence across operations and supply chain management, as well as its role and mechanisms in enhancing various aspects of organizational performance.

2.1.2 Artificial Intelligence in Operations and Supply Chain Management (OSCM)

Maghsoudi et al. (2023) emphasized that AI applications within firms cover a wide range of areas, including management decision-making, manufacturing processes, and design activities. Similarly, Makarius et al. (2020) argued that the growing prevalence of AI technology, coupled with its innovative configurations in areas such as human-machine interaction, automation, and trend prediction, significantly enhances its role in improving organizational performance (Sullivan and Wamba, 2024). AI is crucial in advancing the collection, processing, and analysis of big data, thereby enabling valuable insights and advancing the automation of decision-making processes (Drydakis, 2022). These advancements have garnered considerable attention from management scholars, who highlight the integration of AI with firm management and its transformative impact on reshaping sources of competitive advantage for businesses (Wilson and Daugherty, 2018). For example, Maghsoudi et al. (2023) underscored the extensive scope of AI applications in firms, while Makarius et al. (2020) further highlighted that the broad adoption and innovative configurations of AI amplify its essential role in enhancing organizational performance (Awan et al., 2021).

As academic attention intensifies on harnessing AI capability to propel digital transformation and progress in Industry 4.0 (Lu, 2019), AI has found extensive applications in Operations and Supply Chain Management (OSCM), becoming a focal point of contemporary research (Mithas et al., 2022). Prior studies, such as Eskandari-Khanghahi et al. (2018), attribute AI's transformative impact on supply chains to its capabilities in perceiving, identifying, learning, and intelligently analyzing data (Mithas et al., 2022). As investigations into AI's incorporation into supply chain management advance, it is increasingly acknowledged as a transformative technology that enhances decision-making abilities and boosts the efficiency and effectiveness of supply chain operations (Gupta et al., 2023a).

Firms are harnessing AI to optimize workflows, improve operational efficiency, and elevate customer experiences (Sullivan and Wamba, 2024). AI enables the analysis of extensive datasets, streamlining logistics, reducing transportation-related emissions, and minimizing surplus inventory (Mithas et al., 2022). Recent literature underscores the critical role of AI capability in operations management (Mithas et al., 2022). For instance, Karmaker et al. (2023) contend that AI equips firms to attain enhanced agility in supply chain traceability and increased transparency in supply chain visibility, which consequently elevates operational efficiency and reduces carbon footprints. Moreover, AI overcomes the constraints of cognitive information processing by handling extensive datasets, identifying patterns, and predicting customer demands (Revilla et al., 2023). These capabilities allow businesses to optimize inventory management, reduce waste from excess materials, and improve customer satisfaction (Le et al., 2024). Table 1 presents a detailed framework for AI applications in operations management.

Table 1. AI Applications in Operations Management

Authors	Objectives	Highlights
Jauhar et al. (2024)	Operational performance//Cost-effectiveness	By leveraging AI, firms significantly enhance inventory management efficiency, reduce waste and losses, improve customer satisfaction and profitability, and thereby achieve more resilient operational management.
Helo and Hao (2022)	Inventory management and reducing waste	AI technology significantly improves operational efficiency by automating infrastructure and optimizing business processes.
Hasan and Trianni (2023)	Process efficiency	AI significantly enhances operational efficiency by optimizing internal factory processes, improving equipment utilization, and reducing energy consumption.
Zhang et al. (2021)	Cost reduction	By applying AI, firms can optimize resource allocation and minimize redundant tasks, thereby lowering overall operational costs.
Mariani and Borghi (2024)	Customer service enhancement	AI technologies improve responsiveness to customer demands, enhance customer service experiences and satisfaction, and boost operational efficiency.
Wamba-Taguimdje et al. (2020)	Business value	AI enables firms to rapidly scale their business capabilities while maintaining efficient operational management.
Chowdhury et al. (2023)	Employee productivity	Through intelligent assistance and automation, AI reduces repetitive tasks for employees, increases workforce productivity, and optimizes managerial processes.

In the domain of supply chain management, recent studies on the utilization of artificial intelligence (AI) have demonstrated its substantial benefits and value across multiple areas (Riahi et al., 2021, Richey Jr et al., 2023). From boosting supply chain resilience to improving logistics efficiency, AI is providing new tools and perspectives for supply chain management through its advanced data processing capabilities and deep learning technologies. In terms of supply chain resilience, Bassiouni et al. (2023) highlight that deep learning technologies within the AI domain can accurately predict operational risks and misjudgments, enabling decision-makers to proactively address supply chain disruptions and optimize risk management strategies. Dubey et al. (2022) further emphasize that AI improves responsiveness and coordination by reducing informational blind spots and optimizing resource allocation, thereby enhancing supply chain reliability. Additionally, Belhadi et al. (2024) demonstrate that AI enhances supply chain information processing capabilities, effectively predicting and managing risk factors to achieve more efficient risk management in dynamic and unpredictable environments. Regarding environmental performance, Benzidia et al. (2021) indicate that AI fosters green supply chain collaboration and integrates environmental processes, not only improving supply chain efficiency but also enhancing sustainability, thus positively impacting environmental performance. Meanwhile, Singh et al. (2023) show that AI, by strengthening supply chain data processing capabilities, optimizes demand management processes, thereby improving project execution efficiency and reliability. From an economic and decision-making performance perspective, Kumar et al. (2023) point out that AI significantly reduces costs and enhances efficiency by improving data quality and optimizing supply chain management, thereby substantially boosting economic performance. Modgil et al. (2022) stress that AI provides precise predictive and optimization support in automated data analysis and multi-scenario simulations, enhancing responsiveness and cost efficiency in complex environments. Moreover, with respect to supply chain agility and logistics optimization, Wong et al. (2024) propose that AI technologies improve adaptability and flexibility in supply chains through rapid data processing, aiding in responding to market changes. Chung (2021) demonstrates that AI optimizes logistics path planning and transport adjustments, lowering operational expenses and enhancing supply chain efficiency. Table 2 presents a detailed framework for AI applications in supply chain management.

Table 2. AI Applications in Supply Chain Management

Authors	Objectives	Highlights
Bassiouni et al. (2023)	Supply chain resilience	Deep learning technologies in AI enable precise prediction of transportation risks and delays, assisting decision-makers in proactively addressing supply chain disruptions and optimizing risk management strategies.
Dubey et al. (2022)	Supply chain reliability	AI enhances responsiveness and coordination capabilities by reducing information complexity and optimizing resource allocation, thereby improving supply chain reliability.
Belhadi et al. (2024)	Supply chain risk management	AI enhances information processing capabilities in supply chains, enabling effective prediction and management of risk factors, thereby achieving greater risk management efficiency in dynamic and uncertain environments.
Benzidia et al. (2021)	Environmental performance	AI enhances supply chain decision-making efficiency and sustainability by promoting green supply chain collaboration and integrating environmental processes, thereby significantly improving environmental performance.
Singh et al. (2023)	Demand management	AI optimizes the management processes for complex firm demands by enhancing data processing and predictive capabilities within the supply chain, thereby improving the efficiency and sustainability of project execution.
Kumar et al. (2023)	Economic performance	AI technology optimizes supply chain management by improving data quality, reducing costs, and enhancing efficiency, thereby significantly enhancing economic performance.
Modgil et al. (2022)	Decision-making	AI enhances real-time decision-making capabilities and response efficiency in supply chain management by automating data analysis and multi-scenario simulations, providing accurate forecasting and optimization support for navigating complex and dynamic environments.
Wong et al. (2024)	Supply chain agility	AI technology enhances supply chain responsiveness and flexibility by enabling rapid data processing to adapt to market changes.

Chung (2021)	Logistics optimization	AI optimizes logistics route planning and transportation scheduling, reducing transportation costs and improving overall supply chain efficiency.

In addition, management scholars have increasingly emphasized the significance of AI capability across various business disciplines, each with distinct focal points (Armenia et al., 2024). For example, in human resource management, AI has transformed how organizations manage their workforce by utilizing data stored in Human Resource Information Systems (HRIS) (Chowdhury et al., 2023). AI systems are also employed to support decision-making processes, enabling firms to enhance employee capabilities, foster team collaboration, facilitate flexible working arrangements, and improve performance measures (Chowdhury et al., 2022). These advancements are recognized as critical contributors to organizational success (Merhi, 2023). This study will comprehensively explore the multifaceted interactions between AI capability and operations management. Here, AI capability is defined as a firm's capacity to leverage AI technologies for optimizing internal processes (Sjödin et al., 2021), decision support (Chowdhury et al., 2023), innovation development (Akter et al., 2023), market opportunity exploration (Mikalef et al., 2021), external process optimization (Khan et al., 2024) (e.g., distribution and sales), knowledge management (Iaia et al., 2023), and automation (Manis and Madhavaram, 2023). These capabilities are intended to enhance operational efficiency, innovation capacity, and market competitiveness (Sullivan and Wamba, 2024).

2.1.3 Artificial Intelligence Challenges

While artificial intelligence (AI) offers numerous advantages in enhancing various aspects of organizational performance (Mikalef et al., 2023), it also faces significant challenges across several dimensions (Robles and Mallinson, 2023). These include issues such as ensuring data quality consistency within supply chains (Rashid et al., 2024b) and tackling the time and economic expenses involved in developing and integrating AI capability into existing manufacturing systems (Rashid et al., 2024b). For instance, integrating AI into business operations requires substantial initial investments in capital and human resources to manage and maintain AI systems (Chowdhury et al., 2023). Additionally, implementing AI technologies can be time-intensive and complicated (Enholm et al., 2022), and organizations may encounter challenges such as the "Productivity Paradox," as highlighted by Robert Solow in 1987 (Adbi et al., 2022). The reliability of AI capability is significantly influenced by the quality of input data provided by employees, underscoring the importance of effective human-machine collaboration and mutual understanding (Haesevoets et al., 2021). For example, generative AI tools like ChatGPT, which rely on training data for knowledge, may struggle to address unfamiliar or highly specialized problems (Khennouche et al., 2024).

Additionally, the successful implementation of AI relies on strong support from top management and the establishment of a well-defined AI strategy (Chen et al., 2023a). As a nascent technology, AI requires prioritization and sufficient resource allocation to overcome resistance to change (Campion et al., 2022). Within the Resource-Based View (RBV) framework, Haddud (2024) proposed that AI may serve as either a substitute for or an enhancement to human cognitive functions. However, the ease of imitation and the low replication costs associated with AI may erode traditional competitive advantages rooted in human expertise (Brynjolfsson et al., 2014). To fully leverage AI's potential, organizations must carefully tailor AI capability to their specific contexts and integrate it with other core competencies (Sjödin et al., 2021). This approach will enable firms to establish distinctive and sustainable competitive advantages (Jarrahi et al., 2023).

2.1.4 Theoretical Background of AI Capability on Resource-Based View

This study highlights the various benefits AI capability brings to firms and positions them as critical strategic resources for achieving competitive advantage. These benefits can be further examined within the theoretical framework of the resource-based view (RBV) (Weaven et al., 2021). RBV underscores the significance of internal resources and capabilities, positing that firms can secure a sustained competitive advantage by owning resources that are rare, inimitable, and non-substitutable (Wernerfelt, 1984). AI capability represents high-technology resources characterized by significant barriers to entry, encompassing complex technical domains such as algorithm design, data processing, and model optimization (Chalmers et al., 2021). For many firms, acquiring such capabilities entails high costs and technical expertise, aligning with the RBV criterion of resource rarity (Lavie, 2006). By developing or acquiring AI capability, firms can establish differentiated advantages in competitive markets (Kemp, 2024). The inimitability of AI capability is reflected in several dimensions, including unique data accumulation, algorithm training expertise, and the ability to integrate deeply with business operations (Alm and Chiu Falck, 2024). Notably, the quality of input information in algorithm training significantly affects output results, exemplifying the RBV's core principle of resource inimitability (Helfat et al., 2023). This highlights the distinctive advantages firms gain from data accumulation, algorithm optimization, and business integration (Shan et al., 2019). High-quality, domain-specific data and governance capabilities constitute critical sources of unique resources, while expertise in algorithm tuning and deep business integration further enhance this inimitability (Grover et al., 2018). As a result, firms can build competitive barriers through unique data assets, technical practices, and tacit knowledge (Parente et al., 2022). Even if competitors possess similar technical frameworks, replicating equivalent outcomes remains challenging, enabling firms to gain an edge in AI-driven competition (Kemp, 2024). Moreover, AI capability holds a unique position in driving innovation, optimizing processes, and enhancing efficiency—benefits that are difficult to replicate through alternative resources (Krakowski et al., 2023). For instance, AI-driven automation and predictive analytics have demonstrated unparalleled value in production and supply chain management, leading to transformative improvements in resource allocation and decision-making (Zong and Guan, 2024). However, while the RBV provides a static perspective that underscores the importance of existing resources, it may overlook firms' adaptability and resource reconfiguration processes in dynamic environments, which are crucial in rapidly evolving technological and market landscapes (Teece et al., 1997). The development of AI capability necessitates continuous model optimization, algorithm iteration, and adaptation to external changes, exceeding the explanatory scope of RBV (Wu et al., 2022). Additionally, RBV pays insufficient attention to the learning and development processes involved in building capabilities, making it less effective in capturing the continuous progress achieved through data accumulation, algorithm optimization, and organizational integration (Kero and Bogale, 2023). Furthermore, RBV does not adequately address how firms maintain competitiveness by sensing market changes, seizing new opportunities, and innovating rapidly (McDougall et al., 2022). To address these limitations, the dynamic capabilities framework has been proposed as a complement to RBV (Warner and Wäger, 2019). This framework more effectively elucidates how firms can adapt to evolving environments, reconfigure resources, and maintain competitive advantage in the context of emerging technologies such as AI (Mikalef et al., 2019).

2.1.5 Theoretical Background of AI Capability on Dynamic Capabilities Theory

The dynamic capabilities framework highlights firms' ability to adapt to external environmental changes through resource integration and capability reconfiguration during the processes of sensing, seizing, and transforming (Porter, 1991). AI capability aligns closely with this theoretical framework (Wang and Ahmed, 2007). With robust data processing and analytical functionalities, AI capability enhances firms' ability to sense market shifts, technological trends, and consumer demands (Felin and Powell, 2016). For instance, AI-driven predictive analytics can capture market dynamics in real time, identify potential opportunities and threats, and thus enhance firms' environmental sensing capabilities (Akter et al., 2021). Dynamic capabilities theory also stresses the importance of quickly seizing identified market opportunities and translating them into concrete strategic actions (Priyono and Hidayat, 2024). AI capability facilitates this process by enabling efficient resource allocation and optimization (Hossain et al., 2022). For example, through automated decision-making, supply chain optimization, and personalized product development, AI capability accelerates firms' responsiveness to opportunities and improves execution efficiency (Helo and Hao, 2022). Furthermore, the application of AI capability necessitates deep integration at both the technical and business levels (Dwivedi et al., 2021). This involves redesigning processes, upgrading technological infrastructures, and cultivating new organizational competencies. Such transformations not only enhance the value of existing resources but also enable firms to venture into new competitive domains and propel novelty and efficiency (Sjödin et al., 2021, Coskun-Setirek and Tanrikulu, 2021). The critical role of AI within the dynamic capabilities framework has been underscored in previous literature. For instance, Drydakis (2022) suggests that when AI is appropriately integrated into an organization's socio-technical systems, it can create value by reinforcing dynamic capabilities (Thomas, 2024). Similarly, Hercheui and Ranjith (2020) emphasize the profound impact of AI capability on dynamic capabilities within the manufacturing sector (Abou-Foul et al., 2023). Specifically, this impact manifests in firms' abilities to detect rapid industry changes, capture opportunities for more personalized customer value propositions, and optimize speed and cost-efficiency during digital service transformations, including reconfiguring internal processes and resource (Felsberger et al., 2022). For companies seeking new competitive advantages, leveraging transformative technologies like AI is essential, as these technologies not only solve practical business problems but also address pressing societal challenges (Chari et al., 2022). Especially in fields such as product design, customer service, and manufacturing processes, AI facilitates the identification of opportunities within emerging technologies and captures new revenue streams, unlocking entirely new novelty and efficiency (Teece, 2023a). Thus, within the Dynamic Capabilities framework, AI capability transcends its role as an instrumental technical resources (Jackson et al., 2024). These function as dynamic capabilities that empower firms to continuously sense, seize, and transform, enabling them to adapt to external environmental changes, propel business innovation, and maintain a competitive edge (Simón et al., 2024). This theoretical perspective underscores the strategic significance of AI capability as a fundamental element of dynamic capabilities (Abourokbah et al., 2023).

2.2 Novelty and Efficiency

2.2.1 Novelty and Efficiency in the Context of Digital Transformation

Amid the accelerating wave of digital transformation, novelty and efficiency has emerged as a critical strategic mechanism for firms to create and capture value through dynamic interactions with diverse stakeholders (Phadnis, 2024). The widespread adoption of advanced technologies, particularly Artificial Intelligence (AI), is profoundly reshaping traditional organizational structures and strategic approaches, significantly enhancing firms' capabilities for innovation and operational performance. In this context, scholars have systematically examined the foundational mechanisms and dynamic evolution of digital value creation and capture, with particular focus on its structural configurations, transactional processes, and governance mechanisms (Zott

(Zott and Amit, 2008, Sjödin et al., 2022).

Existing literature has explored novelty and efficiency from multiple perspectives, with substantial emphasis on value proposition reconfiguration, dual strategic pathways, and the role of ecosystem orchestration. For example, prior studies have demonstrated that firms are leveraging digital technologies not only to redefine their value propositions—through personalized offerings, enhanced customer experiences, and optimized operational processes—but also to improve agility and efficiency across their value chains (Wu et al., 2024, Dong et al., 2024). Furthermore, novelty and efficiency are widely recognized as critical drivers of sustained competitive advantage, typically pursued through either novelty-oriented or efficiency-oriented strategic logics (Zott and Amit, 2007). Novelty approaches seek to create distinctive value by recombining products, services, and information in innovative ways, while efficiency approaches emphasize cost reduction and process optimization (Cheng and Wang, 2022).

From a theoretical standpoint, frameworks such as Osterwalder and Pigneur (2010) conceptual architecture offer a comprehensive lens to understand essential elements of value creation, such as value propositions, customer segments, and revenue mechanisms, thereby serving as practical tools for firms to innovate their strategic configurations. Concurrently, Teece (2018) Dynamic Capabilities framework underscores the necessity for firms to sense, seize, and reconfigure opportunities in volatile environments, aligning closely with the agility demanded by digital transformation. Moreover, the resource-based view (RBV) and its extended perspective (ERBV) highlight the strategic importance of both internal and external resources—particularly AI capability and supply chain integration—in fostering novelty and efficiency.

However, despite these advancements, significant gaps remain in our understanding of how AI capability interacts with external integration mechanisms—such as customer and supplier integration—to drive novelty and efficiency. While prior research has predominantly treated efficiency- and novelty-oriented strategies as separate streams (Zott and Amit, 2007), limited attention has been paid to their potential synergistic effects under the umbrella of digital transformation. Specifically, the role of external integration in amplifying the benefits of AI-enabled dynamic capabilities and fostering the co-evolution of these two strategic orientations remains underexplored. Furthermore, existing studies have yet to fully elucidate how AI, as a dynamic capability, enables firms to move beyond internal resource orchestration to achieve transformative novelty, efficiency, and sustained competitive advantage.

To address these research gaps, this study integrates RBV and dynamic capabilities theory to systematically investigate the moderating roles of customer and supplier integration in AI-driven novelty and efficiency. By doing so, it not only advances theoretical understanding of how firms can synergize digital technologies and external collaborations to sustain competitive advantage but also offers actionable insights for practitioners seeking to navigate the complexities of novelty and efficiency in the digital era.

2.2.2 Novelty

Novelty refers to the creation of entirely new forms of business transactions by connecting previously unrelated participants (Wu et al., 2024), designing innovative transaction mechanisms (e.g., the model of Priceline), or linking transaction parties in novel ways (Zott and Amit, 2008). Novelty emphasizes the development of novel combinations of products, services, and information to explore richer and deeper value chain connections, thereby enhancing business innovation through differentiation (Pang et al., 2023). For instance, Novelty not only focuses on innovative transaction mechanisms but also on creating unique value networks by connecting previously unassociated transaction parties (Najafi-Tavani et al., 2023).

Moreover, novelty advocates for establishing industry leadership through first-mover advantages while continuously optimizing other critical business elements to enhance novelty (Chen et al., 2022). This design logic supports firms in maintaining their innovation and value-creation capabilities in highly competitive markets (Wu et al., 2024). Thus, novelty can be understood as a strategy for driving innovation and differentiation through the development of novel products, services, and value networks, showcasing a firm's exploratory capabilities (Jin et al., 2022). These capabilities enable firms to capture unmet market needs, uncover new opportunities, and build first-mover advantages (Pang et al., 2023). From the perspective of dynamic capabilities theory, novelty is closely aligned with a firm's exploratory capabilities—those that allow it to sense market discontinuities, experiment with new approaches, and reconfigure resources to pursue innovation (Teece, 2007, Eisenhardt and Martin, 2000). Moreover, firms engaging in novelty often adopt platform-based or ecosystem-based innovation strategies, fostering value co-creation among complementary actors and enabling rapid market adaptation (Autio et al., 2018). As such, novelty plays a pivotal role in enabling firms to experiment with non-traditional value propositions and business boundaries in response to digital transformation and market turbulence.

In addition, novelty involves a high degree of experimentation under environmental uncertainty. Drawing upon the logic of open innovation and design thinking (Chesbrough, 2010), firms adopt iterative design, rapid prototyping, and feedback loops to continuously refine their novelty and efficiency. This reflects a shift from static strategic planning to agile, learning-oriented novelty and efficiency innovation processes. A detailed discussion of efficiency will be provided in the next chapter.

2.2.3 Efficiency

Efficiency focuses on optimizing the transactional efficiency among participants (Najafi-Tavani et al., 2023). It aims to enhance the overall effectiveness of cross-boundary activities by reducing transaction costs and complexity while strengthening collaboration between firms, customers, and partners (Wu et al., 2024). This leads to more efficient resource allocation and business operations, resulting in greater economic benefits and competitive advantages (Zott and Amit, 2008). The core of efficiency lies in improving collaboration efficiency through effective resource allocation and streamlined operations (Chen et al., 2022). For example, efficiency simplifies transaction processes to enable users to complete transactions conveniently, reduces execution errors through optimized mechanisms, and lowers additional costs such as intermediary fees, thereby enhancing overall economic performance (Wu et al., 2024). Furthermore, efficiency emphasizes increasing transparency and decision-making support among participants, helping all parties make informed decisions quickly (Dong et al., 2024). By enhancing transaction speed and efficiency, efficiency creates significant competitive advantages, driving the novelty and efficiency toward higher transactional efficiency and economic performance (Grabowska and Saniuk, 2022). Thus, efficiency can be understood as a strategy that ensures business stability and economic efficiency by optimizing resource allocation and operational processes, demonstrating the firm's ability to exploit resources effectively (Santa-Maria et al., 2022). Moreover, efficiency aligns with the principles of transaction cost economics (Williamson, 1991), which emphasize the minimization of negotiation, monitoring, and enforcement costs. By improving information transparency and governance efficiency, efficiency enables firms to reduce uncertainty and increase trust in inter-organizational transactions.

In today's data-rich business environment, efficiency increasingly involves leveraging digital technologies such as AI and big data analytics to automate operations, support real-time decision-making, and optimize internal workflows (Wu et al., 2025). These digital tools allow firms to minimize redundancy, improve asset utilization, and enhance customer satisfaction through seamless operational performance. Table 3 provides a detailed comparison of the characteristics of novelty and efficiency.

Table 3. Comparison of Characteristics between Novelty and Efficiency

Comparison Dimension	Novelty	Efficiency
Core Objective	Developing transactions through innovative approaches to help firms create and capture new value (Zott and Amit, 2007).	Creating and capturing value by reducing transaction costs, thereby improving organizational performance (Zott and Amit, 2007).
Value Proposition	Assisting firms in establishing borderless transaction mechanisms to gain unique competitive advantages (Amit and Zott, 2001).	Supporting firms in offering standardized and efficient services, reducing uncertainty in customer transactions (Sousa and da Silveira, 2017).
Value Capture Mechanism	Capturing value through innovative partner structures and operations, such as shared economies and technology platforms (Zott and Amit, 2008).	Streamlining transaction processes and reducing supply chain and customer interaction complexities (Rai and Tang, 2014).
Innovation Orientation	Emphasizing the development of new collaborative relationships to attract external resources and discover new business opportunities (Snihur and Bocken, 2022).	Focusing on simplifying transactions and service processes to improve resource allocation efficiency and reduce risks (Cheng and Wang, 2022).
Ecosystem Impact	Promoting the development of new business ecosystems through a series of business activities enhances the efficient flow of supply chain resources (Shi et al., 2021).	Ensuring closer connections with customers and partners, improving supply chain efficiency through transparency (Zott and Amit, 2007).
Collaborative Relationships	Leveraging extensive partner networks to integrate diverse innovation resources and facilitate collaborative innovation and new novelty, and efficiency development (Reypens et al., 2016).	Simplifying cross-organizational communication and information sharing through optimized agreements and service processes to ensure collaboration quality (Pati et al., 2018).
Performance Measurement	Focusing on the design and experimentation of innovative novelty and efficiency to promote long-term value creation (Sjödin et al., 2020).	Prioritizing short-term performance improvement under low-risk conditions, optimizing input-output ratios (Chen and Liu, 2020).

2.3 Supply Chain Integration

Supply chain integration involves the efficient coordination and management of information, logistics, capital, and cooperative relations between different supply chain segments, aiming to enhance the overall operational efficiency and benefits of the supply chain (Li et al., 2025). The strategic importance of implementing supply chain integration for manufacturing firms lies in its ability to significantly enhance operational efficiency by coordinating various segments (Li et al., 2024). For example, optimizing production (Liu et al., 2024), logistics (Ada et al., 2024), and distribution processes (Atcha et al., 2024) can reduce resource waste and lower operational costs (Wang, 2024). In today's business environment, where traditional efficiency production capacities form the basis of competition, the capacity to quickly adapt to market changes and satisfy consumer demands introduces new strategic challenges (Wang et al., 2025b). Firms are increasingly realizing that coordination across various segments of operations and supply chain management is essential for addressing these challenges, leading to a heightened emphasis on supply chain integration as a fundamental approach to overcoming these issues (Stabler et al., 2024).

The origins of supply chain integration can be traced back to the late 1980s and early 1990s, with the acceleration of globalization and intensification of market competition, businesses began to emphasize the coordination and cooperation between different links in the supply chain (Lummus and Vokurka, 1999). During this period, supply chain management began to emerge as a distinct discipline, emphasizing the enhancement of overall supply chain efficiency through the integration and optimization of logistics, information flows, and financial flows (Salamah et al., 2023). Subsequently, in the 1990s, the rapid development of information technology, particularly the proliferation of the internet, greatly propelled the advancement of supply chain integration (Lummus and Vokurka, 1999). Firms started leveraging technological tools such as Firm Resource Planning (ERP), Warehouse Management Systems (WMS), and Transportation Management Systems (TMS) to facilitate information sharing and automate processes across different segments of the supply chain (Patterson et al., 2003). Entering the 2000s, firms increasingly emphasized strategic partnerships with suppliers and customers, which are founded on trust and the pursuit of common goals (Aditi et al., 2024). Through strategic cooperative relationships, concepts such as lean management, which emphasizes the removal of excess inventory and waste, and agile supply chains, which focus on rapid response in uncertain and changing market conditions, further promote supply chain integration (Xing and Liu, 2023). As such, with the growing emphasis on supply chain integration, scholars have also conducted in-depth studies on its positive effects, such as cost-efficiency enhancement (AlDurgam et al., 2017). Firms can reduce inventory costs and avoid resource wastage by optimizing production and procurement processes (Turaboyeva and Eshkobilova, 2024). Additionally, the responsiveness of the supply chain is accelerated through integration, enabling businesses to adapt more quickly to market changes and meet consumer demands (Chong et al., 2017). Moreover, closer supplier relationships help improve the quality of products and services (Ahmadi-Gh and Bello-Pintado, 2024). By sharing quality control data and implementing joint quality improvement programs, businesses can ensure the provision of high-quality products (Wang et al., 2025b). Integration also enhances firms' innovation capabilities (Lee, 2023). Close cooperative relationships foster knowledge sharing and technology exchange, inspiring the generation of innovative ideas and solutions (Javed et al., 2024). Furthermore, integration helps firms manage and mitigate supply chain risks more effectively (Li et al., 2025). Establishing solid cooperative relationships with suppliers helps in the timely identification of potential supply disruptions and price fluctuations, thereby enabling corresponding risk management measures (Ngo et al., 2024). Although supply chain integration brings many positive effects, some scholars have identified negative effects in different contextual frameworks due to resource conflicts associated with integration (Zhao et al., 2013, Stevens and Johnson, 2016). With the continuous development of literature on supply chain integration, the research field has gradually formed a conceptual framework. Notable research includes Huo (2012), which offers a comprehensive framework for supply chain integration, highlighting the important roles of internal and external integration in enhancing supply chain efficacy. Internal integration refers to the effective coordination and management of processes between different departments, such as procurement, production, sales, and distribution, within an organization, to facilitate smoother information, material, and service flows (Shah and Soomro, 2021). By enhancing the level of information transparency and cooperation among departments, internal integration aids in efficiency improvements, reduces resource wastage, and enhances the supply chain's responsiveness to market changes (Gardner et al., 2019). External integration, on the other hand, emphasizes relationship management and collaboration with supply chain partners, including suppliers and customers, to strengthen cooperation along the supply chain (Yang and Gan, 2024). This includes strategies such as sharing critical information, coordinating business processes, and jointly solving problems (Zhang et al., 2024). Through external integration, firms can more effectively manage supply chain risks, improve transparency and traceability, and optimize the overall performance and efficiency of the supply chain (Ngo et al., 2024). Internal and external integrations can be seen as complementary components; this distinction helps organizations more precisely identify and implement integration strategies, enabling them to more effectively translate strategic objectives into operational practices, thus enhancing competitiveness and market adaptability (Adner and Kapoor, 2010). The next section will introduce customer integration in external supply chain integration, discussing its role and effects within the supply chain.

2.3.1 Customer Integration

Customer integration involves directly incorporating customers' demands, feedback, and processes into a firm's operations and decision-making within the context of supply chain management and business strategy, aimed at enhancing service quality, increasing customer satisfaction, and fostering innovation (Zhong and Um, 2025). This concept is categorized as external integration in the supply chain (Huo, 2012), and it emphasizes the importance for manufacturing firms to establish close strategic collaborations with customers. This facilitates a better grasp of market dynamics and perceptions, enhances integration with information technologies, and transforms resource allocation (Yoo et al., 2024). Such integration is a key strategy in supply chain management, fostering close collaboration with customers to enhance the overall efficiency and responsiveness of the supply chain.

Extensive research has explored the positive effects of customer integration on manufacturing firms, including operational performance (Chavez et al., 2015), product innovation (Lau et al., 2010, Freije et al., 2022), new product development (He et al., 2014, Cui and Wu, 2017), green innovation (Qu and Liu, 2022), financial performance (Yu et al., 2013), and risk management (Chaudhuri et al., 2018, Munir et al., 2020). These beneficial outcomes are primarily derived from three key areas.

(1) Co-development of Products: Co-development is a key facet of a firm's customer integration strategy, involving close collaboration with customers to design and manufacture products (Zhong and Um, 2024). This approach allows firms to engage directly in analyzing customer needs and designing solutions, ensuring that products are closely aligned with specific market and customer requirements. Such collaboration extends beyond mere product improvements, manifesting as a bidirectional exchange and learning process (Le and Nguyen, 2024). Firms can optimize product designs by incorporating direct feedback, adding new features, or adjusting product specifications. Furthermore, co-development enhances customer engagement and loyalty by granting customers decision-making power and a voice during the product development process

(Wang et al., 2024). The direct involvement of customers ensures that their opinions and suggestions are actively implemented, not only enhancing the market adaptability of the products but also providing a competitive edge through customization that meets unique customer needs. Additionally, co-development fosters technological novelty and efficiency. Under this collaborative model, firms and customers jointly explore new technological applications and market opportunities, effectively addressing the rapidly changing market conditions (Fianko et al., 2023). This relationship not only promotes efficient resource integration and accelerates the market introduction of new products but also helps establish a more robust and enduring partnership.

(2) Customer Participation in Supply Chain Planning: Customer involvement in supply chain planning represents an innovative management strategy, where businesses directly involve customers in key segments of the supply chain, such as demand forecasting, inventory management, and logistics planning (Wang et al., 2024). The main advantage of this model is improving the precision and efficiency of supply chain management by integrating real-time customer data and feedback into decision-making processes. Specifically, in demand forecasting, direct customer participation helps firms more accurately grasp dynamic market demands, aligning production plans aligning inventory levels more closely with actual market demands (Fianko et al., 2023).

This method improves forecast accuracy from the source, effectively reducing excesses or shortages, lowering inventory costs, and strengthening the firm's ability to respond swiftly to market fluctuations. In logistics, customer involvement aids in optimizing delivery routes and schedules, ensuring products are delivered to customers efficient and timely manner. Moreover, deep customer involvement not only boosts the flexibility and efficiency of the supply chain but also enhances customer satisfaction and loyalty, as customers see their needs and opinions valued and implemented. In a fast-paced and highly competitive market environment, adopting such strategies is key for businesses to maintain competitiveness and leadership (He et al., 2014).

(3) Provision of Customized Services: Customized service, as an effective customer integration strategy, significantly enhances customer satisfaction and loyalty by providing personalized solutions that meet individual customer needs (Le and Nguyen, 2024). This service extends beyond product customization to include logistics and delivery plans designed specifically for individual customers, offering a more precise and personalized service experience (Xing and Liu, 2023). In practice, customized services may involve adjusting product design, features, packaging, and even service processes tailored to specific customer needs and preferences. For example, a high-end sports equipment company might customize equipment based on an athlete's physique

and sports habits, while an electronics manufacturer may offer customized software and hardware options based on consumer preferences (Gao and Huang, 2021). Additionally, customized services deepen customer relationships and enhance brand differentiation through increased interaction and communication with customers. By continuously tracking customer feedback and changing needs, firms can adjust and optimize their service offerings to sustain a competitive position in the market. This strategy of deep customization not only meets current customer demands but also anticipates and guides future needs, fostering long-term customer loyalty. Through these strategies, customized services become a critical tool for firms to sustain competitiveness in the market (Freije et al., 2022).

In summary, customer integration not only strengthens the relationship between firms and customers but also improves the overall efficiency and market responsiveness of the supply chain. By collaborating closely with customers, firms can more effectively respond to market demand changes, enhance the adaptability of products and services, and also foster novelty and efficiency. Therefore, this study will discuss and examine customer integration in depth within an extended theoretical framework of the resource-based view. Table 4 provides a detailed display of the positive impacts of customer integration in operational management.

Table 4. The Positive Effect of Customer Integration on Operational Processes

Authors	Objectives	Mechanism
Chavez et al. (2015)	Operational performance	By engaging in frequent collaborative interactions and information sharing to reduce inventory costs and enhance quality, operational performance is improved.
Freije et al. (2022)	Product innovation	By closely collaborating with customers, manufacturing firms enhance market knowledge and product development capabilities during the transition to service-oriented novelty and efficiency, thus boosting product innovation capability.
Cui and Wu (2017)	New product development	By structuring cross-organizational strategies, procedures, and behaviors into collaborative, synchronized, and manageable processes.
Zhong and Um (2025)	Green innovation	By engaging in close communication with customers, firms enhance their perception of market green attributes and potential information, thus improving green innovation.
Yu et al. (2013)	Financial performance	By promoting the sharing of information flows and the transfer of knowledge, a better understanding of and response to customer needs is achieved, thereby enhancing customer satisfaction and financial performance.
Munir et al. (2020)	Risk management	Enhanced information processing capabilities, achieved through customer integration, effectively predict and respond to risks, thus improving overall risk management capabilities.

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2.3.2 Supplier Integration

Supplier integration is a pivotal strategy within modern supply chain management, wherein manufacturing firms engage in strategic collaboration with their suppliers to achieve enhanced efficiency and performance (Zhong and Um, 2024). This involves strategically and operationally incorporating suppliers into the company's business processes. Classified as external integration (Huo, 2012), this approach seeks to convert organizational strategies into operational processes through collaboration with key suppliers (Li et al., 2024). The scope of this collaboration transcends the mere exchange of goods and services, critically encompassing the integration of strategies, information, resources, and practices (Shah and Soomro, 2021). This integration aligns strategic objectives, information systems, resource allocation, and daily operational practices between partners, fostering a collaborative and cohesive working relationship (Freije et al., 2022). Consequently, it improves the efficiency and effectiveness of the entire supply chain, facilitates quick market responses, and enhances overall operational efficiency and competitive advantage in the marketplace. Previous literature underscores that supplier integration can confer multiple positive effects on firms (Molinaro et al., 2022), including improvements in operational performance (He et al., 2017, Amoako-Gyampah et al., 2020), product innovation (Lau et al., 2010, Melander, 2018), environmental performance (Li and Zhong, 2024, Du et al., 2018), responsiveness (Danese et al., 2013), cost efficiency (Bae et al., 2023, Kim and Schoenherr, 2018), and risk management (Zhong and Um, 2024, Nimmy et al., 2022). These benefits are principally derived from three critical domains of integration:

(1) Mutual Technological Support: In the manufacturing sector, technological cooperation between manufacturers and their suppliers is critical for enhancing product quality and innovation capability (Chen et al., 2023b). Through the sharing of technical knowledge and tools, both parties can more effectively address technical challenges encountered during production (El Mokadem and Khalaf, 2023). This exchange of technical insights allows suppliers and manufacturers to provide each other with expertise to solve specific technical challenges, such as a deep understanding of material technologies or optimization of product design. Additionally, sharing tools and technological resources can reduce redundant investments and accelerate development processes (Freije et al., 2022). Manufacturers and suppliers may jointly use advanced software and equipment for rapid prototyping and product testing. Joint R&D projects are also an effective mode of collaboration where both parties can invest resources together to develop new materials or processes, not only sharing the costs and risks of

R&D but also accelerating the commercialization of technologies. Moreover, technical training and personnel exchanges are vital for fostering technological cooperation. Regular training and exchanges help enhance technical capabilities and strengthen collaborative relationships (Chen et al., 2023b). Finally, by jointly establishing stringent quality control standards, both parties can ensure that products meet high-quality standards throughout the production process, which not only reduces defect rates but also enhances product competitiveness in the market.

(2) Information Exchange and Sharing: Close communication between manufacturing firms and their suppliers plays a crucial role (Qu and Liu, 2022). Efficient and transparent information exchange ensures real-time updates and accurate transmission of information. This immediate flow of information helps effectively prevent potential disruptions in the supply chain (He et al., 2017). For instance, close communication allows firms to timely adjust production plans and inventory management strategies when there is a sudden fluctuation in market demand or issues in other segments of the supply chain, thereby maintaining stable supply chain operations (Qu and Liu, 2022). Accurate information transmission also helps better coordinate resources, optimize supply chain decisions, and enhance overall supply chain resilience. Additionally, information sharing is equally vital in areas like

inventory management, production planning, demand forecasting, and market dynamics (Oh, 2022). Real-time data sharing enables the collaborative parties to achieve more efficient operational coordination, thus optimizing the overall supply chain's responsiveness and resource allocation (Li et al., 2024).

(3) Collaborative Planning in Interaction: The purpose of collaborative planning is to optimize production and distribution processes through close cooperation with suppliers (Freije et al., 2022). This cooperation strategy not only addresses market fluctuations but also improves the overall flexibility and efficiency of the supply chain (Shah and Soomro, 2021). First, collaborative planning and scheduling greatly enhance the adaptability of the supply chain (Yang et al., 2022). For instance, in response to sudden increases or decreases in market demand, production and distribution plans coordinated with suppliers can be quickly adjusted. This flexibility stems from both parties' joint forecasting of future production needs and sharing of real-time data, allowing firms to rapidly adjust production lines according to actual market demand, optimizing inventory levels, and avoiding overproduction and backlog. Secondly, long-term strategic relationships are key to supplier integration (Espino-Rodríguez and Taha, 2022). This relationship goes beyond traditional transactional interactions to form a partnership based on mutual benefit and long-term considerations. In this model,

suppliers are not only involved in daily transactions but are also deeply integrated into the product design and development stages, sharing risks and innovation outcomes (Deng et al., 2022). Such cooperative relationships help both parties better understand each other's business needs and market dynamics, enhancing the overall stability and competitiveness of the supply chain. Furthermore, information sharing and transparency within the supply chain are essential factors for the success of collaborative planning (Rejeb et al., 2021). By establishing efficient information exchange mechanisms, such as Electronic Data Interchange (EDI) or cloud computing platforms, all parties in the supply chain can access crucial data in real-time, such as inventory levels, production progress, and logistics status. This transparency not only reduces the issues of information asymmetry but also enhances the entire supply chain's responsiveness and coordination capabilities (Siringoringo and Sijabatb, 2023).

In summary, supplier integration not only strengthens the relationships between firms and their suppliers but also helps firms build and maintain a competitive edge (Fontoura and Coelho, 2022). Through mutual technological support, information exchange and sharing, and collaborative planning, firms can more effectively utilize external resources, enhancing their innovation capabilities and market adaptability. Therefore, this study will discuss and examine supplier integration in-depth under the extended framework of the resource-based view (RBV). Table 5 presents in detail the positive effect of supplier integration in operations.

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Table 5. The Positive Effect of Supplier Integration on Operations

Authors	Objectives	Mechanism
He et al. (2017)	Operational performance	Through the strategies of information sharing and joint decision-making, supplier integration can effectively manage relational uncertainties with suppliers, thereby improving firms' operational performance.
Lau et al. (2010)	Product innovation	The processes of information sharing and joint product development directly influence product innovation, which in turn indirectly enhances product performance.
Du et al. (2018)	Environmental performance	Collaboration with environmentally specialized suppliers, coupled with the moderating role of internal integration in green innovation processes, effectively enhances corporate environmental performance.
Danese (2013)	Responsive capabilities	Efforts such as information sharing and joint improvement initiatives accelerate the responsiveness of the supply network, thereby improving efficiency and schedule adherence.
Bae et al. (2023)	Cost performance	Strengthening the intensity of relational ties within the network fosters improvements in supply chain cost and responsiveness, ultimately enhancing cost performance.
Zhong and Um (2024)	Risk management	By enhancing supplier relationships and information sharing, firms can effectively improve their risk management capabilities when facing supply chain disruptions, thereby strengthening their resilience.

3. Hypothesis Development

This chapter is divided into four main parts, detailing the intricate interactions among variables and specifically describing their impact mechanisms within theoretical frameworks. The first section primarily discusses how AI capability can drive novelty through resource optimization, enhanced collaboration, and knowledge generation. From the resource-based view (RBV), AI is considered a strategic resource capable of optimizing supply chain management and creating unique competitive advantages. Additionally, from the perspective of dynamic capabilities theory (DCT), the role of AI in sensing market changes, swiftly seizing opportunities, and transforming them into business value is emphasized. The second section explores how AI facilitates efficiency, particularly in optimizing resource allocation, improving decision-making efficiency, and reducing operational costs. The article discusses from both RBV and DCT frameworks how AI capability becomes a key factor in driving firm efficiency optimization and cost control. The first and second parts combine theory with practical application to form a series of hypotheses aimed at systematically explaining how AI capability functions in different types of novelty and efficiency, thereby enhancing corporate competitiveness.

Subsequently, the third section investigates how customer integration strengthens the positive effects of AI capability on novelty. Customer integration, by fostering closer customer relationships and deeper market insights, enables firms to better utilize AI for market trend analysis and consumer behavior prediction, thus enhancing innovation capability and market responsiveness. The fourth section discusses how supplier integration amplifies the impact of AI capability on efficiency. Through close cooperation with suppliers, firms can more effectively integrate and optimize supply chain resources, leveraging AI technology to enhance the efficiency and transparency of supply chain management, ultimately improving overall operational efficiency. The third and fourth sections demonstrate how moderating variables influence the relationship between AI capability and novelty and efficiency, highlighting the significance of considering supply chain integration when implementing AI strategies. In this way, firms can more effectively leverage AI technology to adapt to complex and dynamic market environments.

3.1 AI Capability and Novelty

Novelty emphasizes differentiation in the market through the creation of unique value propositions and disruptive innovations. While such an approach involves higher risks, it holds the potential for transformative returns. This strategy, which focuses on exploring new markets or redefining existing ones, may be further enhanced by advancements in AI capability (Kumar et al., 2024). As a multifaceted tool, AI capability serves as a driving force for firms to achieve core competitive advantages (Alghamdi and Agag, 2024). This study examines the impact of AI capability on novelty through two theoretical lenses: the resource-based view (RBV) and dynamic capability theory. The mechanism by which AI capability influences novelty primarily arises from three dimensions: resource optimization, enhanced collaboration, and knowledge generation.

3.1.1 The Positive Effect under the Framework of the Resource-Based View

Under the theoretical framework of the resource-based view (RBV), a firm's competitive advantage is derived from resources and capabilities that are rare, inimitable, and non-substitutable. AI capability, as a strategic resource, supports novelty by optimizing supply chain management (Kumar et al., 2024). These capabilities, characterized by their scarcity and high investment requirements, enable firms to differentiate themselves in the competitive landscape. Through efficient data processing, real-time forecasting, and optimization algorithms, AI enhances supply chain operations (Yang et al., 2024). However, its effective application depends on alignment with the firm's industry context, business characteristics, and data assets, creating unique and inimitable advantages (Lee et al., 2024). Moreover, AI offers insights and efficiencies that traditional resources cannot achieve, solidifying its role as an indispensable resource. AI capability contributes to novelty in several ways (Benito and Meyer, 2024).

(1) By automating repetitive tasks, AI allows employees to focus on more innovative activities, enabling firms to explore new markets and address emerging customer needs (Madanaguli et al., 2024b). For example, Google's use of AI technologies in tasks such as email filtering and scheduling allows resources to be redirected toward creative endeavors, such as developing new products like the smart album feature in Google Photos. This ability to automate operations provides strategic advantages by improving efficiency (Kumar and Shankar, 2024).

(2) AI supports data-driven decision-making, helping firms identify market trends and develop innovative products with greater precision (Rejeb et al., 2021). For instance, JD Logistics has implemented AI-based demand-driven logistics services, which analyze regional consumption trends to optimize resource allocation and enhance responsiveness to customer orders. This AI-

driven approach redefines the firm's position within the value chain, transforming it into a strategic partner for its clients while simultaneously creating new revenue streams and competitive barriers (Kumar and Shankar, 2024).

(3) AI enables firms to uncover new market opportunities and create differentiated value by analyzing vast datasets to identify latent customer needs and preferences (Li et al., 2025). For example, Alibaba leveraged AI to detect increased interest in eco-friendly products in certain regions, allowing it to adjust its product offerings swiftly. By integrating and analyzing multidimensional data, firms can design tailored products and services that are difficult to replicate, ensuring agility in dynamic markets and securing a competitive edge (Kumar et al., 2024).

(4) AI optimizes internal processes and resource integration through deep learning, data analysis, and automation (Alghamdi and Agag, 2024). Real-time data processing and demand forecasting allow firms to manage inventory, allocate resources, and plan logistics more effectively (Li et al., 2025). Predictive maintenance and process bottleneck analysis further enhance production efficiency. Li-Ning Sports, for example, has used AI to optimize

inventory management, reducing resource consumption costs and reallocating savings to research and development for innovative products. These improvements enhance operational efficiency, shorten product development cycles, and enable firms to respond quickly to market demands, fostering sustained innovation and competitiveness (Pang et al., 2023).

RBV offers a comprehensive perspective on how AI capability positively impacts novelty by elucidating the underlying mechanisms. dynamic capability theory also provides valuable insights into this relationship, which will be explored in the next section.

3.1.2 The Positive Effect under the Framework of the Dynamic Capabilities

Dynamic capability theory (DCT), originating from the resource-based view (RBV), suggests that firms can perceive, capture, and reorganize both internal and external resources to adjust their business processes and optimize market offerings, such as services, to better meet customer needs and adapt to market changes (Li et al., 2023, Teece, 2018). Similarly, the positive impact of AI capability on novelty-oriented novelty and efficiency can also be understood through the three dimensions of dynamic capabilities: sensing, seizing, and transforming opportunities (Shen and Liu, 2025).

Firstly, sensing capability refers to a firm's ability to utilize its AI capability to discover and identify new market opportunities and demands (Basit et al., 2024). This capability relies on the powerful analytical capacity of AI, which enables the efficient collection, processing, and analysis of vast amounts of external data (Sullivan and Wamba, 2024). For example, AI can monitor social media, news, and industry reports in real-time to capture market dynamics and consumer sentiments; analyze historical and real-time data using machine learning models to predict future customer needs and preferences; and perform comparative analyses of competitors' products, marketing strategies, and technological applications to inspire innovation (Wang et al., 2025a). These AI-driven insights not only shorten decision-making cycles but also enhance decision accuracy, providing scientific foundations for novelty (Cooper, 2024). A practical example can be seen in Amazon's Kindle e-book business. Leveraging its AI sensing capabilities, Amazon analyzed customer browsing and purchasing data, monitored social media reviews, and studied competitors' strategies to identify the demand for lightweight, long-battery-life e-book devices. This insight enabled the swift launch of the Kindle product line. AI further supported predictions about the growth of the e-book market, facilitating inventory and product feature optimization, such as improved screen technology and battery performance. These sensing capabilities allowed Amazon to gain a first-mover advantage in the digital reading market and solidify its leadership through continuous innovation.

Secondly, seizing capability involves a firm's ability to quickly capitalize on emerging opportunities and transform them into actionable business value (Abu Huson et al., 2024). Firms can use AI technologies to analyze market dynamics and customer demands in real-time, identifying high-value opportunities and rapidly adjusting product and service portfolios to deliver competitive and innovative solutions (Scientific, 2024). By integrating process automation, data analysis, and intelligent forecasting, firms can optimize internal resource allocation, minimize redundancy, and enhance resource utilization, creating a model that combines operational efficiency with increased customer value. For example, Tesla's AI-driven seizing capabilities have enabled rapid action and value transformation in the electric vehicle market. Through real-time analysis of market dynamics and customer feedback, Tesla identified the demand for long-range, high-performance electric vehicles and swiftly introduced competitive models like the Model S and Model 3. Tesla also optimized production processes and supply chain management using AI technologies, such as intelligent battery resource allocation and automated manufacturing systems, significantly improving resource efficiency. This approach has established Tesla as an innovation benchmark in the electric vehicle industry while enhancing its market competitiveness and brand value.

Thirdly, transforming capability refers to a firm's ability to leverage AI technologies to optimize and reconfigure existing resources and processes in response to rapidly changing external environments, thereby enhancing the innovativeness of its novelty and efficiency (Madanaguli et al., 2024a). Through AI-enabled process automation, resource release, data empowerment, and modular innovation, firms can reduce operational costs, improve decision-making, and focus resources on high-value innovation activities, thus strengthening their novelty capabilities (Shahzadi et al., 2024). For instance, manufacturing firms can use AI-driven automated production lines to reduce human errors, develop modular products through AI-supported design platforms, and offer personalized services to customers (Shahin et al., 2024). By concentrating resources on innovation and R&D, these firms transition to value-creation models based on customer satisfaction and customization. A case in point is Nike, which has leveraged AI-driven transforming capabilities to achieve novelty and efficiency. By adopting AI automation technologies, Nike optimized its manufacturing processes, such as intelligent cutting and automated assembly systems, reducing errors and significantly improving production efficiency. Additionally, AI-supported design platforms enabled Nike to rapidly develop modular products and launch Nike By You, a personalized customization service that meets consumer demand for tailored athletic footwear. AI-powered consumer data analysis further allowed Nike to focus resources on high-value innovations, such as the development of new eco-friendly materials and smart wearable devices. This resource transformation not only lowered operational costs and waste but also enhanced Nike's flexibility and competitiveness in dynamic markets, laying a solid foundation for sustained innovation and growth.

After exploring the respective perspectives of the RBV theoretical framework and the dynamic capabilities theoretical framework, this study posits that artificial intelligence capabilities provide firms with a unique competitive advantage by enhancing resource optimization and dynamic reconfiguration, thereby fostering the comprehensive development of novelty, efficiency, and novelty innovation. Therefore, this study proposes Hypothesis H1:

H1: AI capability drives the innovation of a novelty.

3.2 AI Capability and Efficiency

The key distinction between efficiency and novelty lies in their strategic focus. Efficiency emphasizes optimizing resource utilization, reducing costs, and improving operational efficiency (Fosso Wamba et al., 2023). It seeks incremental improvements and stable growth by streamlining processes and fostering collaboration. The impact of AI capability on efficiency can similarly be examined from two perspectives: the resource-based view (RBV) and dynamic capability theory (DCT) (Shen and Liu, 2025). The primary mechanisms driving this impact include resource allocation optimization, enhanced decision-making efficiency, and reduced operational costs.

3.2.1 The Positive Effect under the Framework of the Resource-Based View

According to the resource-based view (RBV), AI capability represents unique and scarce resources that can provide firms with a competitive advantage and drive efficiency (Wang et al., 2025a). This influence is realized through mechanisms such as resource allocation optimization, improved decision-making efficiency, and reduced operational costs.

In internal business processes, AI's automation technologies significantly enhance operational efficiency. In production, intelligent planning and resource allocation effectively reduce idle time and waste while improving redundancy management performance (Abu Huson et al., 2024). Real-time data analysis facilitated by AI can optimize inventory management and logistics arrangements, ensuring resources are utilized efficiently at the right time and place. This data-driven approach not only accelerates internal response times but also minimizes errors caused by information asymmetry (Wong et al., 2024). In external processes, technologies such as machine learning and natural language processing enable firms to predict market demand and consumer preferences with precision. By identifying potential customer segments and crafting personalized marketing strategies, firms can enhance customer satisfaction and loyalty (Sullivan and Wamba, 2024). Moreover, AI-driven chatbots and virtual assistants enhance service efficiency while reducing labor costs, allowing firms to deliver high-quality service at lower costs.

AI capability also plays a critical role in improving decision-making efficiency by leveraging data analytics to provide firms with reliable, scientific, and effective decision-making solutions (Neiroukh et al., 2024). The strength of this capability lies in AI's powerful data processing and algorithm optimization functions, which extract valuable insights from large volumes of both structured and unstructured data. These insights enable firms to gain real-time, accurate market understanding. For instance, AI can analyze consumer behavior patterns, competitive dynamics, and market trends to identify key variables and potential opportunities, allowing firms to predict market demand shifts more quickly and accurately (Shin, 2021). Traditional market research and analysis often require significant time and labor, whereas AI can automate data collection, cleaning, analysis, and visualization, turning complex problems into actionable solutions in a fraction of the time. Additionally, AI supports firms in forecasting the outcomes and risks of various decision-making scenarios through simulations and scenario analysis. This ensures firms can adapt their strategies quickly in the face of uncertainty. For example, in new product development, AI enables real-time optimization of product design and marketing strategies based on market feedback, significantly increasing the likelihood of success. AI's decision-support functions make novelty and efficiency more agile in responding to market demands (Cooper, 2024). By integrating multidimensional data and building intelligent recommendation systems, firms can dynamically adjust resource allocation, supply chain arrangements, and customer service models to meet evolving market needs. This flexibility allows firms to seize business opportunities more quickly while minimizing losses from delayed or erroneous decisions (Jauhar et al., 2024). Overall, AI enhances decision-making efficiency while strengthening the agility and competitiveness of novelty and efficiency, providing firms with valuable strategic support in rapidly changing market environments.

In traditional production processes, many stages rely on manual operations, which consume substantial human resources and often lead to quality inconsistencies (Cooper, 2024). AI technologies such as robotic assembly, intelligent inspection, and automated packaging not only improve production efficiency but also ensure product quality consistency, reducing defect rates and rework costs (Dauvergne, 2022). Thus, AI capability effectively supports cost-reduction efforts. Cost savings are achieved not only through automation but also through optimized resource allocation and energy consumption. For example, intelligent production systems can monitor equipment status in real time and dynamically adjust machine operations based on production needs, reducing resource waste and energy costs. AI-driven predictive maintenance technologies can identify potential equipment failures in advance, preventing production interruptions and additional repair expenses. This intelligent operational model enables firms to maintain high production efficiency at lower costs. The cost savings achieved through these measures allow firms to optimize their novelty and efficiency by offering competitive pricing while maintaining product quality. By translating cost advantages into price competitiveness, firms can attract more customers and expand their market share.

The resource-based view offers a crucial theoretical foundation for understanding how AI capability enhances efficiency, offering a comprehensive perspective on the mechanisms involved. Similarly, dynamic capability theory offers unique insights into this relationship, which will be discussed in the next section.

3.2.2 The Positive Effect under the Framework of the Dynamic Capabilities.

Based on dynamic capability theory (DCT), AI capability positively influences efficiency by enhancing firms' sensing, integrating, and transforming capabilities. This theory emphasizes the need for firms to dynamically adjust resources in rapidly changing environments to seize opportunities and address challenges, with AI playing a pivotal role in this process (Wamba et al., 2024).

Firstly, sensing capability refers to the ability of firms to leverage AI technologies to quickly identify opportunities for efficiency improvement in both internal operations and external processes. Through big data analysis and real-time monitoring, AI helps firms identify inefficiencies in their business processes (Armenia et al., 2024). For instance, in internal operations, AI can optimize daily business workflows by analyzing production data in real-time, locating inefficiencies or underperforming equipment, and adjusting operational parameters to improve resource utilization and reduce operational costs. In external processes, AI enhances logistics management by tracking delivery routes and dynamically identifying bottlenecks in the supply chain. By analyzing potential delays and redesigning delivery networks, AI ensures that resources reach their destination as efficiently as possible (Madanaguli et al., 2024b). This capability not only meets customer demands for responsiveness and accuracy but also minimizes wasted time and resources, achieving a dual benefit of operational efficiency and customer satisfaction. For example, real-time route optimization driven by AI ensures simplicity in transactions from the user's perspective while minimizing errors in the process, contributing significantly to efficiency (Abou-Foul et al., 2023).

Secondly, integrating capability highlights how firms use AI technologies to effectively combine internal and external resources, capturing market opportunities for efficiency improvement (Madanaguli et al., 2024b). AI significantly enhances resource integration and allocation through in-depth data analysis and decision-making support. For example, firms can use AI to forecast consumer demand trends more accurately, enabling precise inventory management strategies that avoid overstocking or shortages, thereby reducing costs and improving inventory turnover. This capability is reflected in the optimization of novelty and efficiency, such as cost reduction and improved decision-making for participants (Drydakis, 2022). In the retail sector, firms employ AI to analyze consumer behavior data, design targeted promotions, and provide personalized offers to customers, facilitating efficient inventory turnover and rapid capital recovery. Additionally, AI supports automation and standardization of business processes, reducing dependency on manual operations (Fosso Wamba, 2022). E-commerce platforms, for instance, use AI to optimize supplier selection and inventory allocation processes, minimizing errors and improving supply chain efficiency and reliability. By analyzing market dynamics and supply chain performance in real-time, AI enables dynamic adjustments to resource allocation strategies, ensuring a swift response to market changes. Enhanced integration capability positions AI not only as a tool for efficiency optimization but also as a core engine for strategic resource integration, empowering firms to seize efficiency-driven market opportunities.

Thirdly, transforming capability refers to the dynamic adjustment of resources and processes enabled by AI to respond quickly to market demand changes, thereby supporting efficiency-driven novelty and efficiency (Madanaguli et al., 2024b). AI plays a crucial role in new product development and market opportunity identification. In product development, AI simulation technologies optimize design processes, identify potential flaws early in development, and avoid the time and cost associated with later-stage modifications (Cooper, 2024). This capability reduces development cycles and minimizes resource waste. For example, an automotive manufacturer utilized AI to optimize car model designs, accelerating time-to-market while reducing operating and development costs (Dauvergne, 2022). Additionally, AI's automation features support rapid adjustments in production planning and resource allocation. When firms identify excess production capacity, AI can analyze market demand and reconfigure production lines to meet alternative needs. AI also dynamically adjusts human resource deployment, reducing redundant labor and further enhancing efficiency and flexibility. This ability to adapt dynamically allows firms to maintain efficient operations even amid market changes, positioning AI as both a critical driver of efficiency and a foundation for novelty and efficiency. This aligns with the previously mentioned concept of ambidexterity, as AI supports firms in balancing operational stability with adaptability (Belhadi et al., 2024).

In conclusion, after exploring the respective perspectives of the RBV theoretical framework and the dynamic capabilities theoretical framework, AI capability provides firms with a unique competitive advantage through resource optimization, improved decision-making efficiency, and cost reduction, promoting the comprehensive development of efficiency. Therefore, this study proposes Hypothesis H2:

H2: AI capability drives the operations of efficiency.

3.3 Moderation Extended Resource-Based View and Complementarity Theory

The extended resource-based view (ERBV) serves as a crucial enhancement and development of the traditional resource-based view (RBV), emphasizing not only the management of internal resources but also the importance of cultivating effective external relationships to augment resource acquisition and competitiveness (Kumar et al., 2024). ERBV emerged in response to criticisms of RBV's neglect of dynamic external environmental changes and its introspective, static perspective (Zhong and Um, 2025). Building on the core tenets of RBV—that a firm's competitive advantages arise from its unique and inimitable resources and capabilities—ERBV further emphasizes the crucial role of external network relationships in optimizing resources and enhancing capabilities.

In a dynamic and complex business environment, relying solely on internal resources is often insufficient to meet rapidly evolving market demands and technological advancements (Xiao et al., 2023). ERBV advocates for firms to establish extensive external network relationships, including collaborations with other businesses, institutions, customers, and suppliers, to access necessary external resources and knowledge (Xu et al., 2014). Such engagements not only enhance a firm's innovation capacity but also improve its responsiveness to market fluctuations. In ERBV, external networks are regarded as strategic resources that enable access to resources that would be prohibitively expensive or technically unfeasible to develop independently, such as advanced technology platforms, critical market information, and industry best practices (Wang and Zhang, 2024). For instance, small tech firms can leverage the R&D resources and technical expertise of higher education institutions and research centers to innovate and upgrade technologies at lower costs. Similarly, by establishing strategic alliances or partnerships with global leading companies, firms can quickly enter new markets and expand their customer bases. Dynamic capabilities, another central concept in ERBV, refers to a firm's ability to reconfigure resources in response to continuous environmental changes, including the capabilities to perceive external shifts, seize market opportunities, and integrate both internal and external resources. Effective management of external network relationships allows firms to swiftly acquire information on market changes, respond to shifts in customer demands, and collaboratively develop new products or services with partners (Wong et al., 2024). For example, in the automotive industry, companies can quickly adapt to the technological shifts in new energy vehicles by closely cooperating with global supply chain partners, and aligning with environmental policies and market trends. Additionally, ERBV emphasizes strategies for firms to manage environmental uncertainties, particularly significant in a globalized economic context marked by increased market and technological unpredictability, such as the COVID-19 pandemic and geopolitical conflicts like the Russo-Ukrainian War. By establishing and maintaining robust external relationship networks, firms can more effectively diversify risks and enhance overall adaptability and resilience through resource and information sharing. Multinational corporations mitigate risks of economic fluctuations in single markets or regions by setting up R&D centers and production bases across different countries and regions, leveraging local unique resources and market advantages.

Although the extended resource-based view (ERBV) provides a theoretical foundation for understanding the role of supplier integration and customer integration in enterprise resource allocation, it still has certain limitations in explaining the synergy between these two elements. ERBV primarily emphasizes how firms enhance their competitive advantage by integrating external resources, but it fails to fully elucidate how supplier integration and customer integration generate synergistic effects through complementary resources, thereby further enhancing firms' innovation capabilities and operational efficiency. Therefore, it is necessary to introduce complementarity theory (CT) as a supplementary framework to more comprehensively analyze the value creation mechanisms of supply chain integration (Grant, 1996).

Complementarity theory (Teece, 1986) posits that when two or more resources exhibit complementarity, their joint utilization generates synergistic effects, creating value beyond the simple sum of their contributions. In the context of supply chain management, supplier integration, and customer integration can be regarded as two critical types of external resources, each contributing distinct capabilities: Supplier Integration primarily enhances firms' operational efficiency, supply chain resilience, and cost control, whereas customer integration strengthens firms' market insight, product innovation, and demand responsiveness. According to CT, these two forms of integration do not independently affect performance; rather, they create greater value through their complementarity. For instance, a highly integrated supplier system can ensure precise material supply and production coordination, while close collaboration with customers provides real-time market demand information and feedback mechanisms. When supplier integration and customer integration form a complementary relationship, firms can not only optimize resource allocation but also shorten innovation cycles and improve product adaptability, thereby achieving a higher level of novelty and efficiency.

Moreover, from the perspective of CT, the role of Artificial Intelligence (AI) in supply chain integration becomes more clearly articulated. The core advantage of AI lies in its powerful data processing capabilities and intelligent decision-support functions, which can significantly facilitate information flow between suppliers and customers, enhancing the accuracy of resource matching. From the CT perspective, AI is not merely a tool for optimizing individual supply chain processes but rather a key enabler of complementary resource synergy, further amplifying the value-creation effects of supply chain integration. For example, AI-driven supply chain data analytics can accurately predict market demand fluctuations, allowing suppliers to adjust production plans in advance, thereby better aligning with customer needs. This dynamic coordination mechanism fully leverages the complementary advantages of supplier integration and customer integration, improving overall supply chain agility and innovation efficiency.

In conclusion, compared to ERBV, which primarily focuses on resource acquisition and utilization, complementarity theory provides a more explanatory theoretical framework for understanding the synergistic effects of supplier integration and customer integration. By integrating the CT perspective, future research can further explore how AI technologies facilitate complementary resource effects in supply chain integration and assess the impact of varying degrees of supplier-customer collaboration on firms' novelty, efficiency, and performance. This research direction not only deepens the theoretical understanding of supply chain integration mechanisms but also offers important managerial insights for corporate practice.

3.3.1 Customer Integration as a Catalyst for Novelty in AI Capability

When exploring the mechanism through which customer integration influences AI capability, it is crucial to emphasize its pivotal role in novelty and efficiency. Customer integration is not merely a process of information collection; rather, it serves as a vital bridge for enterprises to transform AI technologies into commercial value. By establishing deep collaborative mechanisms with customers, enterprises can obtain more accurate market demand information, which, after being analyzed and processed by AI systems, can be converted into forward-looking business insights. This bidirectional interaction transforms AI systems from a closed technological black box into an open system capable of continuous learning and optimization. Specifically, the reinforcing effect of customer integration on AI capability manifests in three dimensions. First, at the data input level, real-time feedback and demand information provided by customers serve as high-quality training data for AI systems, significantly improving the accuracy of predictive models. Second, at the value creation level, customer participation in product design and development processes ensures that AI-driven innovation initiatives are more aligned with actual market needs, thereby avoiding technology-driven deviations. Finally, at the continuous optimization level, behavioral data generated during customer usage provides critical input for the iterative upgrading of AI systems, forming a virtuous learning cycle.

This synergistic effect of deep integration is fully demonstrated in Amazon's novelty and efficiency. The company's recommendation system relies not only on advanced AI algorithms but also continuously collects and analyzes customer feedback data to optimize its recommendations. This approach of deeply embedding customers into AI application scenarios enables Amazon to maintain a continuous innovation capability while also validating the critical role of customer integration in amplifying the value of AI. From a theoretical perspective, this synergistic mechanism can be reasonably explained through the lens of the extended resource-based view (ERBV), which posits that the complementary integration of customer resources and AI technologies can create inimitable competitive advantages. The following section will elaborate on the moderating role of customer integration within the framework of the extended resource-based view.

3.3.2 Customer Integration Moderates the Relationship between AI Capability and Novelty on Complementarity Theory

Based on the extended resource-based view (ERBV) theoretical framework, this study focuses on examining the impact of customer integration processes on firms' innovation activities. ERBV is a significant extension of the traditional resource-based view (RBV), as it not only focuses on the strategic utilization of internal resources but also emphasizes building competitive advantages through the integration of external resources (Zhong and Um, 2025).

Within this theoretical perspective, customer integration acts as a key external resource integration strategy, particularly significant for firms engaging in novelty using artificial intelligence (AI) capability. In the contemporary business landscape, the rapid development and application of AI technology have emerged as a key driver of business design. Firms can utilize AI to develop innovative novelty and efficiency by integrating customers' needs and feedback, which not only addresses current market demands but also anticipates and creates future market needs (Shen and Liu, 2025). Customer integration serves as a bridge in the innovation process, aiding firms in better understanding market dynamics, capturing unarticulated customer needs, and creating innovative solutions based on these insights. Through customer integration, firms can acquire valuable information about market trends, consumer behavior, and competitor dynamics, which are indispensable resources for designing novelty and efficiency (Wu et al., 2024). For example, through deep customer engagement and feedback mechanisms, firms can incorporate direct customer insights early in product design, thereby reducing adjustment costs and risks after market launch. Additionally, customer integration helps strengthen relationships between firms and their customers, enhancing customer loyalty and continuously providing the firm with innovative ideas and opportunities.

In the context of AI-driven novelty, this integration enables firms to more effectively utilize AI technology to analyze big data and discern market trends, thus sustaining a competitive edge in a highly competitive market. Customer integration is particularly crucial in the process of using AI for product design and development. This integration approach involves directly incorporating customers into the innovation process, enabling them to provide key insights into market needs, preferences, and future trends during the early phases of product design. Through this approach, firms can obtain feedback on product attributes and performance from the outset, ensuring that product designs align more closely with market needs. In-depth communication with customers also allows firms to gather new ideas and concepts, which may not have been considered by their R&D teams. The intuitive feelings and specific needs of customers are often key drivers of product innovation, helping to enhance product market adaptability and reduce the frequency and costs of market adjustments after product launch. The application of AI technology in customer integration significantly enhances its effectiveness (Chen et al., 2022). AI is capable of processing and analyzing large volumes of customer data, including purchase histories, feedback records, and behavior patterns, which can be used to predict market trends and consumer preferences, thereby guiding product innovation. Through machine learning and data mining techniques, AI can extract valuable information from complex and unstructured data provided by customers, improving product design and increasing market competitiveness (Yoo et al., 2024).

Moreover, although the extended resource-based view (ERBV) provides a solid theoretical foundation for explaining how firms leverage external resources (such as customer integration) to enhance AI-driven novelty and efficiency, its theoretical framework does not fully capture the synergistic effects that arise when AI capability and customer integration function as complementary resources. Complementarity theory (CT) posits that when two resources exhibit complementarity, their combined effect surpasses the simple sum of their contributions (Teece, 1986). This theory offers crucial theoretical support for understanding the synergy between AI capability and customer integration in novelty and efficiency.

In the context of AI-driven novelty and efficiency, AI capability provides firms with advanced data processing, predictive analytics, and automation functions, significantly improving operational efficiency and decision-making quality. However, the potential of AI capability is not limited to technological optimization; its true value lies in how these technological capabilities are closely integrated with market demands. Customer integration, as a key external resource, enhances firms' interaction with end users, providing real-time market sensing, feedback loops, and opportunities for consumer co-creation. This integration not only helps firms better understand market demands but also enables them to respond rapidly to market changes, thereby enhancing the flexibility and adaptability of their novelty and efficiency.

Specifically, AI capability enhances firms' innovation potential by identifying emerging trends, optimizing decision-making processes, and predicting customer preferences. However, without effective customer integration, AI-driven insights may lose accuracy and relevance due to the lack of real-time market perception. As a complementary resource, Customer integration facilitates direct communication between firms and consumers, ensuring that AI-generated insights remain aligned with real-world consumer needs. This synergy not only strengthens the practical application of AI capability but also provides a solid foundation for firms to develop more innovative and market-competitive novelty and efficiency.

For instance, Amazon and Tesla exemplify how AI-driven recommendation systems, when combined with customer feedback mechanisms, continuously optimize their novelty and efficiency. Amazon utilizes AI technology to analyze consumer purchasing behaviors and preferences, generating personalized product recommendations while constantly refining its recommendation algorithms based on customer feedback, thereby enhancing user experience and satisfaction. Tesla, on the other hand, leverages AI technology to analyze vehicle usage data, predict user needs, and continuously improve product design and functionality through customer feedback mechanisms. These cases clearly illustrate how customer integration enhances the innovation potential of AI capability, enabling firms to achieve sustainable competitive advantages.

Consequently, AI capability and customer integration, as complementary resources, generate significant synergistic effects in novelty and efficiency. AI capability provides firms with technological advantages, while customer integration ensures that these technological advantages remain closely aligned with market demands. The combination of these two elements not only enhances firms' innovation capabilities but also provides crucial support for the development of more market-competitive novelty and efficiency.

Therefore, this study predicts that the degree of customer integration will positively moderate the relationship between AI-driven novelty and innovation. Specifically, a higher level of customer integration can provide firms with diverse perspectives and deep market insights, which are obtained through direct customer feedback, market demand analysis, and consumer behavior prediction. This rich input enhances the effectiveness of AI applications, enabling more accurate identification of market trends and consumer needs. With high customer integration, firms can ensure that their AI-driven novelty and efficiency are more closely aligned with actual market conditions, effectively positioning innovation focus and direction (Akter et al., 2023). For example, firms can leverage AI to analyze large volumes of data from customers, discover unmet needs or potential market segments, and further use these insights to design their products and services. This combination of AI-based in-depth analysis and customer feedback not only enhances product market relevance but also provides firms with opportunities to explore new novelty and efficiency. Moreover, a higher level of customer integration may also lead firms to explore entirely new novelty and efficiency, such as through customized or personalized products and services that more effectively meet customer needs. In such models, AI technology can be used to design personalized user experiences and customized product options, not only meeting the high consumer demand for personalization but also creating new growth points and competitive advantages for firms (Wang et al., 2025b).

In summary, the combination of customer integration and AI capability transcends mere technological and data processing levels, manifesting as a strategic resource allocation that powerfully drives firms to sustain innovation and maintain competitive advantages in a fiercely competitive market environment. This approach allows firms to adapt more flexibly to rapid market changes by deeply understanding and meeting customer needs, propelling forward the firms' innovation activities (Wang and Zhang, 2024). This strategic resource allocation ensures that firms can successfully engage in novelty, continuously pushing the boundaries of their business, thereby securing a favorable position in the competition (Kumar et al., 2024). This method ensures that firms can find new paths for growth and innovation in an ever-changing market environment, achieving long-term market leadership. Therefore, this study proposes the hypothesis H3：

H3: Customer integration positively moderates the relationship between AI capability and novelty.

3.3.3 The Synergistic Mechanism of Supplier Integration on AI Capability Enhancement

When exploring the mechanism through which supplier integration influences AI capability, it is essential to emphasize its critical role in the intelligent transformation of supply chains. Supplier integration is not merely a simple supply chain collaboration process; rather, it forms the essential foundation for enterprises to transform AI technologies into operational efficiency gains. By establishing a deeply integrated supplier collaboration network, enterprises can access more comprehensive supply chain data, which, when analyzed and optimized by AI systems, can be translated into precise operational decisions. This end-to-end integration enables AI systems to transcend organizational boundaries and achieve optimal resource allocation on a broader scale. Specifically, the reinforcing effect of supplier integration on AI capability is reflected in three key dimensions. First, at the data foundation level, real-time production, inventory, and logistics data provided by suppliers offer rich training inputs for AI algorithms, making applications such as predictive maintenance and intelligent scheduling feasible. Second, at the process coordination level, a deeply integrated supplier network allows AI systems to optimize the entire supply chain across organizational boundaries, achieving global optimization rather than isolated improvements. Finally, at the risk management level, the integration of supplier quality data with production data enables AI systems to proactively identify potential risks and automatically trigger responsive mechanisms.

This synergistic effect of deep integration has been fully validated in Huawei's global supply chain management. By establishing an AI-enabled supplier collaboration platform, Huawei has integrated real-time production data from over 800 core suppliers into its AI analytics system, thereby improving supply forecast accuracy by 28% and reducing inventory turnover by 19 days. This case vividly demonstrates how supplier integration serves as a critical enabler for the implementation of AI capability. From the perspective of dynamic capabilities theory, supplier integration significantly expands the boundaries through which enterprises can leverage AI technologies to gain competitive advantages: in the sensing dimension, the integrated supplier network forms a distributed data sensing node; in the seizing dimension, the specific investments made by strategic suppliers constitute unique complementary assets; in the transforming dimension, standardized data interfaces enable real-time decision-making across organizational boundaries. The following section will further elaborate on the moderating mechanism of supplier integration within multiple theoretical frameworks.

3.3.4 Supplier Integration Moderates the Relationship between AI Capability and Efficiency on the Complementarity Theory

In modern corporate management practices, supplier integration is widely regarded as a key strategic approach to enhancing a firm's core competitiveness (Kemp, 2024). This strategy involves establishing closer cooperative relationships with suppliers and enhancing the overall efficiency and responsiveness of the supply chain through information sharing, resource coordination, and joint development (Rajaram and Tinguely, 2024). The extended resource-based view (ERBV) offers scholars a theoretical framework, emphasizing that, in addition to managing internal resources, firms must also build and sustain competitive advantage by integrating and coordinating external resources.

Under the ERBV framework, supplier integration is seen as a crucial method of external resource integration, significantly enhancing a firm's market adaptability and innovative capabilities. This deep collaborative relationship fosters efficient information sharing, enabling firms to obtain more accurate inventory and production planning data (Mikalef et al., 2023). For instance, timely communication with suppliers allows firms to more accurately predict market demands, adjust production schedules promptly, and avoid inventory accumulation and resource wastage. Efficient information flow is vital for addressing rapidly changing market conditions, helping firms maintain flexibility and efficiency in a competitive landscape.

The application of AI technology can significantly enhance the data analysis capabilities and decision-making processes of the supply chain, particularly data analytics and machine learning technologies, which can process and analyze large volumes of supply chain data, identifying key factors that impact production and supply (Krakowski et al., 2023). These technologies not only optimize current inventory levels and production processes but also predict future market trends and demand shifts, allowing firms to prepare in advance and adjust strategies to meet potential challenges. AI also improves the speed and precision of supply chain decision-making, quickly identifying problems and proposing effective solutions through machine learning models in complex supply chain networks (Belhadi et al., 2024). Particularly in efficiency, the integration of AI helps firms better predict market demand, adjust supply chain strategies, and precisely meet customer needs, thereby enhancing overall business performance (Sullivan and Wamba, 2024). The expertise and market feedback provided by suppliers during the product development stage allow firms to design products that more effectively meet market needs and optimize cost efficiency. This forward-looking information and technical support from suppliers directly influence the innovation and market competitiveness of products (Krakowski et al., 2023). Thus, this study predicts that supplier integration, by improving the quality and efficiency of information sharing and strengthening collaboration in the product development process, will positively moderate the impact of AI capability on efficiency. When the level of supplier integration is high, firms can more effectively utilize AI technology for resource allocation and production planning decisions, not only improving operational efficiency but also enhancing market adaptability and product competitiveness. This indicates that supplier integration plays a positive moderating role in AI-driven efficiency, promoting efficient responsiveness, information alignment, and the sharing and support of resources (Mikalef et al., 2023).

Similarly, although the extended resource-based view (ERBV) provides a solid theoretical framework for understanding how firms leverage supplier integration to enhance AI-driven efficiency-oriented novelty and efficiency, its theoretical perspective does not fully capture the synergistic effects that arise when AI capability and supplier integration function as complementary resources. Complementarity theory (CT) emphasizes that when two resources exhibit complementarity, their joint utilization generates value that exceeds the simple sum of their contributions (Teece, 1986). This theory provides an essential theoretical foundation for an in-depth analysis of the synergy between AI capability and Supplier Integration in efficiency optimization.

In the context of AI-driven efficiency optimization, AI capability provides firms with robust technological support, including predictive analytics, process automation, and real-time decision support. These technological capabilities enable firms to manage operational processes more efficiently, optimize resource allocation, and respond quickly to market changes. However, the potential of AI capability is not limited to technological efficiency improvements; its true value lies in how these technological capabilities are closely integrated with the actual operations of the supply chain. Supplier Integration, as a key external resource, enhances firms' collaboration with suppliers, providing greater operational flexibility, supply chain responsiveness, and coordination capabilities. This integration not only helps firms better manage supply chain risks but also enables them to meet customer demands more efficiently, thereby improving overall operational efficiency.

Specifically, AI capability leverages big data analytics and machine learning to optimize inventory control, production planning, and logistics coordination, significantly enhancing operational efficiency. However, without a high level of Supplier Integration, AI-driven insights may lose accuracy and applicability due to the lack of real-time awareness of supply chain conditions. As a complementary resource, Supplier integration provides direct access to suppliers' production capacities, real-time inventory data, and logistical constraints, ensuring that AI-generated efficiency recommendations are both actionable and aligned with the actual supply chain conditions. This synergy not only enhances the practical application of AI capability but also provides critical support for firms in building a more efficient and resilient supply chain system. Toyota serves as an example of how AI-driven demand forecasting, when combined with a well-integrated supplier network, significantly improves operational efficiency. Toyota utilizes AI technology to optimize production planning, integrating it with its long-established Supplier Integration network to enable the efficient operation of the just-in-time (JIT) inventory system. This case clearly illustrates how supplier integration enhances the efficiency optimization potential of AI capability, allowing firms to achieve sustained competitive advantages.

Furthermore, the complementarity between AI capability and supplier integration is evident not only in improving operational efficiency but also in enhancing supply chain resilience. AI capability, through real-time data analysis and predictive analytics, helps firms identify potential supply chain risks, while supplier integration strengthens collaborative relationships and information sharing, enabling firms to respond more rapidly to these risks. For instance, in the event of a supply chain disruption, AI-driven predictive analytics can help firms quickly adjust production plans, while supplier integration ensures that firms can rapidly secure alternative resources or adjust logistical arrangements, thereby minimizing the impact of disruptions on operations.

In conclusion, as an important strategy for external resource integration, supplier integration plays a key role in promoting novelty and efficiency driven by AI capability. Through deep supplier cooperation and effective information sharing, firms can maintain cost-effectiveness while improving product quality and market responsiveness, thereby sustaining a competitive edge in fierce market competition. Therefore, this study proposes hypothesis H4:

H4: Supplier integration positively moderates the relationship between AI capability and efficiency.

Figure 1 presents a detailed depiction of the structural equation model used in this study.

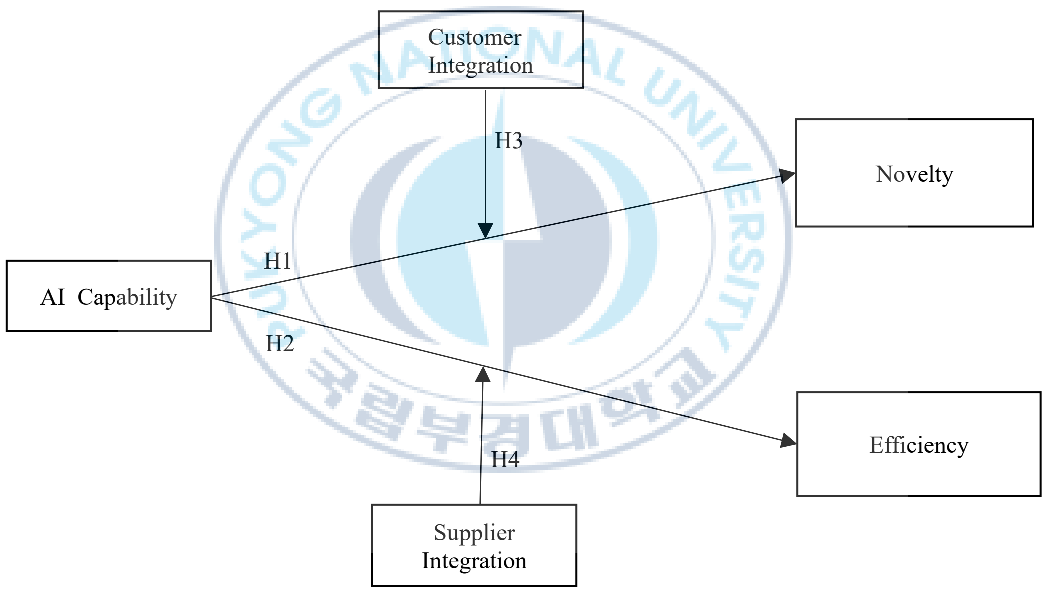

Figure 1. Research Model

4. Research Methodology

This chapter is divided into five sections, focusing primarily on research methodology, detailing how data was collected and analyzed to validate the hypotheses proposed in Chapter Three. This part introduces the specific steps and methods of data collection, including the design of the survey questionnaire, sample selection, and the timing of data collection. It emphasizes measures to ensure data quality and representativeness, such as pre-testing the questionnaire and selecting appropriate survey participants. The second part elaborates on the measurement methods and tools used to assess research variables, such as AI capability, novelty and efficiency, and customer and supplier integration. It discusses how to ensure the reliability and validity of these measurement tools and how they contribute to accurately testing hypotheses in statistical analysis. The third part explores how to verify the validity of the research constructs, including the use of exploratory factor analysis and confirmatory factor analysis, as well as how to handle common method bias issues. The fourth part discusses potential non-response bias and how to identify and mitigate this bias through statistical tests. It also explains the potential impact of common method bias on research results and the preventive measures taken. The fifth part presents the test results of the research hypotheses obtained through hierarchical regression analysis. It explains in detail the process and outcomes of data analysis, as well as the significance of these results for theory and practice. This chapter provides a solid methodological foundation for the research, ensuring the reliability and validity of the results and laying the groundwork for subsequent discussions and conclusions in later chapters.

4.1 Data Collection Procedures

This study among the surveyed firms, the industry distribution shows that 20.4% are in electronics and semiconductors, 18.4% in automotive manufacturing, 16.5% in machinery manufacturing, 14.3% in pharmaceuticals and medical devices, 17.3% in home appliances and consumer electronics, and 13.1% in the service sector.

In terms of firm age, 19.4% of firms were established for less than one year, 20.4% for 1–5 years, 20.8% for 6–10 years, 18.2% for 11–20 years, and 21.2% for over 20 years. Regarding firm size, 22.7% of firms have fewer than 300 employees, 24.5% have between 301 and 500 employees, 27.6% have between 501 and 1000 employees, and 25.3% have more than 1000 employees.

The financial performance, measured through average annual sales, shows that 18.6% of firms reported sales of less than 300 million RMB, 27.3% between 301–500 million

RMB, 36.1% between 501–1000 million RMB, and 18.0% exceeding 1000 million RMB. Investment in AI-related fields also varied, with 20.8% investing less than 3 million RMB, 28.8% investing 3–5 million RMB, 31.8% investing 5–10 million RMB, and 18.6% investing more than 10 million RMB.

The distribution of respondents across departments indicates that 32.4% are from production, 20.5% from quality control, 26.5% from supply chain management, and 20.6% from other departments. Regarding work experience, 16.5% of respondents have less than 1 year of experience, 19.4% have 1–3 years, 31.4% have 4–9 years, 20.8% have 10–15 years, and 11.8% have more than 15 years of experience. For job titles, the distribution is as follows: 11.8% CEOs, 17.6% vice presidents, 19.0% directors, 26.1% officers, and 25.5% service management personnel.

This study primarily investigates the complex relationships among AI capability, supplier integration, customer integration, novelty, and efficiency within the context of China's manufacturing industry. Before defining the target industries, sectors with high levels of AI adoption were selected based on their highly complex production processes, extensive data generation capabilities, and strong reliance on precision, efficiency, and personalized demand. These AI software applications are primarily concentrated in areas such as industrial visual inspection (approximately 35%), new thinking direction

(25%), and production process optimization (20%). Chinese domestic AI platforms such as PaddlePaddle (飞桨) and Huawei Cloud ModelArts (华为云) cover more than 60% of industrial inspection scenarios, whereas foreign AI software such as ChatGPT accounts for less than 10% (News, 2024b). This study reckon that this may be due to restrictions related to foreign IP access. Furthermore, this study found that these artificial intelligence technologies are mainly developed by internal R&D teams within firms, and cost and data security remain the main limiting factors.

A systematic sampling method was employed, guided by the Industrial Classification for National Economic Activities (GB/T 4754-2017) in China, to ensure clarity in industry classification for data collection, analysis, and research. The selected industries include electronics and semiconductors (C39), automotive manufacturing (C36), machinery manufacturing (C35), pharmaceuticals and medical devices (C27), home appliances and consumer electronics (C40), and the service sector (L). This sampling approach was selected to ensure the structural integrity and representativeness of the sample (Etikan and Bala, 2017). Table 6 presents a detailed summary of the demographic characteristics of firms and respondents, including industry sector, firm age, firm size, average annual sales, investment in AI, department, work experience, and job title.

Table 6. The Sample Demographics (N=490)

		Frequency	Percentage
Industry sector (classified by Chinese industry codes)	Electronics and semiconductor industry	100	20.4
	Automotive manufacturing	90	18.4
	Machinery manufacturing	81	16.5
	Pharmaceuticals and medical devices	70	14.3
	Home appliances and consumer electronics	85	17.3
	Service	64	13.1
Firm age	Shorter than 1 year old	95	19.4
	1 - 5 years old	100	20.4
	6 - 10 years old	102	20.8
	11 - 20 years old	89	18.2
	Longer than 20 years old	104	21.2
Firm size (the number of employees)	Less than 300	111	22.7
	Between 300 to 500	120	24.5
	Between 501 to 1000	135	27.6
	More than 1000	124	25.3
Average annual sales	< 300 million RMB	91	18.6
	301-500 million RMB	134	27.3
	501-1000 million RMB	177	36.1
	> 1000 million RMB	88	18.0
Investment in AI (the overall investment within the company in AI-related fields)	< 3 million RMB	102	20.8
	3 - 5 million RMB	141	28.8
	5 - 10 million RMB	156	31.8
	> 10 million RMB	91	18.6
Department	Production	159	32.4
	Quality control	102	20.8
	Supply chain	130	26.5
	Others	99	20.2
Work experience	Shorter than 1 year	81	16.5
	1-3 years	96	19.6
	4-9 years	154	31.4
	10-15 years	102	20.8
	More than 15 years	57	11.6
Job title	CEO	58	11.8
	Vice president	86	17.6
	Director	93	19.0
	Officer	128	26.1
	Service management	125	25.5

The research team first designed a structured English questionnaire covering the key variables and dimensions required for the study. To ensure linguistic accuracy and cultural appropriateness, a group of bilingual experts was invited to translate and review the questionnaire. During this process, the bilingual experts not only focused on the correctness of terminology and phrasing but also considered potential cultural differences and expression preferences of prospective participants. This ensured that the research objectives were conveyed in both languages. Before the formal distribution of the questionnaire, the research team conducted a small-scale pilot test with a representative group of 19 participants, including CEOs, vice presidents, directors, and department heads. The purpose of the pilot test was to evaluate the questionnaire's readability, logical coherence, and the clarity of its items. Based on feedback from the pilot participants, the research team made several rounds of revisions to the questionnaire. These included optimizing the language, adjusting the order of items, and adding or removing questions as necessary to ensure the questionnaire's validity and scientific rigor. During the distribution phase of the final version, the researchers collaborated with a professional survey company to administer the questionnaire. Detailed instructions about the research background, completion requirements, and privacy protection measures were provided. The survey company utilized multiple communication channels, such as email and WeChat, to reach potential participants. An online Q&A session was also arranged to promptly address any questions that participants encountered while completing the questionnaire, thereby reducing potential comprehension biases and improving the quality of data collection. The entire process of designing and distributing the questionnaire reflected a rigorous research approach and a strong emphasis on enhancing participant experience.

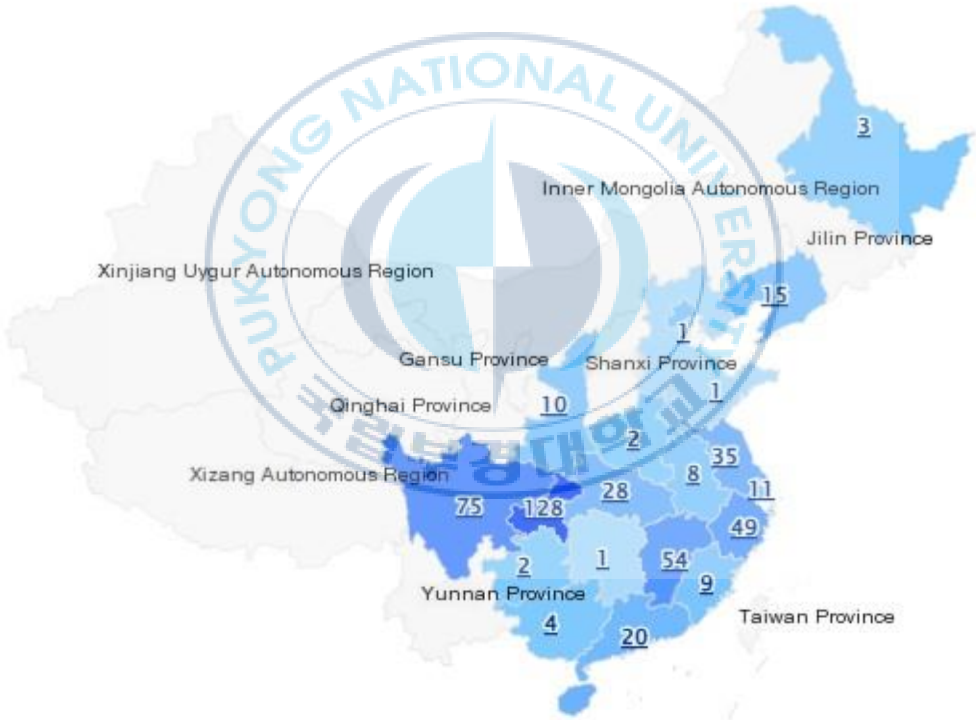

Figure 2. Sample Distribution Map

Data collection commenced on November 10, 2024, and concluded on November 26, 2024, spanning 16 days and targeting 600 Chinese manufacturing firms that utilize AI technology. The survey distribution followed Dillman (2000) total design method (TDM), with reminder emails sent weekly, totaling two reminders. Out of the 600 firms, 563 agreed to participate and provided their contact information, but only 510 respondents completed the questionnaire, resulting in a response rate of 93.8%. After excluding 20 invalid responses, 490 valid questionnaires were retained for analysis.

4.2 Measurement Items

The measurement items for AI capability were adapted from Gupta et al. (2023a), comprising eight items that comprehensively assess various dimensions of AI capability within firms. These include optimizing internal operations, enhancing employee creativity, improving decision-making, planning new product development, identifying new market opportunities, optimizing external processes like distribution and sales, capturing and applying scarce knowledge, and reducing headcount through automation. These measurement items reflect AI's critical role in improving firm efficiency, enhancing innovation capabilities, and optimizing resource allocation.

Supplier integration items were adapted from Liu et al. (2018). Supplier integration was measured using six items that assess key collaborative capabilities between firms and their suppliers. These items include input in product development projects, maintaining close communications regarding quality and design, establishing long-term relationships, maintaining cooperative relationships, helping improve supplier quality, and engaging suppliers in quality improvements. Specific aspects include supplier involvement in product development, communication capabilities regarding quality issues, the willingness and ability to establish long-term partnerships, relationship maintenance levels, and the ability to support and collaborate with suppliers to improve quality. These measurement items highlight firms' strategic goals of fostering mutually beneficial relationships with suppliers and enhancing overall supply chain performance through collaboration.

Customer integration items were adapted from Liu et al. (2018), and assessed using five measurement items that evaluate a firm's capabilities in customer integration, covering customer involvement in product design, responsiveness to customer needs, partnership orientation, maintaining close contact, and feedback on quality and delivery. Specific aspects include deep customer involvement in product design, firm flexibility in rapidly responding to customer needs, the ability to establish partnerships with customers, the frequency and quality of communication with customers, and customers' proactive and effective feedback on quality and delivery performance. These capabilities enable firms to more precisely meet customer demands, improve customer satisfaction, and strengthen market competitiveness.

The constructs of novelty were based on Chen et al. (2022). Novelty was measured using seven items that comprehensively evaluate the novelty of a firm’s novelty and efficiency across multiple dimensions, including customers' active involvement in the product design process; the firm's responsiveness to customer needs; partnership with customers; maintaining close contact with customers; and customer feedback on quality and delivery performance. Specific indicators include innovative product and service combinations, adopting new channels to connect transaction participants, building high-quality and unique linkages, maintaining industry leadership, avoiding threats from homogeneous competition, and enhancing the overall novelty of novelty and efficiency from various dimensions. These capabilities reflect the firm's core advantage of strengthening market competitiveness through unique value creation and differentiated innovation strategies.

Efficiency items were adapted from Chen et al. (2022), and assessed using six items that evaluate the efficiency of a firm’s novelty and efficiency across dimensions such as simplicity from the user's viewpoint, reducing errors in transaction execution, lowering costs for participants, enabling informed decisions, facilitating fast transactions, and overall high transaction efficiency. These items effectively captured the dimensions of novelty and efficiency, crucial for understanding how novelty and efficiency contribute to enhancing firm performance and customer satisfaction. These items focus on simplifying processes to enhance user experience, reducing errors during transaction execution, lowering participant costs, providing information support for decision-making, accelerating transaction speed, and improving overall transaction efficiency. These capabilities illustrate the importance of novelty and efficiency in optimizing operational processes, enhancing customer satisfaction, and reducing operational costs.

Additionally, the study includes five control variables: industry type (categorized based on the Chinese industry classification codes), firm age (measured by the duration since the firm's establishment), firm size (classified by the number of employees), firm type (categorized by ownership structure), and the total investment in AI (the overall internal investment in AI-related areas, including but not limited to employee training, technology application, and system upgrades). These variables provide essential control dimensions and contextual information for understanding the characteristics of firms and their potential impact on AI adoption or other business practices. Table 7-1 presents a detailed breakdown of the specific measurement items for each variable, excluding the control variables. Table 7-1 of this study was developed based on a thorough review of previous research and theoretical foundations, and all items were measured using a seven-point Likert scale. The constructs were operationalized through survey items to ensure their validity and relevance within the research context.

Table 7-1. Measurement Items

Variables	Measurement items
AI capability (Gupta et al., 2023a)	1. AI helps our firm optimize internal business operations. 2. AI helps our employees to be more creative by automating routine tasks. 3. AI helps our firm make better decisions. 4. AI helps our firm plan new product development. 5. AI helps our firm identify new market opportunities. 6. AI helps our firm optimize external processes, such as distribution and sales. 7. AI helps our firm capture and apply scarce knowledge when needed. 8. AI helps our firm reduce headcount through automation.
Supplier integration (Liu et al., 2018)	1. Our key suppliers provide input into our product development projects. 2. Our firm maintains close communications with suppliers about quality considerations and design changes. 3. Our firm strives to establish long-term relationships with suppliers. 4. Our firm maintains cooperative relationships with our suppliers. 5. Our firm helps our suppliers to improve their quality. 6. Our firm actively engages suppliers in our quality improvement.
Customer integration (Liu et al., 2018)	1. Our customers are actively involved in our product design process. 2. Our firm strives to be highly responsive to our customers' needs. 3. Our firm works as a partner with our customers. 4. Our firm frequently maintains close contact with our customers. 5. Our customers provide us feedback on our quality and delivery performance.
Novelty (Chen et al., 2022)	1. Our firm's business model offers new combinations of products, services, and information. 2. Our firm's business model links participants and transactions in novel ways (e.g., through new channels). 3. The richness (i.e., quality and depth) of some of the enabled links between participants in our firm's business model is novel. 4. Our firm business model is pioneer. 5. No competing business model exist in our industry that threaten our firm's business model. 6. Other important aspects of our firm's business model contribute to its novelty. 7. Overall, our firm's business model is novel.
Efficiency (Chen et al., 2022)	1. Our firm's business model ensures transactions are simple from the user's viewpoint. 2. Our firm's business model lowers the number of errors in the execution of transactions. 3. Our firm's business model reduces costs for participants beyond those previously mentioned. 4. Our firm's business model enables participants to make informed decisions. 5. Our firm's business model enables fast transactions. 6. Overall, our firm's business model offers high transaction efficiency.

4.3 Construct Validity

Construct validity refers to the extent to which a measurement tool accurately represents the concept it is intended to measure. It ensures that theoretical constructs are well reflected through the measurement items and that these items truly measure the intended latent variables. Establishing construct validity is crucial in empirical research as it ensures that measurement tools (such as questionnaires or scales) accurately capture the theoretical constructs they aim to measure. Without construct validity, research findings may be flawed or unreliable, leading to incorrect conclusions. Higher construct validity enhances the reliability and robustness of hypothesis testing, ensuring that relationships observed in the data are not due to measurement errors but rather reflect the true associations between variables. Establishing construct validity can be tested using a range of statistical methods. First, confirmatory factor analysis (CFA) is the primary method. This technique is used to assess whether measurement items correspond to their respective theoretical constructs. By examining unidimensionality and model fit, CFA ensures that items load onto the correct factors. Commonly reported fit indices include χ^2/df, RMSEA, CFI, IFI, and SRMR. A good model fit indicates that the items align well with the construct. Second, reliability assessments of the data are also necessary. For instance, calculating Cronbach's alpha and composite reliability (CR) coefficients evaluates the internal consistency of the constructs. Higher values indicate better consistency and reliability among the measurement items. Third, convergent validity is tested to ensure the degree to which measurement items within the same construct are interrelated. This can be assessed through standardized factor loadings and average variance extracted (AVE). Higher factor loadings and AVE values greater than 0.5 indicate strong convergent validity. Fourth, discriminant validity evaluates whether constructs are independent of one another. This can be assessed using the Fornell-Larcker criterion, comparing the square root of the AVE of each construct with the squared correlations between constructs. If the square root of AVE exceeds the squared correlation, discriminant validity is established, indicating that the constructs are independent. Through these methods, construct validity ensures that the measurement model accurately captures the intended constructs, and the research findings are scientifically sound.

To ensure the reliability of hypothesis testing and the robustness of the measurement model, we performed a comprehensive Confirmatory Factor Analysis (CFA) using AMOS 23.0. This analysis evaluated the unidimensionality of the measurement items and the model's fit. CFA was chosen over traditional methods such as Cronbach's α and Exploratory Factor Analysis (EFA) because it offers a more rigorous statistical framework, directly testing whether the theoretical constructs align with the data, thereby providing a more precise evaluation of unidimensionality (Byrne et al., 1989). The CFA results demonstrated excellent fit indices, as shown in Table 7-2: $\chi^2/df = 1.365$, degrees of freedom = 454, RMSEA = 0.027, CFI = 0.982, IFI = 0.982, and SRMR = 0.0302. Specifically, a χ^2/df value below 3 indicates a high level of model fit; an RMSEA value below 0.05 suggests minimal model error; and CFI and IFI values approaching 1 reflect outstanding goodness-of-fit. These robust fit indices strongly support the validity of the proposed measurement model and further confirm the unidimensionality of the measurement items. Table 7-2 shows the results of confirmatory factor analysis for each measurement item.

Table 7-2. Validity Assessment

Variables		Measurement items	SFL	SE
Overall model fit: $\chi^2/df = 1.365$; df = 454; p<0.01; CFI = 0.982; IFI = 0.982; RMSEA = 0.027; SMRM = 0.0302.				
AI capability	1.	Optimize internal business operations. ##	0.791	
	2.	More creative by automating routine tasks	0.772	0.050
	3.	Make better decisions.	0.781	0.052
	4.	Plan new product development.	0.762	0.052
	5.	Identify new market opportunities.	0.800	0.051
	6.	Optimize external processes	0.770	0.051
	7.	Capture and apply scarce knowledge	0.792	0.051
	8.	Reduce headcount through automation.	0.775	0.049
Supplier integration	1.	Supplier involvement, product development ##	0.811	
	2.	Communication, quality, design changes	0.764	0.049
	3.	Long-term relationships, suppliers	0.743	0.048
	4.	Cooperative relationships, suppliers	0.761	0.048
	5.	Assist suppliers, quality improvement	0.777	0.047
	6.	Supplier engagement, quality improvement	0.773	0.049
Customer integration	1.	Customer involvement, product design ##	0.726	
	2.	Responsiveness to customer needs	0.722	0.065
	3.	Partnership with customers	0.712	0.067
	4.	Frequent customer contact	0.769	0.070
	5.	Customer feedback, quality and delivery	0.707	0.067
Novelty	1.	New combinations, products, services, information ##	0.765	
	2.	New channels, novel connections	0.792	0.057
	3.	Link richness, novelty	0.786	0.058
	4.	Business model pioneer	0.778	0.057
	5.	No competing business models	0.767	0.056
	6.	Other novel aspects	0.783	0.057
	7.	Overall business model novelty	0.746	0.054
Efficiency	1.	Simplified transactions, user experience ##	0.753	
	2.	Reduced transaction errors	0.785	0.060
	3.	Lower participant costs	0.764	0.058
	4.	Informed decision-making	0.768	0.058
	5.	Fast transactions	0.772	0.059
	6.	Overall transaction efficiency	0.765	0.059

Note(s):
1. A T value was not obtained for an item marked with ##, as its loading was intentionally fixed at 1 during the Confirmatory Factor Analysis.
2. SFL (Standardized Factor Loadings); SE (Standardized Error).

To evaluate the reliability of the measurement model, Cronbach's α coefficients were calculated for each construct. The results showed that all constructs had α values ranging from 0.849 to 0.926, which are significantly higher than the recommended threshold of 0.700, as suggested by Bonett and Wright (2015). This demonstrates that the measurement items exhibit high consistency and internal reliability, ensuring stable measurement of the intended latent variables. After confirming the reliability of the measurement model, additional assessments were conducted to evaluate the constructs' convergent and discriminant validity. Convergent validity was established as the standardized factor loadings of the measurement items ranged from 0.707 to 0.811, surpassing the minimum standard of 0.5, which signifies a strong explanatory power of the items for their respective latent variables. The composite reliability (CR) values for all constructs were between 0.849 and 0.926, exceeding the recommended threshold of 0.700, reflecting a high degree of internal consistency within the constructs. Moreover, the average variance extracted (AVE) values for all constructs ranged from 0.529 to 0.609, surpassing the threshold of 0.500, indicating that the constructs account for the majority of the variance in their respective measurement items.

In addition, the discriminant validity of the constructs was assessed using the method proposed by Fornell and Larcker (1981). Specifically, the square root of the AVE (average variance extracted) for each construct was compared with the squared correlations between that construct and all other constructs. The results show that the lowest AVE value (0.529) exceeded the highest squared correlation value (0.496), confirming significant discriminant validity among the constructs. Establishing discriminant validity not only demonstrates the independence of each construct but also provides robust statistical support for the theoretical framework of the model. Through the above analysis, the reliability and robustness of the measurement model were validated in terms of model fit, reliability, and validity. These results provide a solid foundation for subsequent hypothesis testing and enhance the credibility and generalizability of the research findings. By conducting rigorous quantitative analysis, the research team effectively minimized the risk of measurement error, ensuring the scientific rigor and reliability of the study's conclusions. Table 8 presents detailed results of the construct reliability, validity, and correlation analyses.

Table 8. Correlation Matrix and Descriptive Statistics

Constructs	CR	AVE	Cronbach'α	Mean	SD
1.AI capability	0.926	0.609	0.926	4.314	1.386
2. Supplier integration	0.898	0.596	0.898	4.786	1.323
3. Customer integration	0.849	0.529	0.849	5.187	1.287
4. Novelty	0.913	0.599	0.913	4.708	1.449
5. Efficiency	0.896	0.590	0.896	4.729	1.456
Constructs	1	2	3	4	5
1. AI capability					
2. Supplier integration	-0.140**				
3. Customer integration	-0.059	0.495**			
4. Novelty	0.645**	-0.259**	-0.127**		
5. Efficiency	0.612**	-0.290**	-0.180**	0.704**	

Note(s):

1. **is significant at 0.01;

2. CR (Composite Reliability); AVE (Average Variance Extracted); MSV (Maximum Shared Variance); SD (Standard Deviation).

4.4 Non-Response Bias Test and Common Method Bias to Address Potential Non-Response Bias

To address potential non-response bias, we followed the method proposed by Armstrong and Overton (1977) by comparing early respondents and late respondents on key characteristics. These characteristics included industry type, firm age, firm size, firm type, and total investment in the AI field. The theoretical basis for this approach lies in the assumption that late respondents are more similar to non-respondents. Therefore, comparing these two groups allows for an indirect assessment of whether non-respondents might introduce bias into the study's results. The analysis revealed no significant differences in the mean values of all key characteristics between early and late respondents, indicating that the study is free from systematic bias caused by non-response. This enhances the representativeness and external validity of the research findings.

To mitigate the effects of common method bias (CMB), we employed two complementary statistical methods for control and validation. CMB arises from the use of a single data source (e.g., collecting all variables through the same questionnaire), which may introduce systematic errors, inflate correlations among variables, and compromise the credibility of research findings. To address this issue, we first conducted an unrotated factor analysis using Harman's Single-Factor Test. The results identified five factors, with the first factor accounting for 34.936% of the total variance. This finding indicates that the variance in the data is not dominated by a single factor, thus initially ruling out the presence of severe CMB.

Next, we performed a stricter examination of CMB using confirmatory factor analysis (CFA). Specifically, we constructed two models: the original model (a multi-factor model based on theoretical constructs) and an extended model (a single-factor model with all items loading onto one factor). The results showed that the fit indices for the original model ($\chi^2/df = 1.365$, RMSEA = 0.027, CFI = 0.982, IFI = 0.982) were significantly better than those for the extended model ($\chi^2/df = 1.341$, RMSEA = 0.026, CFI = 0.982, IFI = 0.983). This strong distinction in model fit further demonstrates that CMB has not significantly influenced the measurement results. As noted by Podsakoff et al. (2003), such factor structure comparisons are crucial for assessing CMB. The principle is that if the fit of a single-factor model is comparable to that of the theoretical model, significant CMB may be present. Conversely, if the theoretical model outperforms the single-factor model, the impact of CMB is likely minimal.

Through the above analyses, we successfully validated the reliability of the data quality and eliminated potential threats posed by non-response bias and common method bias to the research conclusions. The design and implementation of these procedures not only demonstrate the rigor of the study but also establish a solid foundation for subsequent data analysis and hypothesis testing. These steps enhance both the scientific validity and the generalizability of the research findings.

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5. Hypothesis Testing Results

5.1 Hierarchical Regression Design

Hierarchical regression analysis was conducted through a systematic stepwise approach to test the research hypotheses, allowing for a careful examination of how different variables incrementally contribute to explaining the dependent variable. This method is particularly effective in assessing the unique and collective impact of highly correlated predictors, such as AI capability and moderating variables, on novelty and efficiency outcomes. Additionally, hierarchical regression analysis is highly suitable for this study because it provides a comprehensive understanding of both the individual and combined effects of these variables. It offers insights into how AI capability, customer integration, and supplier integration interact to shape novelty and efficiency. The interaction effects reveal how external factors, such as customer and supplier integration, can either strengthen or weaken the influence of AI on innovation, which is crucial for understanding the boundary conditions of the innovation process. Therefore, hierarchical regression analysis was chosen for its ability to uncover the complex relationships and interactions among variables, providing a clear and systematic method to validate the research hypotheses and explore the mechanisms underlying the relationship between AI capability and novelty and efficiency.

Therefore, we employed hierarchical regression analysis using SPSS to evaluate the research hypotheses through a systematic stepwise testing approach. This statistical technique was chosen for its ability to introduce variables incrementally and assess the incremental explanatory power of each variable or variable set on the dependent variable. It is particularly suitable for examining how highly correlated predictors collectively influence changes in continuous variables (de Jong, 1999). Hierarchical regression analysis not only reveals the direct relationships between independent and dependent variables but also tests moderation and interaction effects, enabling deeper exploration of complex relationships among multiple variables. This method is especially appropriate for the present study, as it allows for the examination of the unique contributions of core independent and moderating variables while controlling for potential confounding factors. The hierarchical regression model can be represented as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \epsilon$$

where Y is the dependent variable, $X_1, X_2, \ldots, X_k$ *are the independent variables,* β_0 *is the intercept,* $\beta_1, \beta_2, \ldots, \beta_k$ *are the coefficients, and* ϵ\epsilon$\epsilon$ *is the error term.*

To comprehensively test the research hypotheses, we conducted two separate hierarchical regression analyses to evaluate the influence of the independent variable, AI capability, on two dependent variables: novelty and efficiency. Each regression analysis consisted of four models, with variables introduced stepwise to test the independent and interaction effects of different factors.

Model 1 included all control variables, such as industry type, firm age, firm size, average annual sales, and total investment in AI. The inclusion of these control variables aimed to eliminate potential external factors that could influence the dependent variables, ensuring an accurate assessment of the effects of the core independent and moderating variables. By analyzing the independent effects of the control variables, we established a baseline understanding of the impact of contextual factors on novelty and efficiency, providing a reference point for comparing subsequent models.

$$Model\ 1: Y=\beta_0+\beta_1 Control\ Variables + \epsilon$$

Model 2 introduced the main independent variable, AI capability, in addition to the control variables. This model assessed the direct impact of AI capability on the dependent variables. AI capability, as a key driver of novelty and efficiency, are expected to influence novelty and efficiency significantly through technological integration, data analysis, and the optimized allocation of innovative resources. This model allowed us to evaluate the unique contribution of AI capability after accounting for contextual factors and to verify whether they significantly enhance firms' innovation capabilities.

$$Model\ 2: Y=\beta_0+\beta_1 Control\ Variables + \beta_2 Independent\ Variable + \epsilon$$

Model 3 further expanded Model 2 by including the moderating variables. For the analysis of novelty, customer integration was added as the moderating variable. For the analysis of efficiency, supplier integration was introduced. These moderating variables reflect the degree of interaction between firms and external stakeholders in the innovation process. Customer integration emphasizes demand-driven innovation by uncovering customer needs to foster novelty in design, whereas supplier integration focuses on efficiency optimization by reducing costs and improving operational efficiency through collaborative efforts. This model aimed to reveal how moderating variables influence the relationship between AI capability and novelty and efficiency, verifying the role of external integration capabilities in different types of innovation.

$$Model\ 3: Y=\beta_0+\beta_1 Control\ Variables + \beta_2 Independent\ Variable + \beta_3 Moderator\ Variable + \epsilon$$

Model 4 extended Model 3 by incorporating interaction effects, specifically the interaction between AI capability and customer integration (for novelty) and the interaction between AI capability and supplier integration (for efficiency). Introducing interaction effects allowed us to explore the joint mechanisms of AI capability and the moderating variables, examining whether external integration capabilities amplify or diminish the impact of AI capability on novelty and efficiency. By comparing the significance of interaction effects, we identified the boundary conditions of moderating variables and provided insights into optimal configuration strategies for practice.

$$\textit{Model 4: } Y=\beta_0+\beta_1\textit{Control Variables} + \beta_2\textit{Independent Variable} + \beta_3\textit{Moderator Variable} + \beta_4(\textit{Independent Variable} \times \textit{Moderator Variable}) + \epsilon$$

Through the phased model construction and stepwise introduction of variables in hierarchical regression analysis, we were able to evaluate the independent contributions of each variable to the dependent variables and the complex interactions between variables. This stepwise modeling process not only intuitively demonstrated the incremental contributions of different variable groups to the explanatory power of the model but also effectively controlled for potential confounding factors that might influence the study’s conclusions. Ultimately, this approach provided a scientifically rigorous framework for uncovering the mechanisms underlying the relationship between AI capability and novelty, and efficiency, offering important theoretical and practical implications.

5.2 Hierarchical Regression Analyses for Novelty

In the hierarchical regression analysis for novelty, the hierarchical regression can be represented as:

$$N = \beta_0 + \sum_{i=1}^{17} \beta_1^{(i)} C_i + \beta_2 X + \beta_3 M_{CI} + \beta_4 X \cdot M_{CI} + \varepsilon$$

where N: Novelty; C: Control variable (0-1 variable), C_1-C_5: Industry sector, C_6-C_7: Structure of ownership, C_8-C_{11}: Firm age, C_{12}-C_{14}: Firm size, C_{16}-C_{17}: Investment on AI; X: AI capability; M_{CI}: Moderating variable (Customer Integration).

The results for Model 1 (table 9), which included only the control variables such as industry type, firm age, firm size, average annual sales, and total investment in AI, indicated that none of the regression coefficients reached statistical significance. This suggests that these contextual factors have limited direct influence on novelty.

In Model 2 (table 9), the introduction of the independent variable, AI capability, revealed a significant positive relationship between AI capability and novelty (β = 0.652, $p < 0.000$). This finding supports Hypothesis 1, which posits that AI capability is a critical driving force for novelty-oriented novelty and efficiency. It highlights that leveraging AI technologies to optimize resource allocation and enhance innovation capabilities can substantially promote innovation-oriented initiatives.

Model 3 (table 9) introduced the moderating variable, customer integration, and the results showed a significant negative effect of customer integration on novelty ($\beta = -0.087$, $p < 0.05$). This suggests that, in the context of novelty-driven innovation, customer integration might lead to resource dispersion or constrain innovation pathways, thereby hindering innovative activities.

In Model 4 (table 9), the interaction effect between AI capability and customer integration was tested. The results demonstrated a significant interaction effect ($\beta = 0.176$, $p < 0.000$), indicating that the synergistic effect of AI capability and customer integration significantly enhances novelty. In other words, a high level of customer integration, when effectively combined with AI capability, can deliver more valuable innovation outcomes. This finding supports Hypothesis 3.

In addition, based on the regression results in Model 4, this study finds that among industry types, equipment manufacturing firms tend to receive higher scores (0.057). Within the structure of ownership, foreign-invested enterprises score significantly higher than state-owned enterprises. Furthermore, firms less than one year old may exhibit lower levels of novelty, whereas novelty increases as firm age increases. Regarding firm size, novelty tends to rise with increasing size; however, firms with more than 500 employees show a decline in scores. Lastly, in terms of AI investment, the study finds that the optimal investment range lies between 3 and 5 million RMB.

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Table 9. Hierarchical Regression Analyses for Novelty

Constructs	Model 1		Model 2		Model 3		Model 4	
	β	VIF	β	VIF	β	VIF	β	VIF
Constant(β_0)	4.588***		4.493***		4.472***		4.464***	
Control variables								
Electronics and semiconductor	-0.110	2.101	-0.084	2.103	-0.080	2.105	-0.078	2.106
Automotive manufacturing	-0.036	2.037	-0.051	2.037	-0.044	2.044	-0.043	2.045
Machinery manufacturing	-0.017	1.964	0.049	1.975	0.051	1.976	0.057	1.984
Pharmaceuticals and medical devices	-0.013	1.856	-0.018	1.856	-0.018	1.856	-0.008	1.876
Home appliances and consumer electronics	-0.017	2.000	-0.002	2.000	0.001	2.001	-0.004	2.006
State-owned firm	-0.001	1.465	0.072	1.478	0.072	1.478	0.079	1.491
Foreign-invested firm	0.081	1.427	0.105*	1.429	0.098*	1.436	0.101*	1.438
Firm age < 1-year-old	-0.086	1.604	-0.043	1.609	-0.043	1.609	-0.049	1.618
Firm age 1-5 years old	0.001	1.695	0.006	1.695	0.009	1.696	0.010	1.697
Firm age 6-10 years old	0.024	1.625	0.018	1.625	0.014	1.627	0.013	1.628
Firm age 11-20 years old	0.018	1.546	0.016	1.546	0.023	1.552	0.017	1.559
Firm size < 300 employers	0.075	1.532	0.061	1.533	0.061	1.533	0.061	1.533
Firm size 300-500 employers	0.101	1.590	0.091	1.590	0.097	1.595	0.091	1.604
Firm size 501-1000 employers	0.084	1.579	0.035	1.585	0.037	1.585	0.036	1.585
Investment in AI < 3 million RMB	-0.017	1.747	-0.016	1.747	-0.014	1.748	-0.013	1.748
Investment in AI 3-5 million RMB	-0.011	1.886	-0.011	1.886	-0.009	1.887	-0.006	1.889
Investment in AI 5-10 million RMB	0.006	1.896	-0.024	1.898	-0.020	1.899	-0.016	1.904
Predictor								
AI capability			0.652***	1.034	0.646***	1.038	0.638***	1.053
Moderator								
Customer integration					-0.087*	1.032	-0.055	1.251
Interaction effect								
AI capability × Customer integration							0.176**	1.297
R^2	0.034		0.444		0.452		0.456	
Adjusted R^2	-0.001		0.423		0.429		0.433	
F value	0.975		20.928		20.373		19.664	
F change	0.975		347.930***		6.218*		3.847*	

Note(s):
1. **p<0.001, **p<0.01, *p<0.05;
2. β (Standardized Coefficient Value), VIF (Variance Inflation Factor).

5.3 Hierarchical Regression Analyses for Efficiency

In the hierarchical regression analysis for efficiency, the hierarchical regression can be represented as:

$$E = \beta_0 + \sum_{i=1}^{17} \beta_1^{(i)} C_i + \beta_2 X + \beta_3 M_{SI} + \beta_4 X \cdot M_{SI} + \varepsilon$$

where E: Efficiency; C: Control variable (0-1 variable), C_1-C_5: Industry sector, C_6-C_7: Structure of ownership, C_8-C_{11}: Firm age, C_{12}-C_{14}: Firm size, C_{16}-C_{17}: Investment on AI; X: AI capability; M_{SI}: Moderating variable (Supplier Integration).

The results of Model 1 (table 10) similarly indicated that the control variables, such as industry type, firm background, and investment, did not reach significance. This suggests that these contextual factors have a limited impact on efficiency.

In Model 2 (table 10), the introduction of the independent variable, AI capability, revealed a significant positive relationship with efficiency ($\beta = 0.617$, $p < 0.000$), supporting Hypothesis 2. This finding highlights that AI capability plays a critical role in optimizing business processes, enhancing operational efficiency, and improving resource utilization, thereby driving efficiency-oriented innovation.

Model 3 (table 10) incorporated the moderating variable, supplier integration, which showed a significant negative effect on efficiency ($\beta = -0.212$, $p < 0.000$). This result suggests that deep supplier integration in the context of efficiency optimization may

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increase management complexity or coordination costs, thereby inhibiting efficiency-oriented design.

In Model 4 (table 10), the interaction effect between AI capability and supplier integration was significant ($\beta = 0.170$, $p < 0.000$). This indicates that AI capability can enhance efficiency by optimizing supply chain collaboration, supporting Hypothesis 4.

To further illustrate the moderating effects, we visualized the relationships between AI capability and the two types of novelty and efficiency under high and low levels of customer and supplier integration. High and low levels were defined as ±1 standard deviation from the mean of the moderating variables (Cohen, 2013). The graphs clearly showed that AI capability boosts novelty with high customer integration and improves efficiency with high supplier integration. These visuals confirmed the important role of the moderating variables and clarified the interaction mechanisms.

In addition, based on the regression results in Model 4, this study further reveals that, in comparison to novelty, the regression analysis of efficiency shows that equipment manufacturing and pharmaceutical manufacturing firms perform better among industry types. Similarly, within the structure of ownership, foreign-invested enterprises again score higher than state-owned enterprises. Moreover, firms less than one year old tend to exhibit lower efficiency. The most positive impact on efficiency is observed in firms aged between 1 and 5 years, while firms aged 6 to 10 years also demonstrate favorable scores. However, efficiency declines in firms older than 10 years, which may be attributed to the stronger policy support for younger enterprises in China and the organizational inertia of older firms, which may hinder digital transformation. Regarding firm size, contrary to the results for novelty, smaller firms exhibit higher efficiency, potentially due to the substitution of labor by AI automation. Lastly, in terms of AI investment, this study finds that efficiency improves significantly when investment exceeds 3 million RMB.

Table 10. Hierarchical Regression Analyses for Efficiency

Constructs	Model 1		Model 2		Model 3		Model 4	
	β	VIF	β	VIF	β	VIF	β	VIF
Constant(β_0)	4.733****		4.643***		4.577***		4.605***	
Control variables								
Electronics and semiconductor	-0.072	2.101	-0.047	2.103	-0.037	2.105	-0.026	2.111
Automotive manufacturing	-0.063	2.037	-0.078	2.037	-0.045	2.063	-0.035	2.067
Machinery manufacturing	-0.033	1.964	0.029	1.975	0.056	1.992	0.063	1.994
Pharmaceuticals and medical devices	0.000	1.856	-0.005	1.856	0.035	1.894	0.041	1.896
Home appliances and consumer electronics	-0.075	2.000	-0.061	2.000	-0.035	2.017	-0.037	2.017
State-owned firm	-0.029	1.465	0.040	1.478	0.053	1.482	0.059	1.484
Foreign-invested firm	0.005	1.427	0.028	1.429	0.017	1.432	0.005	1.438
Firm age < 1 year old	-0.090	1.604	-0.049	1.609	-0.040	1.611	-0.051	1.617
Firm age 1-5 years old	0.021	1.695	0.026	1.695	0.020	1.696	0.021	1.696
Firm age 6-10 years old	0.041	1.625	0.036	1.625	0.015	1.636	0.018	1.636
Firm age 11-20 years old	-0.001	1.546	-0.003	1.546	0.003	1.547	-0.003	1.548
Firm size < 300 employers	0.042	1.532	0.028	1.533	0.030	1.533	0.026	1.534
Firm size 300-500 employers	0.063	1.590	0.053	1.590	0.043	1.593	0.033	1.597
Firm size 501-1000 employers	0.067	1.579	0.021	1.585	0.020	1.585	0.014	1.587
Investment in AI < 3 million RMB	-0.002	1.747	-0.002	1.747	-0.004	1.748	-0.001	1.748
Investment in AI 3-5 million RMB	0.018	1.886	0.018	1.886	0.018	1.886	0.022	1.887
Investment in AI 5-10 million RMB	0.047	1.896	0.019	1.898	0.015	1.898	0.020	1.899
Predictor								
AI capability			0.617***	1.034	0.589***	1.052	0.563***	1.082
Moderator								
Supplier integration					-0.212***	1.087	-0.150***	1.253
Interaction effect								
AI capability × Supplier integration							0.170***	1.247
R^2	0.024		0.392		0.433		0.457	
Adjusted R^2	-0.011		0.369		0.410		0.433	
F value	0.689		16.871		18.918		19.709	
F change	0.689		284.917***		34.291***		20.120***	

Note(s):
1. **p<0.001, **p<0.01, *p<0.05;
2. β (Standardized Coefficient Value), VIF (Variance Inflation Factor).

Tables 10 and 11 provide a detailed account of the statistical results from the hierarchical regression analyses, offering robust quantitative support for the model's validity and the hypothesis tests. Figures 3 and 4 visualize the complex relationships of the moderating effects, providing intuitive guidance for both academic research and practical applications. These findings not only reveal how AI capability drives different dimensions of novelty and efficiency through moderating variables but also emphasize the distinct roles of customer and supplier integration in innovation and efficiency optimization. This offers valuable insights for firms in strategic decision-making and resource allocation.

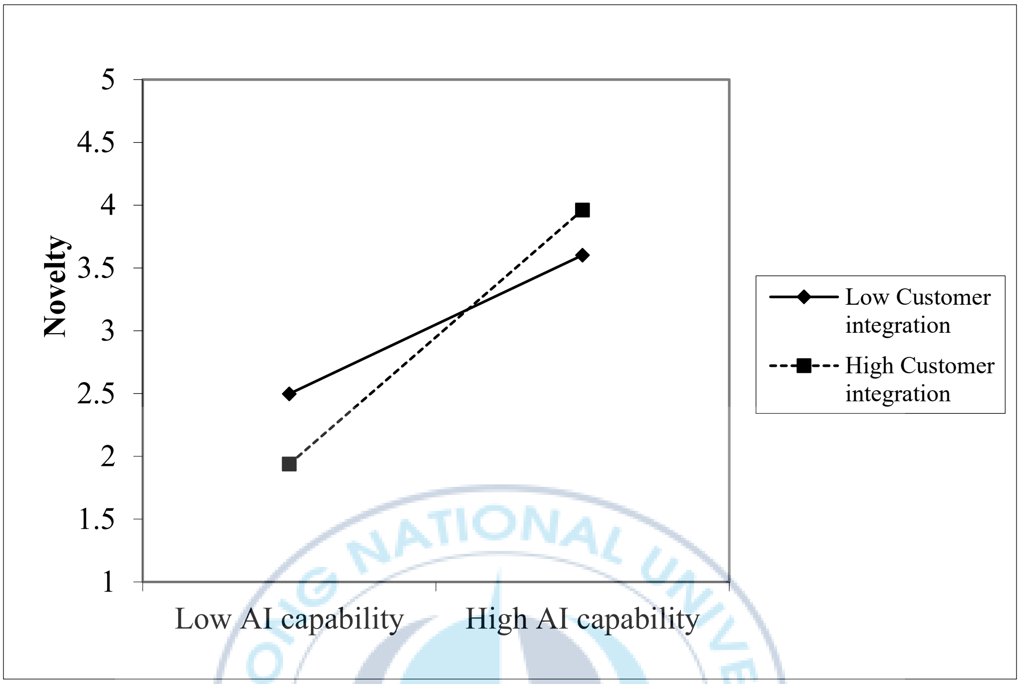

Figure 3. The Moderation Effect of Customer Integration

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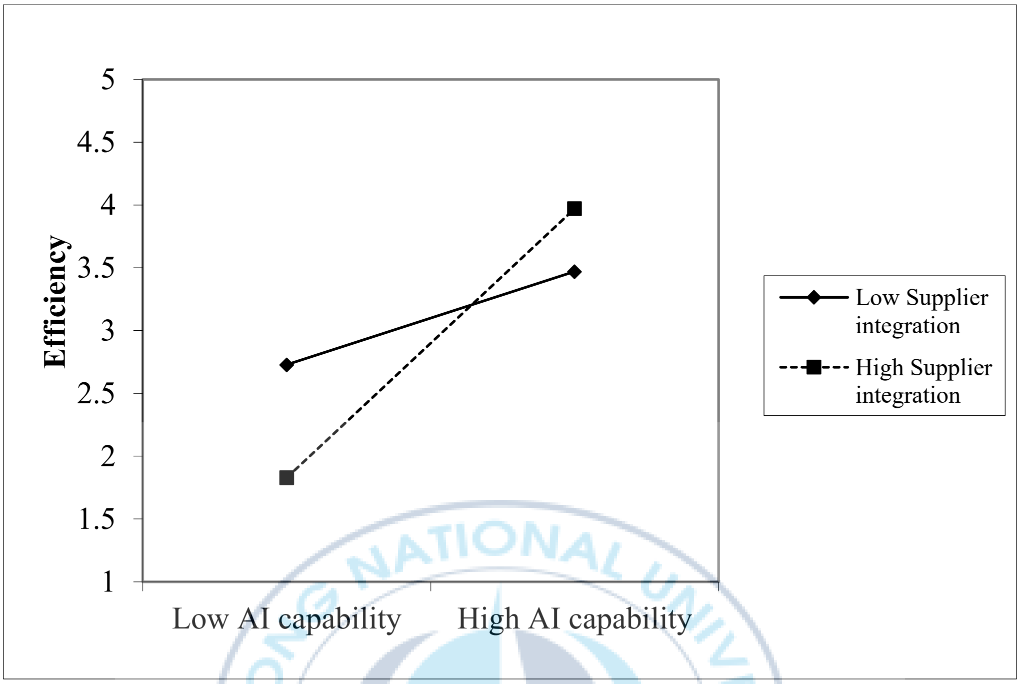

Figure 4. The Moderation Effect of Supplier Integration

In addition, to explore the impact of AI capability across different industries and to conduct a more nuanced analysis of their complex relationships, this study categorized each industry type and conducted separate regression analyses, table 11 summarizes the regression results across the six industries. The results indicate that in the electronics and semiconductor industry (n = 100), AI capability positively influences both novelty (0.581***) and efficiency (0.648***), while the moderating effects of customer integration and supplier integration are not significant. In the automotive manufacturing industry (n = 90), AI capability also positively influences novelty (0.712***) and efficiency (0.534***), with the moderating effects of customer integration and supplier integration again being insignificant. In the machinery manufacturing industry (n = 81), AI capability likewise exerts a positive influence on novelty (0.600***) and efficiency (0.635***), and the moderating effects of customer integration (0.369***) and supplier integration (0.361***) are both significant. In the pharmaceuticals and medical devices industry (n = 70), AI capability similarly has a positive impact on novelty (0.554***) and efficiency (0.518***), with significant moderating effects of customer integration (0.319**) and supplier integration (0.386***). In the home appliances and consumer electronics industry (n = 85), AI capability also positively influences novelty (0.725***) and efficiency (0.641***), yet the moderating effects of customer integration and supplier integration remain insignificant. Lastly, in the service industry (n = 64), AI capability shows a significant positive effect on novelty (0.496***), but its effect on efficiency is not significant (0.240; p = 0.120), and the moderating effects of customer integration and supplier integration are also not significant. These results reveal that AI capability has a significantly positive impact on both novelty and efficiency in most industries, highlighting its role as a key driver of technological innovation and process optimization within firms. However, the moderating effects of customer integration and supplier integration exhibit clear industry-specific differences. Such effects are significant only in the machinery manufacturing and pharmaceuticals and medical devices industries, suggesting that in these highly collaborative and customization-dependent sectors, the full potential of AI capability is realized only through deep integration with customers and suppliers. In contrast, in industries with a higher degree of standardization—such as electronics, automotive, and home appliances, as well as the service sector—the moderating role of integration mechanisms is not significant, reflecting diverse value realization pathways of AI applications. These findings underscore the critical moderating role of industry characteristics in the value realization of AI capability and provide a theoretical basis for enterprises to formulate differentiated AI application and integration strategies.

Table 11. Industry-Specific Impacts of AI Capability

Industry	Sample size (n)	AI → Novelty (β)	AI → Efficiency (β)	Customer integration (Moderation)	Supplier integration (Moderation)
Electronics and semiconductor	100	0.581***	0.648***	Not significant	Not significant
Automotive manufacturing	90	0.712***	0.534***	Not significant	Not significant
Machinery manufacturing	81	0.600***	0.635***	0.369***	0.361***
Pharmaceuticals and medical devices	70	0.554***	0.518***	0.319**	0.386***
Home Appliances and consumer electronics	85	0.725***	0.641***	Not significant	Not significant
Service	64	0.496***	0.240(p=0.120)	Not significant	Not significant

5.4 Endogeneity Issue

Additionally, AI capability may present an endogeneity issue, as the enhancement of a firm's AI capability is typically influenced by external factors such as internet information, data accessibility from partners, and information provided by collaborators. Given that customer integration and supplier integration serve as critical mechanisms for a firm's external interactions, they may influence the formation and development of AI capability. If the raw values of AI capability are directly used in regression analysis, there is a risk of confounding the effects of AI capability on novelty and efficiency with the moderating variables (customer integration/supplier integration). According to Hamilton and Nickerson (2003), when both strategic decisions (e.g., AI capability) and performance outcomes (e.g., novelty/efficiency) are continuous variables, the two-stage least squares (2SLS) regression can be employed to address endogeneity concerns. Accordingly, this study conducted two separate endogeneity tests for novelty and efficiency.

In the first stage, we initially performed an ordinary least squares (OLS) regression analysis in Stata 17 to examine the model. In the test where novelty was the dependent variable, the R-squared value was 0.4236, with an F-statistic of 178.91 ($p = 0.0000$), indicating that the model was significant overall. Moreover, the coefficient values for

AI capability ($p < 0.01$) and customer integration ($p < 0.05$) were statistically significant. Similarly, when efficiency was used as the dependent variable, the R-squared value was 0.4175, with an F-statistic of 174.55 ($p = 0.0000$), demonstrating overall model significance. Additionally, the coefficient values for AI capability ($p < 0.001$) and supplier integration ($p < 0.001$) were statistically significant.

In the second-stage 2SLS regression, AI capability is treated as an endogenous variable, with investment in AI and the average sales revenue over the past three years used as instrumental variables. The results indicate that in the regression where novelty is the dependent variable, the model fit is represented by an R-squared value of 0.3131, with a Wald chi-squared statistic of 12.12 and a p-value of 0.0023, suggesting that the overall model is significant. However, the coefficient estimates for AI capability ($p=0.409$) and customer integration ($p=0.382$) are not statistically significant. Similarly, in the regression where efficiency is the dependent variable, the model fit is reflected by an R-squared value of 0.3501, with a Wald chi-squared statistic of 51.01 and a p-value of 0.0000, indicating overall model significance. Nevertheless, the coefficient estimates for AI capability ($p=0.438$) and supplier integration ($p=0.454$) remain statistically insignificant.

Finally, in the third-stage Hausman test, the results for the regression with Novelty as the dependent variable yield a chi-squared statistic of 0.09 ($p=0.7583$), which fails to reject the null hypothesis at the 5% significance level, indicating that the OLS estimator is consistent. Similarly, in the regression with efficiency as the dependent variable, the p-value is also non-significant ($p=0.5668$), supporting the validity of the OLS estimator. These findings suggest that, within the context of this study, the endogeneity issue of AI capability is not prominent, and the OLS regression results are reliable. Table 12 shows the detailed results of 2SLS.

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Table 12. Instrumental Variable Regression Results.

	First stage		Second stage		Third stage
Variables	OLS	OLS	2SLS	2SLS	Hausman test
	Novelty	Efficiency	Novelty	Efficiency	/
AI capability	($p < 0.01$)	($p < 0.001$)	$p = 0.409$	$p = 0.438$	Novelty: $\chi^2 = 0.09$, $p = 0.7583$
Customer Integration	($p < 0.05$)	/	$p = 0.382$	/	/
Supplier Integration	/	($p < 0.001$)	/	$p = 0.454$	Efficiency: $\chi^2 = 0.09$, $p = 0.5668$
R^2	0.4236	0.4175	0.3131	0.3501	/
F statistic / Wald χ^2 statistic	178.91($p =$ 0.0000)	174.55($p =$ 0.0000)	12.12 ($p =$ 0.0023)	51.01 ($p =$ 0.0000)	/
Conclusions	OLS model is significant	OLS model is significant	AI capability model is nonsignificant	AI capability model is nonsignificant	OLS estimates are consistent, and no serious endogeneity issues were found

6. Discussion

This chapter is structured into three parts, primarily analyzing the theoretical and managerial implications of the research findings, while also addressing the limitations of the study and suggesting directions for future research. Additionally, this study aims to explore the shaping mechanisms of artificial intelligence (AI) capabilities in novelty and efficiency. With a specific focus on the moderating effects of customer integration and supplier integration in this process. By integrating the extended resource-based view (ERBV) and dynamic capabilities theory (DCT), we construct a theoretical framework to elucidate the interactions between these theoretical perspectives and their impact mechanisms in the novelty and efficiency of manufacturing firms. In developing the theoretical model, we adhere strictly to the Parsimonious Principle in academic research, carefully selecting and configuring the moderating variables: customer integration is positioned as the moderator between AI capability and novelty and efficiency, while supplier integration is designated to moderate the relationship between AI capability and novelty and efficiency. This theoretical configuration is grounded in the following logic: Market information obtained through customer integration is unique and irreplaceable, enabling firms to gain a more granular understanding of market dynamics. When combined with AI capability, such information allows firms to precisely design and innovate novel products and services that align with market expectations and customer needs. The heterogeneous nature of this information, which suppliers cannot easily provide, grants customer integration a significant advantage in enhancing novelty and efficiency. However, the direct impact of customer integration on efficiency may be relatively limited. In contrast, supplier integration provides firms with critical operational efficiency-related information, such as production planning optimization and inventory management. When empowered by AI technology—leveraging its advanced data processing and automation capabilities—firms can significantly improve resource allocation efficiency and decision-making accuracy, ultimately maximizing overall profitability. In the context of rapid technological advancements and dynamic market environments, the effective utilization of AI capability to enhance novelty, efficiency, and operational efficiency has become a central issue for manufacturing firms and broader industries.

Furthermore, we find that in hierarchical regression, the moderating variables (customer integration and supplier integration) have a negative impact on the dependent variables (novelty and efficiency). Although this is not the primary hypothesis examined in this study, it contradicts prior research that highlights the positive effects of external partnerships, necessitating further in-depth discussion. We observe that in the present research context AI capability is the primary perspective. Under such circumstances, firms rely on AI's powerful computational abilities to maximize resource utilization, including the integration of customers and suppliers. However, in this scenario, integration tends to be excessive, exceeding the level of integration observed in general contexts. Thus, in this study, customer and supplier integration can be understood as positively moderating the relationship between AI capability and the mechanisms influencing novelty and efficiency, primarily leveraging AI's computational power as support. Without this support, excessive integration alone may negatively affect performance (i.e., novelty and efficiency) due to demand processing overload, leading to response delays and efficiency reductions. Consequently, under this particular context, integration alone (no AI support) negatively affects the dependent variables.

Additionally, we explore potential variations in these moderating effects across different industries and firm sizes, offering corresponding strategic insights. This study contributes to the literature in three key ways:

(1) By integrating RBV and DCT, we extend the application boundaries of AI capability in novelty and efficiency.

(2) We conceptualize and empirically validate the differentiated moderating roles of

customer integration and supplier integration in the relationship between AI capability and novelty, and efficiency.

(3) We provide a new theoretical perspective and practical guidance for firms on effectively integrating and leveraging internal and external resources in dynamic environments.

(4) The interaction between customer integration and AI capability has no significant effect on efficiency, and the interaction between supplier integration and AI capability has no significant effect on novelty.

6.1 Theoretical Implications

Firstly, this study combines the resource-based view (RBV), dynamic capabilities theory, extended resource-based view (ERBV), and the complementarity theory to provide in-depth theoretical insights on how diversified internal and external factors interact to positively influence novelty and efficiency. The RBV primarily emphasizes the value, rarity, inimitability, and non-substitutability of resources, offering a theoretical framework to explain how the scarcity of AI capability enhances market positioning by forming difficult-to-imitate core competencies. Specifically, the unique and complex nature of AI technology positions it as a powerful competitive tool, enabling firms to maintain advantages in fierce market competition. However, while the traditional RBV offers a fundamental perspective on resource management, it shows limitations in explaining rapidly changing technological contexts and dynamic market demands. To address this, the study further incorporates dynamic capabilities theory, which supplements the RBV by explaining how firms adapt to rapidly changing environments by sensing market changes, integrating internal and external resources, and reconfiguring these resources effectively. Dynamic capabilities enable firms not only to utilize existing resources effectively in the current market but also to anticipate and build future competitive advantages. Additionally, this paper explores the ERBV, which suggests that firms should not only manage existing resources and capabilities but also develop new resources and capabilities through innovation and strategic transformations to address the evolving technological and market conditions. This perspective is particularly applicable to digital capabilities like AI technology, as these capabilities require continual technological updates and knowledge reconfiguration to maintain competitiveness in the digital economy. By integrating these three theoretical perspectives, the study not only deepens the understanding of factors influencing novelty and efficiency but also provides practical strategies and guidance for firms on effectively utilizing AI capability in dynamic competitive environments. Moreover, the ERBV offers important insights into how firms enhance internal performance through external resources. By integrating ERBV into the theoretical perspective of the main effects, a more comprehensive explanation of how AI capability interacts with external resources to drive novelty, efficiency, and design is achieved. This theoretical integration strategy has also been emphasized and widely recognized by scholars in past research. For example, studies by Baard et al. (2014) and Markóczy and Deeds (2009) pointed out that theoretical integration complements the deficiencies of a single theoretical perspective, enhancing the complexity and explanatory power of models. Mellahi et al. (2016) further articulated that integration not only introduces new perspectives, fostering the development of innovative ideas, but also enriches our understanding and interpretation of existing constructs. This indicates that employing multiple theoretical frameworks can better capture and explain phenomena in complex and dynamic business environments. Further, Beamish and Chakravarty (2021) in their research also emphasized the importance of theoretical integration, noting that it addresses limitations encountered with single theories while enhancing the applicability and explanatory power of theories. Through such integration, researchers can better identify and leverage the interaction between external resources and internal capabilities, providing more profound and comprehensive theoretical support for novelty and efficiency. The integration of ERBV with other theories offers a more flexible and profound theoretical tool for understanding and addressing challenges in rapidly changing business environments, enabling a more effective harnessing and utilization of external resources to enhance internal performance and innovation capabilities. From the perspective of the resource-based view (RBV), AI capability drives novelty and efficiency in different ways. In the case of novelty, AI capability's high scarcity and uniqueness position it as a valuable resource that drives product, service, process, and value creation innovations. RBV emphasizes the competitive advantage derived from inimitable resources, and AI capability, particularly its machine learning, autonomous learning, and data insight abilities, provides firms with unprecedented data processing power. This allows firms to identify unmet customer needs and market gaps, thereby fostering novel and forward-looking novelty and efficiency. Such innovations are highly path-dependent, making it difficult for competitors to replicate them in the short term, thus demonstrating the "strategic exclusivity" of AI capability in novelty. In contrast, for efficiency, the value of AI capability is primarily reflected in its ability to optimize processes and improve resource allocation efficiency. According to RBV, high-value, embedded resources contribute to the core support of operational efficiency through process knowledge and systematic capabilities. AI systems enhance operational efficiency by automating tasks, enabling predictive analytics, and providing real-time responses, which significantly reduce operational costs and improve decision-making quality and responsiveness in production and supply chain processes. This resource-driven operational optimization not only reduces internal resource waste but also strengthens the overall value creation system's robustness and scalability. Thus, from the RBV perspective, AI capability, as a high-value, inimitable, and firm-specific resource, has significantly different impacts on novelty and efficiency. The former focuses on the resource's rarity and the innovation it fosters, while the latter emphasizes the resource's value and its role in improving operational efficiency.

Secondly, based on the resource-based view (RBV), this research offers a unique interpretation of the impact of AI capability on novelty and efficiency in manufacturing firms. These capabilities enable firms to respond flexibly in rapidly changing market environments, optimizing their business processes and product innovations through efficient data processing and automated operations. AI capability, as a scarce resource that is difficult for market competitors to imitate, derives their value from their uniqueness and the difficulty of replication. The scarcity of such capabilities primarily arises from the substantial resources required for their development and enhancement, including capital, technology, and skilled personnel. Additionally, the accumulation of these capabilities involves continuous technological innovation and knowledge accumulation, increasing the difficulty and cost of imitation. Thus, AI capability are not only high-value resources but also capabilities that are not readily obtainable through simple investments. Moreover, AI capability provides operational advantages through its powerful data processing abilities, which are difficult to replace with traditional resources. For example, AI can optimize production scheduling, reduce raw material waste, and enhance production efficiency, while also supporting more precise market positioning and customer service through data analysis. These operational optimizations not only increase the efficiency of firms but also strengthen their competitive position in the market. Therefore, AI capability serves as a critical tool for transformation and upgrading in manufacturing firms, enabling them to maintain a leading position in intense market competition. Building on this, dynamic capabilities theory further deepens our understanding of how AI capability enhances the level of novelty and efficiency. This theoretical framework stresses the need for firms to continuously sense, capture, and respond to environmental changes, and the intelligent and automated features of AI provide essential tools for executing these capabilities.

The intelligent capabilities of AI, especially in data analysis and decision support, effectively address the bounded rationality issues faced by managers in complex and dynamic market environments. Through AI systems, firms can process and analyze large volumes of data, enriching the possibilities for innovation and providing data-driven decision support, which not only improves the quality of decisions but also accelerates the innovation process. Additionally, AI's automation capabilities, by autonomously performing repetitive and time-consuming tasks, save substantial time and costs related to innovation for firms. Automation also helps firms adjust and allocate resources more flexibly, ensuring optimal resource utilization and maintaining or enhancing competitiveness in fierce market competition. These theoretical viewpoints align with current academic literature. For example, Gama and Magistretti (2023) emphasized the key role of AI capability in driving the novelty aspect of novelty and efficiency, while Madanaguli et al. (2024a) highlighted the significant role of AI in enhancing operational efficiency. Moreover, studies by Abou-Foul et al. (2023) and respectively confirmed the positive correlation between AI and innovation capabilities, and the positive effects of AI on process efficiency. Supported by these empirical studies, this research not only confirms the key role of AI capability in novelty and efficiency in manufacturing firms but also provides empirical support for the resource-based view and dynamic capabilities theory, highlighting the significance of the competitive advantages driven by the intelligence and automation of AI capability. This finding not only enriches the existing theoretical frameworks but also provides concrete, practical guidance for firms on how to effectively utilize AI capability.

Finally, this research further highlights the importance of inter-organizational collaboration, particularly the critical roles of customers and suppliers in enhancing the influence of AI capability on the novelty and efficiency. In this multi-layered interaction, the extended resource-based view (ERBV) provides a more apt theoretical framework to analyze and explain these relationships. Specifically, customer integration enhances the firm's ability to use AI for innovation and meeting market demands. Through close collaboration with customers, firms can more effectively utilize AI technology to collect and analyze customer data, thereby developing products and services that more effectively meet market and customer needs, which directly enhances the novelty and efficiency. Furthermore, customer feedback and changes in demand provide firms with direction and motivation for innovation, allowing for more targeted and innovative applications of AI capability. Conversely, supplier integration strengthens the firm's ability to optimize supply chain management and production processes through AI, thus improving efficiency. Through close cooperation with suppliers, firms can more effectively integrate information and resources along the supply chain, utilizing AI for demand forecasting, inventory management, and logistics optimization. This not only reduces production costs but also speeds up the response to market changes, thereby enhancing the overall operational efficiency of the firm. ERBV, building on the foundations of RBV, further emphasizes how firms can enhance their competitive advantage through the integration of external resources. ERBV is particularly suited to explaining and analyzing how firms in a digital and technology-driven economic environment can utilize external resources through cross-organizational collaboration to enhance the novelty and efficiency of their novelty and efficiency. This theoretical perspective considers external collaboration and resource sharing as key strategies for enhancing a firm's innovative capabilities and market adaptability. Our research findings reveal that customer integration plays a crucial and positive role between AI capability and novelty, as the market dynamic information it provides acts as a catalyst in an effective innovation environment, accelerating the enhancement of innovative capabilities. This conclusion aligns with the research of Fosso Wamba (2022), who explored, under the framework of dynamic capabilities theory, how customer-driven innovation opportunities help firms not only capture but also maintain competitive advantages through interactions with AI-related technologies.

Additionally, our findings indicate that the interaction between supplier integration and AI capability promotes operational efficiency, with the core mechanism being the optimization of information flow and decision-making efficiency, thereby enhancing the efficiency and responsiveness of the entire operational process. This is empirically supported by Shahzadi et al. (2024), who pointed out that the application of AI in supply chain management can enhance the organization's resilient dynamic capabilities. Through the tight integration of AI with suppliers, synergistic effects that boost efficiency are generated (Modgil et al., 2022, Kumar et al., 2023).

In summary, by integrating AI capability with supply chain management strategies to drive the design of novelty and efficiency, firms not only enhance the novelty of their innovations and operational efficiency but also significantly strengthen their sustained competitiveness in the market, thereby securing a favorable position in intense market competition.

6.2 Managerial Implications

Our research focuses on how AI capability enhances the core values of novelty and efficiency within manufacturing firms. A key finding of the study is that utilizing the advanced intelligence capabilities of artificial intelligence for decision-making plays a crucial role in promoting novelty and efficiency based on innovation. Especially in operational decision-making processes, managers often face the challenge of bounded rationality, which may be influenced by prospect theory and cognitive dissonance theory. These theories reveal how individuals might miss or overlook key opportunities to promote novelty due to biases in information processing during the perception, exploration, and evaluation of decisions. In this context, AI's capabilities act as a bridging agent, effectively compensating for human decision-makers' deficiencies in information processing and opportunity recognition by connecting operational management with potential opportunities. Consequently, AI not only optimizes decision quality but also accelerates the implementation of innovation-driven novelty and efficiency, thereby creating unique competitive advantages in the market. Through this mechanism, firms can more effectively identify and utilize the potential for novelty, ensuring continuous innovation and optimization of novelty and efficiency. For example, Philips has adopted AI technology in its production department to significantly enhance the innovativeness of its product design by optimizing production processes and product design. The application of AI enables Philips to maintain production efficiency while introducing innovative design elements, thereby preserving a dominant position in the competitive marketplace. On the other hand, Tesla extensively applies AI and machine learning technologies in its manufacturing processes. The integration of these technologies not only achieves high automation of the production line but also drives rapid product innovation through fast iteration and continuous design improvements. This automation capability greatly enhances the efficiency of novelty and efficiency, allowing Tesla to continuously introduce innovative products while maintaining efficient production. Our research finds that the application of AI technology in novelty and efficiency not only demonstrates the dual characteristics of intelligence and automation but also enhances efficiency in scenarios based on novelty and, conversely, enhances novelty in scenarios focused on efficiency. This indicates that AI-driven novelty and efficiency possess the unique ability to integrate innovation with efficiency, stimulating the innovative potential of design and product development while improving operational efficiency. Therefore, by integrating AI technology, firms can not only optimize existing operational models but also drive continuous product and service innovation in the market.

Secondly, customer integration plays a crucial catalytic role in strengthening the connection between artificial intelligence capabilities and novelty. The market dynamics information provided by customer integration can inject a more diverse and in-depth perspective into AI systems. Since the quality of AI's computational outcomes greatly relies on the quality and accuracy of its input data, integrating customer insights into the firm's data pool can significantly enhance the output quality of AI. Through this approach, firms can utilize AI technology based on rich market information to generate higher-quality decisions and innovations. On the other hand, the interaction between supplier integration and AI capability plays a key role in driving efficiency. Although the information provided by suppliers may lack the novelty concerning product expectations that customer integration offers, suppliers possess a wealth of important production process information regarding raw materials, inventory levels, and production plans. Under the processing and analysis of AI, this information can not only significantly enhance production efficiency but also provide more precise planning and optimization recommendations for the production process. Therefore, through close integration with suppliers, firms can use AI technology to manage and optimize their supply chains more effectively, thereby maintaining production efficiency while also enhancing responsiveness and flexibility to market changes. This integration not only promotes increased production efficiency but also provides firms with an opportunity to comprehensively optimize and improve the production process. In practical application cases, Schneider Electric has successfully integrated artificial intelligence with IoT technology through its EcoStruxure platform, optimizing deep insights into customer needs and market dynamics. The platform, by harnessing vast amounts of data collected from end-to-end devices combined with direct customer feedback, utilizes advanced AI models for deep analysis, effectively predicting and meeting customer demands in energy efficiency management and automation solutions. This deep level of customer integration enables Schneider not only to respond swiftly to current market demands but also to accurately predict future industry trends, thereby introducing unprecedented novel elements into product design and service innovation. In terms of supplier integration, Schneider Electric utilizes a combination of AI technology to integrate critical data from suppliers about raw material availability, production timing, and logistics information, achieving real-time adjustments in production planning and inventory management. This efficient supply chain management not only improves operational efficiency but also boosts the transparency and predictability of the production process. Furthermore, through AI's predictive analytics capabilities, Schneider can more accurately forecast the demand and supply conditions of raw materials, thereby optimizing procurement decisions and inventory levels, significantly reducing the risks of surplus and shortage. The implementation of these strategies ensures that the firm maintains efficient operations while also retaining a forward-looking and innovative novelty and efficiency in a competitive market.

Furthermore, this study finds that foreign-invested firms exhibit a significantly stronger influence on novelty compared to domestic firms. This practical implication highlights the distinctive advantages of foreign firms, such as greater sensitivity to international market dynamics, superior access to cutting-edge technologies, and extensive experience in cross-cultural management. These capabilities allow them to adopt a more proactive and forward-looking approach to AI-driven innovation practices. With a global perspective, foreign firms are more likely to identify emerging opportunities and integrate AI technologies with their existing innovation strategies to develop differentiated products and services. Moreover, their typically flexible organizational structures and higher tolerance for trial-and-error experimentation provide a robust foundation for the rapid iteration and continuous optimization of novelty-driven novelty and efficiency. Therefore, domestic firms should draw insights from the innovation practices of foreign firms, particularly in establishing AI-enabled innovation mechanisms, integrating cross-market resources, and deploying global innovation assets. By doing so, they can enhance their capabilities in novelty, efficiency, and improve responsiveness to evolving market demands.

In addition, the practical significance of this study lies not only in the efficiency improvements brought by artificial intelligence (AI) but also in the profound impact of its "novelty" on enterprises' ability to explore new markets, attract consumer attention, and stimulate product/service innovation. Specifically, AI possesses the capability to rapidly generate creative content, automate design processes, and respond to consumer preferences, thereby significantly shortening product development cycles and enabling the creation of highly personalized and differentiated products or services. This technological capability not only helps enterprises enhance their competitiveness in existing markets but also provides opportunities to enter emerging markets. From the consumer perspective, the enhancement of novelty contributes to improving customer experience and increasing brand loyalty, particularly in emerging markets that value innovation and unique offerings. For example, in the sustainable consumption market, consumers are more inclined to embrace products that incorporate eco-friendly concepts, customized designs, or technological appeal; in high-tech markets such as smart homes and virtual reality, AI endows products with greater creativity and interactivity, substantially enhancing user engagement and satisfaction. Based on these findings, this study proposes the following managerial implications: (1) enterprises should move beyond the limited perception of AI as merely an "Efficiency Tool" and instead build an "Ambidextrous Capability" that simultaneously balances operational efficiency and innovation output; (2) during the formulation of digital transformation strategies, management should establish a Balanced Scorecard mechanism that incorporates "novelty metrics" (such as creative output rate and market novelty) into the performance evaluation system; (3) enterprises should adopt differentiated AI application strategies based on the characteristics of specific market segments — focusing on efficiency improvements in mature markets while emphasizing the creation of innovative value in emerging markets. Therefore, when deploying AI technologies, enterprises should not confine themselves to considerations of cost optimization or process efficiency alone, but should actively identify the additional value that AI can offer in guiding innovation, expanding markets, and enhancing consumer engagement. The findings of this study also remind managers to balance an "efficiency-oriented" and a "novelty-oriented" approach when formulating digital transformation and AI adoption strategies, to achieve dual value creation for the enterprise: enhancing internal efficiency through process optimization on the one hand, and capturing external market opportunities through innovation output on the other.

To enhance the practical relevance of this study, a hypothetical scenario is presented to illustrate how firms may strategically deploy AI capability in conjunction with supply chain integration to facilitate novelty and efficiency innovation. Consider a midsized manufacturing enterprise undergoing digital transformation. This firm invests in AI capability development, particularly in machine learning-based customer analytics and predictive supply chain management systems. By leveraging real-time data insights, the firm identifies unmet customer needs and initiates co-development projects with key customers through interactive feedback mechanisms and joint design platforms. These collaborative efforts result in the rapid development of modular and customizable products, enabling the firm to respond proactively to dynamic market demands. This process exemplifies how AI capability, reinforced by customer integration, enables novelty through enhanced differentiation, personalization, and first-mover advantage.

Concurrently, the firm applies AI-driven forecasting to optimize procurement and production planning in collaboration with core suppliers. Through the integration of inventory data, logistics schedules, and supplier performance metrics, the firm develops a digital interface that facilitates real-time decision-making and inventory synchronization. This supplier integration, supported by AI-enabled transparency and responsiveness, significantly reduces lead times and operational costs. It illustrates the mechanism through which AI capability, when combined with supplier integration, supports efficiency by streamlining cross-organizational coordination and maximizing resource utilization.

This imagined application scenario reinforces the dual-path mechanism proposed in this study. It demonstrates how AI capability, when effectively aligned with external integration strategies, can simultaneously drive novelty and efficiency in novelty and efficiency. These findings offer valuable insights for managers seeking to operationalize AI initiatives in complex and uncertain business environments.

In summary, firms can effectively capture and utilize potential information and emerging opportunities that enhance innovation by strategically integrating customer information with artificial intelligence capabilities. Through this deep integration, firms can more acutely perceive market changes and respond swiftly to consumer demands, thereby achieving a lead in product and service innovation. Additionally, by leveraging key resources provided through supplier integration, firms can expand the application scope of AI technology and enhance their capabilities in optimizing production processes, improving inventory management, and enhancing transaction efficiency. Implementing these strategies not only enhances a firm's strategic position in fierce market competition but also promotes its sustainable development and long-term success. With such strategic configurations, firms can achieve immediate market advantages and maintain sustained competitiveness and innovation capability in the face of future market changes, ensuring their long-term market leadership and business growth. This strategic integration of customers and suppliers, combined with advanced AI technology, will be key in driving firms toward more efficient and innovative directions.

6.3 Limitations and Future Research Directions

This study has made certain achievements in exploring the integration of artificial intelligence with novelty and efficiency strategies, but it also faces some limitations, which suggest possible directions for future research. The primary sample data used in this study comes from manufacturing firms in Mainland China, providing us with profound insights into the application of AI technology and novelty and efficiency strategies in that region. However, given that China is a rapidly developing country with a specific economic and technological context, it may not be sufficient to represent the global situation. Therefore, while this study offers important insights into AI integration, its conclusions need to be appropriately adjusted and carefully evaluated when applied to countries and regions outside China.

Considering the differences in digital development levels, government policy support, and the extent of AI technology promotion among different countries, future research should broaden the sample scope to include more countries with diverse levels of economic development, especially other developing and developed countries. Such cross-national studies would offer a broader perspective, increase the universality and applicability of the research findings, and foster a deeper understanding of the impact of AI capability across various economic and technological environments. By conducting comparative analyses of AI integration effects across different regions, a more comprehensive assessment of the opportunities and obstacles of AI technology in fostering novelty and efficiency worldwide can be realized. This would offer more scientific and comprehensive recommendations for the future development of the manufacturing industry, helping it adapt and succeed in the face of global technological advancements and market changes.

Secondly, our sample selection employed a systematic sampling method conducted within a specific time frame, which might not have adequately represented all types of businesses or their practices, potentially introducing sample selection bias. Additionally, the use of self-reported data, although providing direct information on corporate characteristics and AI practices, may be subject to subjectivity, thus somewhat compromising the objectivity and accuracy of the data. To overcome these limitations and improve the reliability of the research results, future studies may consider employing a mixed-methods approach. Specifically, the combination of quantitative surveys and qualitative research methods, such as in-depth interviews and detailed case studies, would allow researchers to capture and understand the motivations and actual performance of businesses in applying AI technology and novelty and efficiency strategies from various angles and levels more comprehensively. Through this integrated research approach, the complex dynamics of businesses adopting AI strategies can be more effectively revealed, thereby enhancing the depth and breadth of the research and providing more scientific and meticulous guidance for the practical operation and strategic decision-making in the application of AI in manufacturing.

Thirdly, our sample encompassed businesses with highly heterogeneous characteristics, such as forms of ownership, size, industry types, and operational practices. We attempted to control the impact of these variables by categorizing businesses based on ownership and size; however, it must be acknowledged that different organizational structures and sizes may influence firms' AI investment decisions and implementation effects differently. Such differences could lead to biases in the data, thereby affecting the assessment of AI's impact on the success of novelty and efficiency. To overcome these challenges and enhance the depth of future research, subsequent efforts could more thoroughly investigate how different business characteristics interact with their AI strategies. By employing a more detailed segmented analysis approach, the research could reveal the specific behavioral patterns and strategic choices of different types of businesses in adopting AI technologies and assess how these choices influence the effectiveness of their novelty and efficiency. This approach not only provides a clearer perspective on the complex relationship between business characteristics and successful AI applications but also helps firms develop more effective AI integration strategies tailored to their specific circumstances, thus securing a competitive edge in the fierce market competition.

Fourthly, although this study investigates the moderating effects of supplier integration and customer integration on the relationship between AI capability and novelty and efficiency, it adopts a holistic measurement approach for both constructs. Specifically, the measurement items for supplier integration and customer integration were designed to capture their overall influence across the supply chain without distinguishing between different stages, such as pre-development, development, or post-development. This integrated approach was chosen to reflect the general level of external collaboration and information sharing within the firm's supply chain relationships, which aligns with the broader strategic focus of this research. However, we acknowledge that supplier and customer integration can manifest differently across various stages of product or service development. For instance, early-stage involvement may influence innovation more strongly, while later-stage collaboration may be more relevant for cost efficiency or delivery performance. Future studies could address this limitation by designing multidimensional measures that differentiate between the timing and nature of integration activities. Such refined measurement could yield more nuanced insights into how temporal aspects of supply chain integration influence AI-enabled novelty and efficiency.

Fifth, from a methodological perspective, this study primarily relied on subjective evaluation scales to measure AI capability and the effectiveness of novelty and efficiency. Although these scales provided deep insights and valuable qualitative information about the implementation of AI in businesses, they may have limitations in ensuring the comprehensiveness, reliability, and objectivity of the research findings. Particularly in terms of data verifiability and measurement consistency, reliance on subjective scales could result in outcomes that are susceptible to individual biases, thus affecting the universal applicability and accuracy of the conclusions. To address these limitations and improve the quality and depth of future research, it is suggested that future studies adopt more robust and varied research methodologies. Specifically, a variety of objective evaluation indicators could be introduced, such as financial performance metrics, quantified measures of organizational inertia, and detailed records of employee performance. These objective indicators could be combined with subjective evaluation scales to form an integrated assessment system, not only improving the accuracy of the research results but also providing a more comprehensive perspective to understand and assess the actual effects and the efficacy of the strategy implementation of AI technology in corporate novelty and efficiency. In addition, future research may consider incorporating quantitative data, such as collecting specific numerical information related to AI applications, including system log data, platform interaction data, or customer feedback scores, to conduct a quantitative analysis of firms' AI capability and their impact on novelty and efficiency. Such numerical data can not only enhance the objectivity and verifiability of the research but also contribute to strengthening the external validity and generalizability of the findings.

Sixth, this study has certain limitations in its discussion of artificial intelligence (AI) security risks. Although the research systematically analyzes the strategic value of AI capability in enhancing the novelty and efficiency of enterprise operations, it fails to adequately consider the potential security vulnerabilities associated with AI technologies in manufacturing and supply chain application scenarios. Specifically, firms today may increasingly rely on OpenAI for simple business processes due to its free access and convenience, but there is a potential risk of information leakage during the uploading process. For example, Gupta et al. (2023b) mentioned in their study that malicious users could exploit a bug in ChatGPT to steal information. But Sai et al. (2024) advocate for the integration of generative artificial intelligence (GAI) into cybersecurity systems, arguing that GAI possesses various technical features that can enhance defensive capabilities and prove more effective than traditional approaches in strengthening cybersecurity. Therefore, despite the many positive effects of AI, its security issues remain one of the key concerns that need to be closely monitored and considered in the future.

Additionally, the study predominantly utilized traditional hierarchical regression analysis for data analysis, which, to a certain extent, supported our hypothesis testing, but this method may not fully capture the complexity and dynamics of the variables involved, especially when integrating theories and building multivariable models. For this reason, we encourage future research to explore and adopt more advanced and adaptive statistical techniques, such as structural equation modeling (SEM) and Bayesian methods. Structural Equation Modeling can effectively test multiple causal relationships and handle complex issues of latent variables, allowing researchers to assess the direct and indirect impacts between variables, which is extremely valuable for deeply analyzing the complex interactions between AI capability and novelty, and efficiency. Meanwhile, the introduction of Bayesian methods enables researchers to incorporate existing prior knowledge and theories into statistical analysis, adjusting and optimizing models through continuous data updates. This approach is particularly suited to address data uncertainties and complexities commonly encountered in empirical research. By employing these advanced data analysis techniques, future research can more precisely and profoundly explore the specific impacts and effects of AI capability on novelty and efficiency under different conditions and environments, thereby providing more scientific and systematic decision support for businesses.

Finally, while this study focuses on exploring how the external integration of supply chains and the integration of AI capability collectively impact novelty and efficiency, future theoretical developments should explore additional dimensions, particularly how businesses practice and strategically deploy AI capability within the institutional environment framework. This includes analyzing how regulatory policies, industry norms, and market imitation pressures affect the development and application of corporate AI capability. Understanding these broader environmental factors and their interaction with AI capability can provide manufacturing firms not only with a more comprehensive perspective on digital transformation but also with enhanced insights into how to achieve sustained competitive advantage through AI. Future research should build on the existing foundation of supply chain and AI integration studies to further examine how businesses adjust their AI strategies to adapt to external pressures and opportunities in different institutional settings. For instance, exploring how regulatory environments in different countries and regions shape businesses' decisions on the adoption and application of AI technology, and how these decisions influence their novelty, efficiency, and execution. Moreover, the research could detailed analysis of how industry standards facilitate or restrict the adoption of specific AI technologies, and how the imitative behaviors of leading firms in the market guide the overall industry trends in AI applications. By deeply investigating these complex interactions and dependencies, theoretical foundations and practical guidelines can be provided for manufacturing firms to develop more precise and forward-looking AI strategies in global competition. This multi-dimensional exploration not only extends our understanding of the role of AI capability in different settings but also reveals how firms can optimize their novelty and efficiency through efficient resource allocation and intelligent technology application, thereby maintaining and expanding their competitive edge in the increasingly fierce market competition.

7. Conclusion

This study delves into the impact of Artificial Intelligence (AI) capabilities on firm novelty and efficiency, with a focus on the moderating roles of supplier integration and customer integration. By drawing on the resource-based view (RBV), dynamic capability theory (DCT), and complementarity theory, the research develops a theoretical and empirical framework. Analyzing 490 valid responses from manufacturing firms, this study systematically validates the dual mechanisms through which AI capability influences innovation-based and efficiency. The key findings and academic contributions are as follows:

First, the study confirms the dual positive effects of AI capability on novelty and efficiency. On one hand, AI capability significantly drives innovation-based novelty and efficiency by optimizing resource allocation, enhancing inter-firm collaboration, and generating new knowledge. These capabilities enable firms to identify latent market demands and create differentiated market value. On the other hand, AI capability effectively promotes efficiency by improving decision-making efficiency, reducing operational costs, and optimizing resource utilization. This finding not only broadens the understanding of AI technology in business applications but also underscores its critical role in novelty and efficiency.

Second, the study identifies the positive moderating roles of customer integration and supplier integration in the relationship between AI capability and novelty and efficiency. Customer integration enhances the effectiveness of AI technology in new product development and market trend forecasting by strengthening customer engagement and improving firms' sensitivity to market dynamics. Supplier integration, by enhancing supply chain collaboration and improving resource integration efficiency, amplifies the advantages of AI in supply chain transparency and operational efficiency. This suggests that firms should fully consider the synergistic effects of supply chain integration when implementing AI strategies to better adapt to complex and volatile market environments.

Third, based on the extended resource-based view (ERBV) and dynamic capability theory (DCT), the study proposes a systematic theoretical framework that incorporates the interactions among AI capability, supply chain integration, and novelty and efficiency. This framework deepens the understanding of the mechanisms through which AI capability functions in firm management and provides a novel perspective on how AI dynamically shapes firms' competitive advantages in the context of digital transformation.

Lastly, the managerial implications of this research highlight that firms should fully leverage the potential of AI technologies during digital transformation by enhancing customer and supplier integration to establish flexible and efficient supply chain collaboration networks. This will enable firms to gain a competitive edge in the market. Additionally, firms should emphasize the alignment between AI capability and organizational strategies to build inimitable competitive advantages.

In summary, this study makes significant contributions to academia and industry across theoretical, practical, and methodological dimensions. Theoretically, it extends the resource-based view and dynamic capability theory by incorporating supplier and customer integration as moderating variables, providing a more nuanced perspective on how internal and external resources can interact to effectively leverage AI capability. Practically, the findings offer strategic insights for managers on maximizing the benefits of AI in novelty and efficiency through supplier and customer integration and guide managing stakeholder relationships in the era of digital transformation. Methodologically, the integration of qualitative and quantitative approaches not only introduces a robust framework for assessing the interaction effects of AI capability and stakeholder integration on novelty and efficiency but also enhances empirical understanding through hierarchical regression analysis. This methodological advancement contributes to the field of novelty and efficiency research and offers actionable strategies for practitioners.

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APPENDIX 1

AI Implementation Management Strategies in Chinese Manufacturing Firms

I am Zhong, DeYu, a Ph.D. Candidate from the School of Management at Pukyong National University, South Korea. As part of my research, I am collecting survey data on the strategic views, related activities, and outcomes of AI in Chinese manufacturing firms.

We sincerely invite your company to participate in this survey, as your company qualifies as a manufacturing firm (i.e., it falls within categories C-27 to C-40 of the Chinese National Economic Industry Classification, which is the selection criterion for this study). Your responses to the survey will play a key role in deepening our understanding of factors that enhance operational performance.

This survey should be completed by personnel responsible for AI technology, the General Manager, or senior management, and such personnel should have a deep understanding of your company's AI implementation strategies and performance. The survey includes 28 main questions and will take about 25 minutes to complete. There are no right or wrong answers to these questions; what matters is your honest opinion.

Please carefully select the statements that best reflect your company's actual situation objectively. Avoid consecutive selection of the same answer to ensure the questionnaire's effectiveness. The numbers 1 to 7 represent a gradual strengthening process.

You can choose any number from 1 to 7, with 1 indicating complete disagreement and 7 indicating agreement. Please answer all questions to maintain the completeness of the questionnaire. Choose only one answer for each question. If you encounter any questions during the process, please make a note and contact us.

Please be assured that personal information will be kept strictly confidential, treated anonymously, and used only in aggregate form for research purposes; no companies or individuals will be individually identified.

By completing and submitting this survey, you agree to participate in this study.

We greatly appreciate your participation.

Contact Information

Zhong, DeYu

Pukyong National University, South Korea

中国制造企业的AI实施管理策略

我是韩国国立釜庆大学管理学院的博士生钟德宇。作为我研究的一部分，我正在收集中国制造企业对AI的战略、相关活动及其成果的看法的调查数据。

我们诚挚地邀请贵公司参与此次调查，因为贵公司是一家制造企业（即符合中国国民经济行业分类中C-27至C-40的企业，这是本研究的选取标准）。您对调查的回复将对加深我们对提高运营绩效的因素的理解起到关键作用。

该调查应由负责AI技术或董事总经理或高级管理人员完成，并且该管理人员应对贵公司的AI实施战略以及绩效有深入了解。调查包含28个主要问题，大约需要25分钟完成。对于这些问题并没有正确或错误的答案，重要的是您的真实看法。请仔细选择最能客观反映贵公司实际情况的陈述。避免连续选择同一答案，以确保问卷的有效性。数字1至7代表一个逐渐加强的过程。您可以选择1到7之间的任何数字，1表示完全不同意，7表示同意。请回答所有问题，以保持问卷的完整性。每个问题只选择一个答案。如果您在过程中遇到任何问题，请记下来并与我们联系。

请放心，个人信息将严格保密，匿名处理，并仅以汇总形式用于研究，任何公司或个人不会被单独识别。

填写并提交本调查即表示您同意参与本研究。我们非常感谢您的参与。

联系方式

钟德宇

韩国国立釜庆大学

第一部分：基本属性 Part 1.

Q1. 您在公司的哪个部门？（Which department are you in within the firm?）
□ 生产部（Production Department）
□ 质检部（Quality Control Department）
□ 采购部（Supply Chain Department）
□ 其他（Others)

Q2. 您在公司中的职位是什么？What is your job title in the firm? (mandatory)
□ 首席执行官(Chief executive officer)
□ 副总裁(Vice president)
□ 总监 (Director)
□ 部门负责人(Officer)
□ 服务官（Service Manager）
□ 其他（Others)

Q3. 您在公司中有多少年的工作经验？How many years of working experience do you have in the firm? (mandatory)
□ 少于1年 (Shorter than 1 year)
□ 1-3年 (1-3 years)
□ 4-9年 (4-9 years)
□ 10-15年 (10-15 years)
□ 超过15年 (More than 15 years)

Q4. 您公司是否获得了ISO 14000系列（14001环境管理体系，14015环境评估）认证？（必填）Did your firm achieve the ISO 14000 series certification（such as ISO 14001 Environmental Management System and ISO 14015 Environmental Assessment） ? (mandatory)
□ 是（Yes）
□ 否 (No)

Q5. 过去三年内，您的公司平均每年在AI相关投资上的总额是多少？（此问题指的是企业内部在AI相关领域的总体投资，包括但不限于员工培训、技术应用、系统更新等）？（单位：百万元）（必填）What has been the average annual total investment in AI-related areas by your company over the past three years? (This question refers to the overall investment within the company in AI-related fields, including but not limited to employee training, technology application, system updates, etc.) (mandatory)
□ < 300万元 (< 3 million RMB)
□ 300-500万元 (3-5 million RMB)

□ 501-1000万元（5-10 million RMB)
□ > 1000万元（> 10 million RMB)

Q6. 您的公司属于哪个子行业？（必填）Which sub-industry does your firm belong to? (mandatory)
□ 电子与半导体行业（C39）Electronics and Semiconductor Industry
□ 汽车制造业 （C36）Automotive Manufacturing
□ 机械制造（C35）Machinery Manufacturing
□ 制药和医疗器械（C27）Pharmaceuticals and Medical Devices
□ 家电和消费电子（C40）Home Appliances and Consumer Electronics
□ 服务业（L）Service
□ 其他（Others)

Q7. 您的公司过去三年的年均销售额是多少？（单位：百万元）（必填）What is your firm's average annual sales (million RMB) in the past three years? (mandatory)
□ < 300万元（< 300 million RMB)
□ 300-500万元（300-500 million RMB)
□ 501-1000万元（500-1000 million RMB)
□ > 1000万元（> 1000 million RMB)

Q8. 您的公司成立了多少年？（必填）How old is your firm? (mandatory)
□ 少于1年（Shorter than 1 year old)
□ 1-5年（1 - 5 years old)
□ 6-10年（6 - 10 years old)
□ 11-20年（11 - 20 years old)
□ 超过20年（Longer than 20 years old)

Q9. 您的公司的所有权结构是什么？（必填）What is the ownership structure of your firm? (mandatory)
□ 国有企业（State-owned firm)
□ 私营企业（Private firm)
□ 外资企业（Foreign-invested firm)

Q10. 您的公司有多少名全职员工？（必填）How many full-time employees work for your firm? (mandatory)
□ <300 (Less than 300)
□ 300-500 (Between 300 to 500)
□ 501-1000 (Between 501 to 1000)
□ >1000 （More then 1000）

第二部分 Part 2.

(1-7表示合规程度越来越高，其中1=完全不同意，2=不同意，3=大多不同意，4=不确定，5=大多同意，6=同意，7=完全同意。请根据贵公司的实际情况选择合适的级别。)

(1-7 indicates increasing levels of compliance, where 1=completely disagree, 2=disagree, 3=mostly disagree, 4=uncertain, 5=mostly agree, 6=agree, 7=completely agree. Please choose the appropriate level based on the actual situation in your company.)

Q11. AI能力（如机器学习、自然语言处理（NLP）和智能自动化等）

1. 我们公司运用人工智能优化内部业务运营 (Our firm uses AI to optimize internal business operations)
2. 我们公司运用人工智能自动化日常工作，以帮助员工更具创造性地工作 (Our firm uses AI to automate routine tasks, allowing employees to work more creatively)
3. 我们公司运用人工智能做出更好的决策 (Our firm uses AI to make better decisions)
4. 我们公司运用人工智能支持新产品开发计划 (Our firm uses AI to support new product development plans)
5. 我们公司运用人工智能帮助寻找新的市场机会 (Our firm uses AI to help find new market opportunities)
6. 我们公司运用人工智能优化分销和销售等外部流程 (Our firm uses AI to optimize external processes such as distribution and sales)
7. 我们公司运用人工智能在需要时捕捉并应用稀缺知识 (Our firm uses AI to capture and apply scarce knowledge when needed)
8. 我们公司运用人工智能通过自动化减少劳动力 (Our firm uses AI to reduce workforce through automation)

Q12. 供应商整合 Supplier Integration

1. 我们的关键供应商为我们的产品开发项目提供意见。(Our key suppliers provide input into our product development projects.)
2. 我们公司与供应商就质量考量和设计变更保持紧密沟通。(Our firm maintains close communications with suppliers about quality considerations and design changes.)
3. 我们公司致力于与供应商建立长期关系。(Our firm strives to establish long-term relationships with suppliers.)
4. 我们公司与供应商保持合作关系。(Our firm maintains cooperative relationships with our suppliers.)
5. 我们公司帮助供应商提高其质量。(Our firm helps our suppliers to improve their quality.)
6. 我们公司积极参与供应商的质量改进工作。(Our firm actively engages

suppliers in our quality improvement.)

Q13. 客户整合 Customer Integration

1. 我们的客户积极参与我们的产品设计过程。(Our customers are actively involved in our product design process.)
2. 我们公司努力对客户的需求做出高度响应。(Our firm strives to be highly responsive to our customers' needs.)
3. 我们公司与客户作为合作伙伴共同工作。(Our firm works as a partner with our customers.)
4. 我们公司经常与客户保持紧密联系。(Our firm frequently maintains close contact with our customers.)
5. 我们的客户向我们反馈质量和交付表现。(Our customers provide us feedback on our quality and delivery performance.)

Q14. 供应链整合 Supply chain integration

1. 我们公司与合作伙伴共同制定战略计划。(Our firm develops strategic plans in collaboration with our partners.)
2. 我们公司积极与合作伙伴在预测和规划方面进行合作。(Our firm collaborates actively in forecasting and planning with our partners.)
3. 我们公司与合作伙伴共同预测和规划未来的需求。(Our firm projects and plans future demand collaboratively with our partners.)
4. 我们公司在需求预测和规划方面与合作伙伴持续合作。(Our firm consistently collaborates in demand forecasting and planning with our partners.)
5. 我们公司始终与合作伙伴共同预测和规划活动。(Our firm always forecasts and plans activities collaboratively with our partners.)

Q15. 响应性供应链 Responsive Supply Chain

1. 我们的供应链在短时间内处理客户需求的多样性。(Our supply chain handles variety in customer demand in a short time.)
2. 我们的供应链保持高容量缓冲以应对波动的市场需求。(Our supply chain maintains a high capacity buffer to respond to volatile market demand.)
3. 我们的供应链具备应对客户不断变化和多样化需求的灵活性。(Our supply chain has the flexibility to cope with changing and diverse needs of customers.)
4. 我们的供应链主要基于供应商的交付可靠性选择供应商。(Our supply chain selects suppliers primarily based on their delivery reliability.)
5. 我们的供应链有能力根据实际客户订单生产产品(按订单生产)。(Our supply chain has the ability to make products according to actual customer orders (make-to-order).)
6. 我们的供应链使用模块化设计来增加产出的多样性。(Our supply chain uses

modular design to increase the variety of output.)

Q16. 效率性供应链 Efficient Supply Chain
1. 我们公司采用大规模生产来降低加工成本。(Our firm adopts mass production to reduce processing costs.)
2. 我们公司根据供应商的成本和质量表现选择供应商。(Our firm selects suppliers based on their cost and quality performance.)
3. 我们公司与少数供应商保持长期且固定的关系。(Our firm maintains a long and rigid relationship with a small number of suppliers.)

Q17. 资源重组 Resource reconfiguration
1. 我们公司调整资源和流程以应对环境变化。(Our firm realigns its resources and processes in response to environmental changes.)
2. 我们公司重新配置资源和流程以应对动态环境。(Our firm reconfigures its resources and processes in response to the dynamic environment.)
3. 我们公司重组资源基础以应对变化的商业环境。(Our firm restructures its resource base to react to the changing business environment.)
4. 我们公司更新资源基础以应对变化的商业环境。(Our firm renews its resource base in response to the changing business environment.)

Q18. 运营绩效 Operational Performance
1. 我们公司的单位制造成本低于竞争对手。(Our firm's unit manufacturing cost is lower than our competitors.)
2. 我们公司提供优质的产品质量。(Our firm offers superior product quality.)
3. 我们公司保持准时交付绩效。(Our firm maintains on-time delivery performance.)
4. 我们公司在改变产品组合方面具有高度灵活性。(Our firm has high flexibility to change product mix.)
5. 我们公司在调整产量方面具有高度灵活性。(Our firm has high flexibility to change volume.)

Q19. 环境绩效 Environmental Performance
1. 我们公司的政策有助于减少空气排放 (Our firm's policies help to decrease air emissions)
2. 我们公司的政策有助于减少危险废物 (Our firm's policies help to decrease hazardous waste)
3. 我们公司的政策有助于与许多绿色供应商建立合作关系 (Our firm's policies help in the establishment of a partnership with many green suppliers)
4. 我们公司的政策有助于提高对全球环境法规的合规性 (Our firm's policies help to increase compliance with global environmental regulations)

5. 我们公司的政策有助于提高商品和材料的环保采购率 (Our firm's policies help to increase the environmentally friendly purchase rate of goods and materials)
6. 我们公司的政策有助于减少环境事故风险，如废物泄漏、中毒或辐射排放 (Our firm's policies help in the reduction of environmental accident risks such as waste leakage, poisoning, or radiation emissions)

Q20. 新颖性 Novelty
1. 我们公司的商业模式提供了新的产品、服务和信息组合。(Our firm’s business model offers new combinations of products, services, and information.)
2. 我们公司的商业模式以新颖的方式（例如，通过新的渠道）连接参与者和交易。(Our firm’s business model links participants and transactions in novel ways (e.g., through new channels).)
3. 我们公司商业模式中某些参与者之间所启用的链接在质量和深度上具有新颖性。(The richness (i.e., quality and depth) of some of the enabled links between participants in our firm’s business model is novel.)
4. 我们公司的商业模式是行业先锋。(Our firm’s business model is pioneer.)
5. 我们所在行业中没有威胁我们公司商业模式的竞争性商业模式存在。(No competing novelty and efficiency exist in our industry that threaten our firm’s business model.)
6. 我们公司商业模式的其他重要方面也有助于其新颖性。(Other important aspects of our firm’s business model contribute to its novelty.)
7. 总体而言，我们公司的商业模式具有新颖性。(Overall, our firm’s business model is novel.

Q21. 效率性 Efficiency
1. 我们公司的商业模式确保交易从用户的角度来看是简单的。(Our firm’s business model ensures transactions are simple from the user's viewpoint.)
2. 我们公司的商业模式减少了交易执行中的错误数量。(Our firm’s business model lowers the number of errors in the execution of transactions.)
3. 我们公司的商业模式降低了参与者除之前提到的成本之外的其他成本。(Our firm’s business model reduces costs for participants beyond those previously mentioned.)
4. 我们公司的商业模式使参与者能够做出明智的决策。(Our firm’s business model enables participants to make informed decisions.)
5. 我们公司的商业模式实现了快速交易。(Our firm’s business model enables fast transactions.)
6. 总体而言，我们公司的商业模式具有高效的交易效率。(Overall, our firm’s business model offers high transaction efficiency.)

Q22. 技术不确定性 Technology Uncertainty

1. 我们公司所在的行业以技术快速变化为特征。(Our firm operates in an industry characterized by rapidly changing technology.)
2. 如果我们公司不能跟上技术变化，将难以保持竞争力。(Our firm will find it difficult to remain competitive if it doesn't keep up with changes in technology.)
3. 我们公司所在的行业有很高的工艺过时率。(Our firm's industry has a high rate of process obsolescence.)
4. 我们公司的生产技术经常且充分地发生变化。(Our firm's production technology changes frequently and sufficiently.)

Q23. 探索性创新 Exploratory Innovation
1. 我们公司接受超出现有产品和服务范围的需求。(Our firm accepts demands that go beyond existing products and services.)
2. 我们公司在新产品和服务的开发上处于先锋地位。(Our firm pioneers the development of new products and services.)
3. 在我们公司的本地市场，进行新产品和服务的试验是常见的。(Experimentation with novel products and services is common in our firm's local market.)
4. 我们公司成功地将完全新颖于我们组织的产品和服务推向市场。(Our firm successfully brings to market products and services entirely novel to our organization.)
5. 抓住未开发市场中的新机会是我们公司的一项常见做法。(Seizing new opportunities in untapped markets is a frequent practice for our firm.)

Q24. 利用性创新 Exploitative Innovation
1. 我们公司持续改进现有产品和服务的提供。(Our firm consistently refines the provision of existing products and services.)
2. 我们公司定期针对本地市场推出现有产品和服务的增强版本。(Our firm regularly introduces enhancements to existing products and services specifically for our local market.)
3. 我们公司积极追求在现有市场中提高规模经济的策略。(Our firm actively pursues strategies to increase economies of scale in the existing market.)
4. 我们公司不断努力扩展对现有客户的服务。(Our firm continuously strives to expand services for existing clients.)

Q25. 可靠性(例如，机器学习、自然语言处理 (NLP) 和智能自动化) Credibility (AI) e.g. machine learning, natural language processing (NLP), and intelligent automation)
1. AI 对我们公司来说是可靠的。(The AI is credible for our firm.)
2. AI 对我们公司来说是可信的。(The AI is believable for our firm.)
3. AI 对我们公司来说是值得信赖的。(The AI is trustworthy for our firm.)

4. AI 被我们公司视为真实的。(The AI is referred to as true by our firm.)
5. AI 被我们公司接受为正确的。(The AI is accepted as correct by our firm.)

Q26. 强制性压力 (Coercive Pressure)
1. 我们公司被政府要求使用人工智能。(Our firm is required by the government to use AI.)
2. 我们公司被行业协会要求使用人工智能。(Our firm is required by the industry association to use AI.)
3. 我们公司被客户协会要求实施人工智能。(Our firm is required by client associations to implement AI.)

Q27. 规范性压力 (Normative Pressure)
1. 我们公司的客户欣赏人工智能的使用。(Our firm's customers appreciate the use of AI.)
2. 我们公司的客户已经采用了人工智能。(Our firm's clients have already adopted AI.)
3. 我们公司受到专业机构推广人工智能的影响，积极采用人工智能。(Our firm is influenced by the professional body's promotion of AI to actively adopting artificial intelligence.)

Q28. 模仿性压力 (Mimetic Pressure)
1. 使用人工智能的主要竞争对手已经获得了广泛的收益。(Our firm's key competitors who use AI have benefitted extensively.)
2. 使用人工智能的主要竞争对手受到其他行业参与者的好评。(Our firm's key competitors who use AI are favorably perceived by other industry players.)
3. 使用人工智能的主要竞争对手受到客户的好评。(Our firm's key competitors who have used AI are favorably perceived by customers.)