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The Impact of Artificial Intelligence Technology on the Innovation Performance of the High-End Equipment Manufacturing Industry: A Case of Shenzhen

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December, 2025

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INSTITUTO UNIVERSITÁRIO DE LISBOA

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GAO Pei

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I declare that this thesis does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university and that to the best of my knowledge it does not contain any material previously published or written by another person except where due reference is made in the text.

Signed: GAO Pei Date: 2025.12.10

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Abstract

Artificial intelligence (AI) is driving the high-quality transformation of the manufacturing industry, requiring an in-depth investigation on the mechanism through which AI is integrated into high-end equipment manufacturing. This study focuses on Shenzhen and investigates how AI adoption affects innovation performance, industrial upgrading, and enterprise value in high-end equipment manufacturing. Using panel data from 222 listed enterprises from 2010 to 2023, through fixed effects models and mediating effect analysis, this study shows that AI significantly enhances innovation performance, with human capital structure and government support serving as important mediating channels; improved innovation performance further drives industrial upgrading toward higher-end and more intelligent development, while increasing enterprise value.

To open the "black box" of AI-enabled innovation, the study incorporates disruptive innovation and dynamic capabilities theory and empirically tests a chain mediation model based on survey data. The findings reveal that AI enhances innovation performance by stimulating disruptive innovation and strengthening enterprises' dynamic capabilities.

This study has the following contributions: (1) It provides empirical evidence on the positive effect of AI technology on innovation performance of high-end equipment manufacturing enterprises. (2) It identified the mediating effects of human capital structure and government support. (3) It established an integrated analytical framework of "macro-level transmission – micro-level mechanism", thereby extending the application of AI and innovation theories in the context of high-end equipment manufacturing and offering theoretical and practical implications for the industry's intelligent transformation and high-quality development.

Keywords: Artificial Intelligence; High-End Equipment Manufacturing; Innovation Performance; Industrial Upgrading; Disruptive Innovation

JEL: G24; O31

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Resumo

A inteligência artificial (IA) está a impulsionar a transformação de elevada qualidade da indústria da manufatura, exigindo uma análise aprofundada dos mecanismos através dos quais a IA é integrada na manufatura de equipamentos de alta tecnologia. Este estudo foca em Shenzhen e investiga como a adoção de IA afeta o desempenho de inovação, a atualização industrial e o valor empresarial no setor de equipamentos de alta tecnologia. Utilizando dados em painel de 222 empresas listadas entre 2010 e 2023, recorrendo a modelos de efeitos fixos e análise de efeitos de mediação, os resultados mostram que a IA melhora significativamente o desempenho de inovação, enquanto a estrutura de capital humano e o apoio governamental atuam como canais mediadores importantes; a melhoria do desempenho de inovação promove, por sua vez, a atualização industrial em direção a níveis mais elevados e inteligentes, ao mesmo tempo que aumenta o valor das empresas.

Para aprofundar a compreensão dos mecanismos subjacentes à inovação impulsionada pela IA, o estudo integra as teorias de inovação disruptiva e das capacidades dinâmicas, testando empiricamente um modelo de mediação em cadeia com base em dados de inquérito. Os resultados indicam que a IA melhora o desempenho de inovação ao estimular a inovação disruptiva e ao reforçar as capacidades dinâmicas das empresas.

Este estudo apresenta as seguintes contribuições: (1) fornece evidência empírica sobre o efeito positivo da IA no desempenho em inovação das empresas de manufatura de equipamentos de alta tecnologia; (2) identificou os efeitos mediadores da estrutura do capital humano e do apoio governamental; (3) estabeleceu um quadro analítico integrado de "transmissão ao nível macro – mecanismos ao nível micro", alargando a aplicação das teorias da IA e da inovação no contexto da manufatura de equipamentos de alta tecnologia, oferecendo implicações teóricas e práticas para a transformação inteligente e o desenvolvimento de elevada qualidade deste setor.

Palavras-chave: Inteligência Artificial; Manufatura de Equipamentos de Alta Tecnologia; Desempenho de Inovação; Atualização Industrial; Inovação Disruptiva

JEL: G24; O31

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摘　要

人工智能正推动制造业高质量转型，高端装备制造与 AI 的融合机制亟待深化研究。本文以深圳市为研究场景，系统考察人工智能对高端装备制造业创新绩效、产业升级与企业价值的传导机理。基于 2010—2023 年深圳 222 家上市企业面板数据，采用固定效应模型与中介效应分析发现：人工智能显著提升企业创新绩效，人力资本结构优化与政府支持发挥关键中介作用；创新绩效进一步驱动产业高端化、智能化升级，并促进企业价值增长。

为打开 AI 赋能“黑箱”，本文引入颠覆性创新与动态能力理论，结合问卷调研实证检验链式中介模型，结果表明：人工智能通过激发颠覆性创新、增强企业动态能力，最终提升创新绩效。

本文的理论贡献在于：实证检验 AI 对高端装备制造企业创新的促进效应，揭示人力资本与政府支持的双中介路径，构建“宏观传导 — 微观机制”整合框架，拓展 AI 与创新理论在高端装备制造业的应用边界，为智能化转型与高质量发展提供理论参考与决策支撑。

关键词：人工智能；高端装备制造；创新绩效；产业升级；颠覆式创新

JEL: G24; O31

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The completion of this dissertation is not an end but a new beginning. Carrying the guidance of my mentors, the love of my family, and the support of my friends, I will continue to explore with dedication, move forward with courage, and strive for excellence in my future academic and life journey—so as to repay all those who have supported and cared for me.

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Content

Chapter 1: Introduction 1
1.1 Research background 1
1.3 Research significance 9
1.3 Research questions 12
1.4 Research methods 15
1.5 Research content and technical route 17
Chapter 2: Literature Review 21
2.1 Artificial intelligence (AI) and manufacturing 21
2.1.1 The development of AI and its impact 21
2.1.2 Applications of core AI technologies in manufacturing 26
2.1.3 AI technology and industrial upgrading in manufacturing 34
2.1.4 AI technology and innovation performance in manufacturing 35
2.2 AI and high-end equipment manufacturing in China 37
2.2.1 Technological innovation and China's high-end equipment manufacturing industry 37
2.2.2 Innovation input and output in high-end equipment manufacturing industry 39
2.2.3 Influencing factors and development pathways of high-end equipment manufacturing industry 40
2.3 Disruptive innovation and innovation performance in high-end equipment manufacturing 42
2.3.1 Disruptive innovation and incremental innovation 42
2.3.2 Disruptive innovation and dynamic capabilities 43
2.3.3 Disruptive innovation and innovation performance 44
2.4 Review on AI technology and high-end equipment manufacturing 45
Chapter 3: Relevant Concepts and Theoretical Foundations 47
3.1 Economic theories of artificial intelligence (AI) 47
3.2 Advanced equipment manufacturing industry 48
3.2.1 Equipment manufacturing and advanced equipment manufacturing 48
3.2.2 Definition and characteristics of high-end equipment manufacturing enterprises 52

3.3 Innovation performance theory 59
3.4 Economic growth theory 61
3.5 Industrial upgrading theory 63
3.6 Technological innovation and industrial upgrading theory 65
Chapter 4: Empirical Study on Impact of AI Technology on the Development of the High-End Equipment Manufacturing Industry 69
4.1 Research model and hypotheses 69
4.1.1 The impact pathways of AI on innovation performance in manufacturing enterprises 70
4.1.2 The impact of AI technology advancement on high-end equipment manufacturing enterprises 72
4.1.3 Model construction 74
4.2 Research design 75
4.2.1 Sample selection and data sources 75
4.2.2 Variable measurement 76
4.3 Data analysis results 80
4.3.1 Descriptive statistical analysis 80
4.3.2 Regression analysis 81
4.3.3 Mediation effect testing 85
4.3.4 Testing for endogeneity 86
4.3.5 Robustness testing 87
4.4 Chapter summary 88
Chapter 5: Extended Study: Impact of Disruptive Innovation and Dynamic Capabilities on Innovation Performance 91
5.1 Research questions 91
5.2 Research hypotheses 92
5.2.1 Disruptive innovation and innovation performance 92
5.2.2 Disruptive innovation and dynamic capabilities 93
5.2.3 Mediating effect of dynamic capabilities 95
5.3 Research design 97
5.3.1 Enterprise innovation performance 97
5.3.2 Disruptive innovation scale 98
5.3.3 Dynamic capabilities scale 98
5.3.4 Sample and data collection 99
5.4 Data analysis results 100

5.4.1 Reliability analysis 100
5.4.2 Validity analysis 101
5.4.3 Path analysis 102
5.4.4 Mediation analysis 103
5.5 Summary of findings 104
Chapter 6: Conclusions and Recommendations 107
6.1 Conclusions 107
6.2 Limitations and future research 112
Bibliography 115
Webliography 131

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List of Tables

Table 1.1 Summary of major AI policies of various countries as of 2023 2
Table 1.2 Summary of major AI policies in China as of 2023 4
Table 2.1 Representative figures and views on the essence of AI in domestic and international research 21
Table 2.2 Summary of domestic and international perspectives on intelligent manufacturing 30
Table 4.1 Variables of this study 79
Table 4.2 Descriptive statistics of variables 80
Table 4.3 Regression analysis results 82
Table 4.4 Mediation effect testing of human capital structure and government support 85
Table 4.5 Endogeneity test 86
Table 4.6 Model robustness test results 87
Table 4.7 Research hypotheses and results 89
Table 5.1 Scale for enterprise innovation performance 98
Table 5.2 Scale for disruptive innovation 98
Table 5.3 Scale for dynamic capabilities 99
Table 5.4 Descriptive statistics for the survey sample 100
Table 5.5 Reliability (Cronbach's α) 101
Table 5.6 CFA results 101
Table 5.7 Path analysis and hypothesis tests 102
Table 5.8 Mediation test results 104
Table 5.9 Summary of hypothesis tests 105

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List of Figures

Figure 2.1 A visual representation of the status of AI technology and its applications 29

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Chapter 1: Introduction

1.1 Research background

In 2020, the outbreak of the COVID-19 pandemic swept across the globe, severely impacting the global economy. The intensification of the U.S.-China trade war and the Russia-Ukraine conflict has presented unprecedented challenges to the world economy, making it crucial for countries to address issues of economic growth. As the core of the real economy, manufacturing plays a pivotal role in a nation’s economic revenue and stability. The high-quality development of the manufacturing sector is essential for national economic growth, and high-end equipment manufacturing represents the top tier of this sector (Fang, 2021). It serves as a key pillar for accelerating industrial transformation and upgrading, as well as for enhancing the manufacturing strength of nations. Therefore, the sustained high-quality development of the high-end equipment manufacturing industry is of great significance for building a strong manufacturing nation.

In recent years, China's high-end equipment manufacturing industry has experienced rapid growth, achieving significant breakthroughs in areas such as high-end energy equipment, intelligent manufacturing equipment, marine engineering equipment, advanced rail transit equipment, and aerospace equipment. However, in certain fields, domestic high-end equipment manufacturing enterprises still lag behind developed countries in terms of independent research and development (R&D) capabilities, product stability, key technologies, and some core components. Additionally, the development of related supporting products and services has been relatively slow, and the overall service system remains underdeveloped, making it challenging to promote widespread application. Thus, the question of how to rapidly advance the high-end equipment manufacturing industry has become a pressing issue for enhancing China’s international competitiveness.

Following the global financial crisis, developed countries began to refocus on the development of their real economies, formulating strategies such as Smart Planet, Next-Generation Energy, Low-Carbon Economy, and Re-industrialization to regain competitive advantages in emerging industries and high-end manufacturing (Matyushok et al., 2021). This trend poses real threats to the development of China's high-end equipment manufacturing

industry. At the same time, artificial intelligence (AI) is driving a comprehensive transformation of industrial manufacturing, as the Fourth Industrial Revolution is marked by advancements in AI. With the rapid development of cloud computing, information technology, and the internet, AI has made breakthroughs worldwide, propelling society into an era of intelligence (Girasa, 2020), thus presenting new strategic opportunities for the high-end equipment manufacturing sector.

From the perspective of fostering and developing China's strategic emerging industries and promoting the transformation and upgrading of key manufacturing sectors, the high-end equipment manufacturing industry is expected to evolve toward intelligence, greenness, and servitization. AI technologies facilitate the development of high-end equipment manufacturing by optimizing production processes, improving product quality and stability, reducing costs, shortening production cycles, and enhancing resource utilization efficiency. For example, the application of AI technologies enable high-end equipment manufacturing enterprises to achieve intelligent upgrading of production equipment, optimize production processes, and increase the level of automation, thereby improving production efficiency and product quality. In addition, through data analytics and predictive maintenance, AI can reduce failure rates, maintenance costs, and extend equipment service life (Çınar et al., 2020; J. Zhang & Wu, 2021).

On a global scale, countries are competing to seize new development opportunities and build international competitive advantages by engaging in a new round of AI competition. Since 2013, major industrialized nations have been systematically incorporating AI into their strategic agendas, enacting various supportive policies. For example, the United States has launched the *National Artificial Intelligence Research and Development Strategic Plan*, the European Union has formulated the *Artificial Intelligence Act*, and Japan has proposed its *AI Technology Strategy*. These policies provide governmental backing and financial support for AI development, while also creating a favorable external environment for the growth of high-end equipment manufacturing. The AI policies of major industrialized nations are summarized in Table 1.1.

Table 1.1 Summary of major AI policies of various countries as of 2023

No.	Country	Date	Policy
1	America	April 2013	Brain Research through Advancing Innovative Neurotechnologies (BRAIN) Initiative
2		Oct-Nov 2016	Preparing for the Future of AI National AI Research and Development Strategic Plan AI, Automation, and the Economy Report
3		Dec 2017	Future of AI Act
4		2018	Executive Order on Maintaining American Leadership in AI
5		May 2018	2018 White House Summit on AI: Summary Report
6		2019	National AI Strategy: 2019 Update Launch of American AI Initiative

No.	Country	Date	Policy
7		Sep 2020	Declaration on AI Research and Development Cooperation with the UK
8		May 2023	National AI R&D Strategy Plan
9		2014	2014-2020 European Robotics Strategy
10		Dec 2015	Multi-Year Roadmap for Robotics
11	EU	June 2016	AI Legislative Initiative
12		April 2018	EU AI
13		April 2021	AI Regulations
14		2012	Future High-Tech Strategy Plan
15		2014	New High-Tech Strategy
16	Germany	2015	Smart Data Project
17		July 2018	Federal Government AI Strategy Highlights
18		Nov 2019	National Industrial Strategy 2030
19		2013	French Robotics Development Plan
20	France	March 2017	AI Strategy
21		July 2018	National AI Strategy
22		May 2023	AI Action Pla
23		July 2014	2020 National Development Strategy for Robotics and Autonomous Systems
24		Oct 2016	Robotics and AI
25		Dec 2016	AI: Opportunities and Implications for the Future of Decision Making
26	UK	Jan 2017	Modern Industrial Strategy
27		March 2017	UK Digital Strategy
28		Oct 2017	Developing AI in the UK
29		2018	New Policies for the AI Industry
30		Sep 2021	National AI Strategy
31		Jan 2015	Japanese Robotics Strategy: Vision, Strategy, Action Plan
32		Jan 2016	5th Science and Technology Basic Plan (2016–2020)
33		May 2016	New Industrial Structure Vision," "Advanced Integrated Intelligence Platform Project
34	Japan	March 2017	AI Industrialization Roadmap
35		March 2018	AI 'BRAIN' Plan
36		May 2018	AI Development Strategy
37		June 2018	Comprehensive Innovation Strategy
38		Dec 2018	Principles for a Human-Centered AI Society
39		April 2022	AI Strategy 2022
40	India	June 2018	National AI Strategy

Source: P. Jiang (2019)

In China, AI technology has also garnered significant attention from the government. China aims to leverage AI to gain a first-mover advantage, enhance the nation's level of technological innovation, and advance its innovation-driven development. The concept of "smart manufacturing" was first introduced in the *Made in China 2025 Initiative*, which emphasized integrating manufacturing technologies with new network technologies. It also set forth the goal of advancing intelligent manufacturing as the key to driving industrialization and the application of informatization within the manufacturing sector. The initiative called for active research and development of smart products and equipment to achieve full automation and intelligence in the manufacturing process.

Since 2015, China has elevated AI to a national strategic priority. To achieve the goal of establishing itself as a global leader in AI development by 2030, China has proactively introduced a range of supportive measures. As of 2023, China has issued a total of 26 policies aimed at promoting AI development, underlining its commitment to seizing the global strategic high ground in AI (see Table 1.2).

Table 1.2 Summary of major AI policies in China as of 2023

No.	Time	Policy
1	May 2015	Made in China 2025
2	July 2015	State Council Guiding Opinions on Actively Promoting the AI Industry
3	March 2016	13th Five-Year Plan for National Economic and Social Development of the People's Republic of China
4	April 2016	Robotics Industry Development Plan (2016-2020)
5	May 2016	Three-Year Action Implementation Plan for AI
6	July 2016	13th Five-Year National Science and Technology Innovation Plan
7	September 2016	Special Action Plan for the Innovation Development of Intelligent Hardware Industry (2016-2018)
8	November 2016	13th Five-Year Plan for the Development of National Strategic Emerging Industries
9	March 2017	Government Work Report 2017
10	July 2017	State Council Notice on Issuing the Next Generation AI Development Plan
11	October 2017	19th National Congress Report
12	December 2017	Three-Year Action Plan for Promoting the Development of a New Generation of AI Industry (2018-2020)
13	April 2018	Higher Education Institutions AI Innovation Action Plan
14	November 2018	Key Tasks for Innovation in the New Generation of AI Industry
15	March 2019	Guiding Opinions on Promoting the Deep Integration of AI and the Real Economy
16	June 2019	Governance Principles for the New Generation of AI—Developing Responsible Artificial Intelligence
17	August 2019	Guidelines for the Construction of National New Generation AI Open Innovation Platforms
18	September 2019	Guidelines for the Construction of National New Generation AI Innovation and Development Pilot Zones
19	November 2019	Guiding Opinions on Promoting the Development of Forestry and Grassland AI
20	January 2020	Several Opinions on Promoting Disciplinary Integration and Accelerating Postgraduate Training in the Field of AI by 'Double First-Class' Universities
21	February 2020	Intelligent Automotive Innovation Development Strategy
22	July 2020	Guidelines for the Construction of the National New Generation AI Standard System
23	November 2021	14th Five-Year Plan for Informatization and In-depth Integration of Industrialization
24	August 2022	Notice on Supporting the Construction of New Generation AI Demonstration Application Scenarios" and "Guiding Opinions on Accelerating Scenario Innovation to Promote High-Quality Economic Development with High-Level Applications of AI
25	March 2023	Initiation of 'AI-Driven Scientific Research' Special Deployment Work

Source: P. Jiang (2019)

Under the guidance of relevant Chinese government policies, the application of AI technology has achieved significant results across various sectors of manufacturing, creating

substantial advantages. For instance, in the manufacturing industry, AI technology has optimized production processes and improved productivity, notably enhancing Total Factor Productivity (TFP) in enterprises (J. Zhang & Wu, 2021).

In the financial sector, the application of AI technology has greatly improved the efficiency of data processing and analysis. For example, by utilizing AI-driven Software as a Service (SaaS) applications, financial institutions can enhance risk management and customer service, significantly improving operational efficiency (Stutz et al., 2024). A 2019 Deloitte survey reported that the application of AI in finance increased data processing speeds by over 30% and reduced risk management costs by 20% (Lafferty, 2019). These cross-industry practices indicate that AI has become a critical technological foundation for enhancing organizational efficiency and driving innovation. Its role in the manufacturing sector is particularly noteworthy.

At the regional level, Shenzhen, as a pioneer city in China's reform and opening-up and a national hub for technological innovation, possesses prominent advantages in the high-end equipment manufacturing industry. The advancement of this sector in Shenzhen not only drives related industries, promotes breakthroughs in key technologies, and accelerates productivity growth, but also facilitates industrial upgrading and the shift in economic development modes. In terms of the existing conditions, Shenzhen, as an innovation hub, benefits from a strong industrial base and a favorable innovation ecosystem. In recent years, Shenzhen has made remarkable progress in high-end equipment manufacturing and has become one of China's major centers for advanced manufacturing and innovation, particularly excelling in fields such as intelligent robotics, precision instruments, and industrial machine tools. In 2022, the Shenzhen Municipal Government issued the *Three-Year Action Plan for Industrial Machine Tools, Intelligent Robotics, and Precision Instrument Equipment Industries*, setting targets for 2025, including an added value of 35 billion RMB for the industrial machine tool sector, 20 billion RMB for the precision instrument sector, and 16 billion RMB for the intelligent robotics sector. According to official data, the number of high-tech enterprises in Shenzhen increased to 14,000 in 2023, with 3,185 newly established enterprises in that year. In the fields of intelligent robotics and industrial machine tools, product categories continued to diversify, industrial robotics industry chains were continuously improved, and the output of service robots increased by 36%. In the first half of 2024, Shenzhen's total foreign trade reached 2.2 trillion RMB, representing a year-on-year growth of 31.7%. In particular, exports of electromechanical products reached 948.9 billion RMB, with a year-on-year increase of 21.4%; exports of new energy vehicles and photovoltaic products increased by 51.7% and 81.6%, respectively. These figures demonstrate that Shenzhen not only has a solid foundation in high-end manufacturing

but also exhibits strong vitality in AI-driven industrial upgrading.

The Shenzhen Municipal Government has attached great importance to the development of AI and high-end equipment manufacturing, successively issuing policies such as the *Shenzhen New Generation Artificial Intelligence Development Action Plan (2019–2023)* and the *Shenzhen Industrial Internet Development Action Plan*, actively promoting the application of AI technologies in high-end equipment manufacturing. In 2023, Shenzhen allocated an industrial guidance fund of 2 billion RMB to support high-end equipment manufacturing clusters and proposed a policy framework of "major scientific and technological projects + first-of-its-kind funds + municipal government guidance funds + post-subsidy incentives" to foster industrial development. Meanwhile, Shenzhen was committed to constructing 20 high-end manufacturing industrial parks across multiple districts, such as Bao'an, Guangming, Longhua, Longgang, Pingshan, and Shenshan, aiming to cultivate and strengthen strategic emerging and future industries, such as telecommunications, semiconductors, intelligent terminals and sensors, software, intelligent robotics, precision instruments and equipment, new energy, intelligent connected vehicles, new materials, and biomedicine, providing favorable conditions for the integrated development of high-end equipment manufacturing and AI.

In terms of innovation input and output, Shenzhen's high-end equipment manufacturing industry has demonstrated strong growth driven by AI. In recent years, R&D investment in high-end manufacturing has increased significantly. In 2023, R&D expenditure in Shenzhen's high-end manufacturing sector witnessed a year-on-year increase of 22.2%, while investment in this sector increased by 64.0% (Shenzhen Municipal Bureau of Commerce, 2024). For instance, the *Shenzhen High-Tech Industry Development Plan (2021–2025)* explicitly prioritized the development of high-end equipment manufacturing, encouraging enterprises to continuously increase R&D investment in AI and intelligent manufacturing. Through fiscal subsidies and tax incentives, the Shenzhen government has reduced innovation costs, stimulating enterprises to intensify R&D efforts (Office of Information Disclosure of the People's Government of Shenzhen Municipality, 2021). At the enterprise level, Huawei and other enterprises have established R&D centers in Shenzhen focusing on intelligent manufacturing technologies and continuously enhanced innovation capabilities through collaboration with universities and research institutions; Apple has also planned to establish an applied research laboratory in Shenzhen to enhance product testing and research capabilities, while deepening cooperation with local suppliers across the entire value chain, including design, R&D, commercialization, and production (Shenzhen Municipal Bureau of Commerce & Shenzhen Investment Promotion Bureau, 2024). In terms of talent, Shenzhen has implemented

comprehensive “policy packages”, including career platforms, research funding, team support, and living subsidies, to attract top global talent and promote technological innovation in high-end equipment manufacturing (L. Yang, 2025).

In terms of innovation output, AI has not only improved production efficiency and product quality but has also driven the emergence of numerous new products and technologies. Studies indicated that the application of AI in intelligent manufacturing could increase production efficiency by over 30% and reduce production costs by 20% (Mitchell, 2023). Taking DJI as an example, through the application of AI technologies, it has launched a series of highly intelligent drone products, achieving a leading position in both domestic and international markets (DJI, 2025). In addition, AI has also contributed to product quality improvement. Through AI-driven quality analysis systems, enterprises can monitor production processes in real time and rapidly identify and address quality issues. Research showed that AI-based quality control could increase product qualification rates by 25% and significantly reduce defect rates (Mitchell, 2023). According to statistics, Shenzhen’s high-end manufacturing enterprises filed more than 5,000 patents in 2023, of which AI-related patents accounted for 35%, highlighting the significant role of AI in promoting technological innovation (Office of Information Disclosure of the People’s Government of Shenzhen Municipality, 2021). Shenzhen enterprises also performed strongly in global PCT patent applications in 2023, reflecting the international influence of Shenzhen’s technological innovation (World Intellectual Property Organization, 2024).

Shenzhen’s high-end equipment manufacturing industry also demonstrates strong competitiveness in international market. For example, at the 2024 Shenzhen International Industrial Manufacturing Technology and Equipment Exhibition, more than 2,000 enterprises showcased high-end equipment and manufacturing technologies over an exhibition area exceeding 200,000 square meters, attracting over 100,000 visitors, demonstrating Shenzhen’s technological leadership and market appeal in high-end manufacturing. In addition, Shenzhen has attracted substantial foreign investment. In 2023, 8,002 new foreign-invested enterprises were established in Shenzhen, representing a year-on-year increase of 86.6%, with actual foreign investment reaching 62.62 billion RMB. The continuous inflow of foreign enterprises and the increased international technological cooperation has enhanced Shenzhen’s industrial openness and provided new technological sources and market opportunities for innovation in high-end equipment manufacturing.

However, despite the significant progress in integrating AI with high-end equipment manufacturing, Shenzhen still faces several challenges. 1) Technological innovation

capabilities require further enhancement. Some enterprises remain dependent on external technologies, and their capabilities for independent R&D in high-end sectors such as semiconductor manufacturing equipment and advanced CNC machine tools remain limited. 2) There is a structural mismatch in the supply of high-end talent. Although the government and enterprises have implemented various measures to attract and cultivate talent, the demand for interdisciplinary and highly skilled talent in high-end equipment manufacturing has not yet been fully met (L. Yang, 2025). 3) Limitations remain in the industrial chain, particularly in key sectors such as high-precision sensors, high-performance chips, and advanced materials, where bottlenecks persist (Office of Information Disclosure of the People's Government of Shenzhen Municipality, 2021). 4) The coverage and efficiency of policy and financial support remain uneven across different types of enterprises, with some small and medium-sized enterprises still facing difficulties in accessing policy support and innovation resources. 5) In terms of international market expansion, Shenzhen's high-end equipment manufacturing enterprises continue to face challenges such as intellectual property protection issues, different technical standards, and trade barriers (Lamarre et al., 2023).

The continuous development and application of AI technology in China has garnered increasing academic interest, particularly regarding its impact on various domains. Scholars have focused on studying AI's influence on technological innovation, economic growth, productivity, labor skills and employment structure, labor income, industrial structure optimization and upgrading, as well as its role in enhancing the efficiency and competitiveness of cultural industries. Several empirical studies have demonstrated the positive effects of AI on the development and transformation of the manufacturing sector (Buchmeister et al., 2019; Moinuddin et al., 2024). However, research on AI's impact on the development of the high-end equipment manufacturing industry remains relatively scarce, with only a few scholars addressing it in their works.

For instance, Damioli et al. (2021) suggest that AI application significantly enhances labor productivity in enterprises. J. Liu et al. (2020) found that AI's application in high-end manufacturing promoted both technological innovation and production efficiency. K. L. Wang et al. (2023) studied AI's impact on the total factor productivity (TFP) of Chinese manufacturing enterprises and found that AI significantly improves TFP. J. Liu et al. (2024) indicated that AI plays an important role in elevating the global value chain position of the manufacturing industry. Additionally, Pansare et al. (2024) pointed out that AI fosters industrial upgrading by improving production efficiency, promoting technological innovation, and reducing trade costs. Dwivedi et al. (2021) emphasized the challenges and opportunities AI presents across multiple

disciplines and outlined potential directions for future research.

Existing literature indicates that research on the impact of AI technology on the development of high-end equipment manufacturing is still in its early stages, with theoretical discussions primarily focused on defining related concepts. Studies exploring the relationship between AI technology and high-end equipment manufacturing development are relatively limited, leaving many questions yet to be explored and resolved. Based on this gap, this thesis delves into the key factors influencing the development of Shenzhen's high-end equipment manufacturing industry and its underlying mechanisms. It deeply analyzes the ways in which AI technology affects the industry, the degree of this impact, and the pathways through which these influences occur. The aim is to investigate how AI drives the development of high-end equipment manufacturing, thereby facilitating the rapid growth of this sector in Shenzhen.

High-end equipment manufacturing is the backbone of a nation’s industrial system and a strategic industry that determines the international competitiveness and overall strength of the national economy. According to the 12th Five-Year Plan for the Development of High-end Equipment Manufacturing Industry, the promotion and cultivation of high-end equipment manufacturing is a key strategic choice for securing a leading position in technological development. It is also crucial for transforming China from a major manufacturing country into a manufacturing powerhouse and for accelerating changes in the economic development model. As China enters a golden strategic opportunity period for developing high-end equipment manufacturing, it is essential to fully leverage AI technology as a strategic opportunity in the global reallocation of economic roles. By accurately understanding industry trends, China can maximize strengths, address weaknesses, and increase efforts to cultivate high-end equipment manufacturing, thus achieving "Made in China" excellence in this field.

1.3 Research significance

In the report of the 19th National Congress of the Communist Party of China, it was emphasized that China’s economy was transitioning from high-speed growth to high-quality development. This transformation requires not only macroeconomic policy adjustments but also qualitative leaps across various industrial sectors. As a core and strategic sector of the nation’s manufacturing industry, high-end equipment manufacturing plays an essential role in achieving high-quality development of this industry. Therefore, promoting the shift from rapid growth to high-quality development in high-end equipment manufacturing is crucial for building China into a strong manufacturing nation. National policies, such as the *Intelligent Manufacturing*

Development Plan (2016–2020) and *Made in China 2025*, provided guidance by emphasizing intelligent manufacturing and the industrial internet. Against this backdrop, studying the key factors and mechanisms influencing the development of high-end equipment manufacturing, as well as how AI impacts this sector (the mechanism and outcomes), holds significant theoretical and practical value.

(1) Theoretical significance

First, this study extends AI research into the high-end equipment manufacturing sector and constructs an industry-specific theoretical framework (Chapters 2-3). Most international studies on AI focus on general manufacturing, automotive, electronics, or digital service industries. Research on AI in high-end equipment manufacturing, which is characterized by technological intensity, long product life cycles, and stringent reliability requirements, however, remains limited. Existing studies typically analyzed AI technologies and Industry 4.0 applications in broader manufacturing contexts (Frank et al., 2019; L. Li et al., 2022; Mao & Wang, 2019), leaving a major disciplinary gap. By situating AI within the specific context of high-end equipment manufacturing, this study provides a unique industry-specific perspective and enriches the theoretical foundations for intelligent manufacturing and industrial transformation.

Second, this study constructs a comprehensive mechanism framework that explains how AI affects innovation performance and industrial upgrading, addressing the "black box" problem in prior research (Chapters 4-5). Although previous studies have confirmed the positive impacts of AI on productivity, innovation output, and operational efficiency (Hu et al., 2024; Waltersmann et al., 2021), their explanations of the underlying mechanisms remain insufficient. Some scholars emphasized that AI-driven improvements require long-term intangible investment and may follow a "productivity J-curve" (Brynjolfsson et al., 2021), but they did not clarify how enterprises build the required capabilities to realize these gains. Other studies highlighted the role of dynamic capabilities (Le et al., 2025), AI capability heterogeneity (Cockburn et al., 2018), and human capital restructuring, but they fell short of integrating these elements into a unified mechanism model. This study attempts to address this gap by constructing a multi-dimensional mechanism framework involving technological innovation capability, dynamic capabilities, human capital structure, resource integration, and government support, thus opening the "AI → innovation performance" black box.

Third, this study develops an integrated model of "AI – dynamic capabilities – innovation performance – industrial upgrading", filling the gap in domestic research, which largely remains at the macro level (Chapter 4). Emerging studies in China have examined AI and product innovation or strategic emerging industries (Y. Gao et al., 2025; D. Li et al., 2024), yet they

primarily focused on macro policy, industry trends, or conceptual analysis. What has been missing is a micro-level, empirically testable model linking AI adoption with enterprise capabilities, innovation outcomes, and industrial upgrading. Thus, by constructing a logically coherent and empirically testable integrated model, this study contributes to filling this theoretical gap and provides a comprehensive framework for understanding how AI drives innovation in high-end equipment manufacturing.

Fourth, by identifying AI's comprehensive enabling pathways, this study enriches theory related to the development of high-end equipment manufacturing (Chapters 5-6). The empirical results of this study revealed how AI enhances production efficiency, optimizes management processes, strengthens technological innovation, and increases enterprise value. These results align with the findings of J. Xu and Zhai (2020), who showed that intelligent production and service-oriented support could promote high-quality development, and with Lafferty (2019) and Bahoo et al. (2023), who demonstrated AI's contribution to supply chain optimization and technological capability enhancement. Moreover, the study supports and extends Piao (2024)' perspective of AI as a "new quality productive force", showing how AI generates competitive advantages and spillover effects across organizational and industrial levels.

(2) Practical Significance

First, despite China's advancements in AI, challenges remain amid intensifying international competition. Leveraging AI to secure technological advantages is essential for maintaining global competitiveness. Guangdong Province, a key manufacturing hub, has outlined a clear strategy to accelerate intelligent, automated, and digital transformations in its *Five-Year Action Plan for High-Quality Manufacturing Development (2021-2025)*. In this context, AI adoption provides strategic guidance for enterprises aiming to enhance their competitiveness and for industrial upgrading.

Second, understanding the key factors influencing high-end equipment manufacturing development has practical implications for enterprises seeking strategic advantages. AI applications enable intelligent and automated production processes, improving production efficiency, product quality, and operational precision while reducing costs (D. Li et al., 2024). Implementing AI-driven production lines can help enterprises strengthen their competitive position in both domestic and international markets.

Third, in the context of recent economic pressures and industry challenges, AI can provide new impetus for industrial growth. Research on AI's impact in high-end equipment manufacturing can inform government policies to encourage technology adoption. For instance, tax incentives and R&D subsidies can encourage enterprise to invest in AI, thereby enhancing

their technological innovation capability and market competitiveness (Y. Gao et al., 2025). Such measures can contribute to enterprise performance and drive sector-wide technological advancement and industrial upgrading.

Fourth, AI adoption can enhance innovation performance through optimized human capital and increased government support. By attracting and cultivating high-quality talent, enterprises can improve workforce capabilities, while supportive policies and financial incentives can increase AI adoption intention, driving both technological innovation and industrial transformation (Hu et al., 2024). Understanding these combined effects provides policymakers with insights to design more effective strategies for sustainable development.

In summary, investigating the impact of AI technology on high-end equipment manufacturing can help enterprises strengthen global competitiveness and provide scientific evidence for government policy formulation, ultimately promoting this industry's sustainable development and generating both economic and societal value.

1.3 Research questions

In the context of the ongoing global technological revolution and industrial transformation, AI has emerged as a key driver of innovation, productivity, and digital transformation in manufacturing industries. Existing studies indicate that AI can enhance production efficiency, improve product quality, and facilitate smart and automated processes across multiple manufacturing sectors (D. Fan & Liu, 2021; Mao & Wang, 2019). However, while the potential of AI has been widely acknowledged, empirical evidence on its specific impact on high-end equipment manufacturing remains limited, particularly regarding the mechanisms through which AI generates value and promotes high-quality development.

Prior research highlights several pathways through which AI may influence manufacturing performance. For instance, J. Xu and Zhai (2020) demonstrates that smart equipment processes, intelligent product functionalities, service-oriented product support, and green production practices positively affect the high-quality development of manufacturing enterprises. Similarly, Lafferty (2019) and Bahoo et al. (2023) find that AI applications can optimize supply chain management, enhance technological capabilities, and improve labor productivity. Brynjolfsson et al. (2021) research on AI's impact on productivity presents Productivity J-curve through intangible investment Despite these insights, clear gaps remain in understanding how AI affects high-end equipment manufacturing enterprises, which are characterized by high technological intensity, long product life cycles, and intensive R&D requirements.

Critical gaps in the literature include:

Life cycle integration gap: Although AI is recognized as a productivity enabler, few studies examine its integration across the entire life cycle of high-end equipment products, from design and production to sales and after-sales service. Existing studies provide important insights into AI's role in improving efficiency, productivity, and technological innovation (Aghion et al., 2020; Brynjolfsson et al., 2021). X. Zhang et al. (2022) noted that most research focused on isolated production phases, lacking a systematic analysis of how AI continuously creates value across key business processes within enterprises.

Mechanism gap: Existing studies identify broad outcomes of AI adoption, such as increased productivity or innovation, but the underlying mechanisms—such as technological innovation, human capital optimization, dynamic capabilities (Le et al., 2025), institutional support, and economic conditions—remain underexplored. Moreover, existing literature tends to treat AI as a homogeneous technology rather than analyzing how different AI capabilities (e.g., perception, prediction, decision-making) interact with enterprise-level factors to shape performance outcomes (Cockburn et al., 2018). Bahoo et al. (2023) highlight the need to open this "black box" to clarify how AI translates into tangible enterprise and industry outcomes.

Industry-specific gap: Most empirical studies focus on general manufacturing, overlooking the unique characteristics of high-end equipment manufacturing, including complex supply chains, stringent performance standards, and the dual need for incremental and disruptive innovation. This gap has been emphasized in recent reviews (e.g., X. Zhang et al., 2022).

Impact evaluation gap: While AI is expected to drive industrial upgrading and enhance enterprise competitiveness, quantitative evidence on its effects on enterprise-level innovation performance, enterprise value, and industry development is scarce (Mishra et al., 2022). L. Yang and Liu (2020) call for rigorous empirical studies to quantify the strategic impact and ROI of AI investments in specific manufacturing sub-sectors.

Based on these gaps, this study focuses on Shenzhen's high-end equipment manufacturing sector and aims to investigate the following research questions (RQs):

RQ1. How can AI be embedded into key processes of high-end equipment manufacturing, such as R&D, production, and operational management, to facilitate enterprises' intelligent transformation?

This question addresses the life cycle integration gap by exploring AI applications in product design, production, quality control, logistics, and after-sales service, focusing on how AI can create value across all stages.

RQ2. In the high-end equipment manufacturing industry, how do internal innovation

behaviors and capability structures within enterprises further influence innovation performance?

This question targets the industry-specific gap by examining AI's role in facilitating business transformation, including management process optimization, operational efficiency, and supply chain digitalization. While prior research (D. Fan & Liu, 2021; Lafferty, 2019) shows general benefits, sector-specific empirical evidence remains limited.

RQ3. Through what mediating mechanisms does AI influence the innovation performance of high-end equipment manufacturing enterprises?

This question addresses the mechanism gap by investigating how AI interacts with organizational and institutional factors to affect enterprise and industry outcomes. Potential mechanisms include dynamic capabilities, technological innovation, human capital optimization, and government support. Although prior studies indicate broad effects of AI on productivity and innovation (Bahoo et al., 2023), the specific pathways in high-end equipment manufacturing require empirical validation.

RQ4. Does AI significantly enhance the innovation performance of high-end equipment manufacturing enterprises and further contribute to industrial upgrading and enterprise value?

This question fills the impact evaluation gap by quantifying AI's effects on enterprise-level innovation performance, enterprise value, and industrial upgrading. Previous studies (L. Yang & Liu, 2020) suggest positive outcomes, but sector-specific evidence, particularly for high-end equipment manufacturing, is scarce.

By addressing these research questions, this study contributes to the literature by (1) providing empirical evidence on the effect of AI in the specific context of high-end equipment manufacturing, (2) revealing the underlying mechanisms linking AI, human capital structure, government support, disruptive innovation, and dynamic capabilities, 3) revealing the logic through which AI influences innovation performance, industrial upgrading, and enterprise value from both macro-level empirical identification and micro-level mechanism extension, and (4) quantitatively evaluating the specific effects of AI on the high-quality development of the high-end equipment manufacturing industry. These findings are of significant theoretical and practical value, offering guidance for policymakers and enterprises and facilitating the sustainable and high-quality development of the high-end equipment manufacturing industry through the application of AI.

1.4 Research methods

This study adopts a comprehensive methodological approach, combining literature review, quantitative analysis, empirical research, and questionnaire survey, with a two-step research design of "macro-level empirical identification – micro-level mechanism extension".

First, based on panel data from listed high-end equipment manufacturing enterprises in Shenzhen from 2010 to 2023, this study employed multiple regression models, mediating effect tests, endogeneity tests, and robustness tests to examine the impact of AI on enterprise innovation performance, industrial upgrading, and enterprise value and further identify the mediating effects of human capital structure and government support, thereby addressing the questions of "whether" and "to what extent" AI exerts its effects.

Then, building on the macro-level empirical findings, this study conducted a questionnaire survey among high-end equipment manufacturing enterprises in Shenzhen and employed structural equation modeling (SEM) to examine the relationships among disruptive innovation, dynamic capabilities, and innovation performance, with a particular focus on the role of internal capability mechanisms in shaping innovation performance, thereby addressing the question of "through which organizational mechanisms AI exerts its effects".

To clarify the alignment between the research questions and the research methods, we present the methodological approaches corresponding to each research question as follows.

(1) To address RQ1, "How can AI be embedded into key processes of high-end equipment manufacturing, such as R&D, production, and operational management, to facilitate enterprises' intelligent transformation?", this study primarily employed literature review and theoretical analysis. By systematically reviewing research on AI, intelligent manufacturing, high-end equipment manufacturing, and enterprise digital transformation, we summarized the application modes and value creation pathways of AI in key processes such as product design, production, quality control, logistics coordination, after-sales service, and business decision-making, thereby revealing the fundamental logic of how AI is embedded into core business processes and drives intelligent transformation.

(2) For RQ2, "In the high-end equipment manufacturing industry, how do internal innovation behaviors and capability structures within enterprises further influence innovation performance?", this study primarily employed a questionnaire survey and SEM. Using primary data collected from high-end equipment manufacturing enterprises in Shenzhen, we examined the impact of disruptive innovation on innovation performance and the mediating effect of dynamic capabilities therein, thereby revealing the micro-level mechanisms through which

internal innovation behaviors and capability structures shape innovation performance.

(3) To answer RQ3, “Through what mediating mechanisms does AI influence the innovation performance of high-end equipment manufacturing enterprises?”, this study conducted empirical research. At the macro level, panel data of listed enterprises were used to examine the mediating effects of human capital structure and government support in the relationship between AI and innovation performance. Specifically, human capital structure reflects enterprises’ internal resource allocation and capability optimization mechanisms, while government support represents the transmission pathway of external policy resources and institutional support in the process of AI adoption and technological upgrading. These two jointly constitute key mediating mechanisms through which AI is transformed from technological application into innovation performance.

(4) To address RQ4, “Does AI significantly enhance the innovation performance of high-end equipment manufacturing enterprises and further contribute to industrial upgrading and enterprise value?”, this study adopted quantitative and empirical analysis methods. By constructing regression models and extended effect models, we quantitatively evaluated the impact of AI on innovation performance, industrial upgrading, and enterprise value, and verified the reliability of the findings through endogeneity and robustness tests.

Based on the above research design, this study specifically adopts the following methods.

(1) Literature Review Method

This method involves collecting, identifying, and organizing relevant literature on the influence of AI technology, high-end equipment manufacturing, and intelligent manufacturing. By studying the literature, the research obtains useful insights into how AI technology impacts the development of high-end equipment manufacturing. Based on these insights, a relationship model between AI technology and high-end equipment manufacturing development is constructed, along with performance evaluation standards. This enables an objective and accurate assessment of the current status and effects of AI technology on the development of the high-end equipment manufacturing sector.

(2) Quantitative Analysis Method

This method analyzes publicly available and reliable data from the high-end equipment manufacturing industry. By examining relationships such as industry type, enterprise size, revenue, and profits, the research uncovers the internal relationship between AI technology and high-end equipment manufacturing. Additionally, it identifies patterns and trends in the industry.

(3) Empirical Research Method

This study selects data from Shenzhen's high-end equipment manufacturing enterprises

listed from 2010 to 2023 as the research sample. After excluding samples with missing or unreasonable data, empirical analysis is conducted using STATA 16.0. The research includes descriptive statistics, regression analysis, mediation effect testing, and heterogeneity analysis based on the data and models. To ensure the robustness of the conclusions, placebo tests, parallel trend tests, and propensity score matching (PSM) tests are employed. These methods further validate the study's hypotheses and enhance the credibility of the research findings.

(4) Questionnaire Survey Method

This study conducts a structured questionnaire survey using Shenzhen's high-end equipment manufacturing enterprises as the sample. The respondents include frontline technical staff as well as middle- and senior-level managers, ensuring coverage of different functional roles and managerial perspectives. The questionnaire is designed to capture indicators such as disruptive innovation, dynamic capabilities, innovation performance, and overall enterprise development. A seven-point Likert scale is employed to measure all items, which ensures the comparability, reliability, and scientific validity of the quantitative data collected.

1.5 Research content and technical route

Under the wave of the Fourth Industrial Revolution, how the high-end equipment manufacturing industry can seize opportunities, achieve rapid development, and reshape its core competitiveness is a crucial prerequisite for its sustained and robust growth. This study focuses on the impact of AI innovation on the development of the high-end equipment manufacturing industry. It examines the internal mechanisms by which AI technology affects the industry, providing directional guidance for the development of high-end equipment manufacturing enterprises. The research framework of this thesis is as follows:

Chapter 1: Introduction

This chapter provides an overview of the current state and developmental challenges facing the high-end equipment manufacturing industry. It explains the research background, outlines the research direction, significance, and the methods used in this study.

Chapter 2: Literature Review

Based on existing theoretical foundations regarding the impact of AI technology, high-end equipment manufacturing, and intelligent manufacturing, this chapter summarizes previous research findings and provides insights to support the current study. The theoretical foundation is based on the impacts of AI technology, intelligent manufacturing, and high-end equipment manufacturing. However, the applicability of these theories varies across specific industries.

Only by building on the research of flexible manufacturing and reverse customization can accurate conclusions be drawn regarding the theoretical direction and pathway of AI's impact on the development of the high-end equipment manufacturing industry.

Chapter 3: Relevant Concepts and Theoretical Foundations

To explore the impact of AI technology on the high-end equipment manufacturing industry in-depth, this chapter elaborates on key concepts and theoretical foundations related to the study. First, it defines "AI technology," its development history, key technologies, and current applications in the industrial sector. Then, it defines the "high-end equipment manufacturing industry," analyzing its characteristics, major fields, and current challenges. Building on this, the concept of "intelligent manufacturing" is introduced as a bridge connecting AI technology and high-end equipment manufacturing, and how intelligent manufacturing can facilitate the transformation and upgrading of the high-end equipment manufacturing industry is explored. Furthermore, this chapter introduces related theories such as technological innovation theory and industrial upgrading theory. Technological innovation theory helps understand how AI drives technological progress and product innovation in high-end equipment manufacturing, while industrial upgrading theory reveals the development direction and pathways for the high-end equipment manufacturing industry in the context of globalization.

Chapter 4: Empirical Study on Impact of AI Technology on the Development of the High-End Equipment Manufacturing Industry

This chapter conducts empirical tests on the direct effects, mediating mechanisms, and extended effects of AI technology on the innovation performance of high-end equipment manufacturing enterprises. It first proposes research hypotheses and constructs regression models; then, the sample, data sources, and variable measurement are described; finally, employing descriptive statistics, regression analysis, mediating effect tests, endogeneity tests, and robustness tests, it systematically examines the mechanisms through which AI influences innovation performance, industrial upgrading, and enterprise value.

Chapter 5: Extended Study: Impact of Disruptive Innovation and Dynamic Capabilities on Innovation Performance

Building on the macro-level empirical results in Chapter 4, this chapter further extends the analysis to internal enterprise mechanisms. Through a questionnaire survey and SEM, it examines the impact of disruptive innovation on innovation performance and the mediating effect of dynamic capabilities therein, thereby revealing the micro-level organizational mechanisms through which AI drives innovation performance.

Chapter 6: Conclusions and Recommendations

This chapter summarizes the overall findings of the study, highlights the theoretical contributions and practical implications, identifies the limitations of the research, and outlines directions for future studies.

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Chapter 2: Literature Review

2.1 Artificial intelligence (AI) and manufacturing

2.1.1 The development of AI and its impact

Artificial Intelligence (AI) is a branch of computer science that aims to simulate, expand, and enhance human intelligence capabilities. The concept of AI was first introduced by John McCarthy and others at the Dartmouth Conference in 1956, defined as "the science and engineering of making intelligent machines, especially intelligent computer programs." This definition marked the inception of AI research and initiated the era of machine intelligence (McCarthy, 1959). Early AI research focused predominantly on symbolism and logical reasoning, attempting to replicate human logical reasoning abilities through programming. Key works from this period include Shannon (1993) and Weaver (1986) on information theory, and Newell and Simon's Logic Theorist program, which established the fundamental theoretical framework for AI (Newell et al., 1957). Thesis organizes and presents several interpretations of the essence of AI from both domestic and international literature, as shown in Table 2.1.

Table 2.1 Representative figures and views on the essence of AI in domestic and international research

No.	Author	Viewpoint
1	McCarthy et al.	Machines should behave in ways that appear intelligent when observed by humans (McCarthy et al., 1955).
2	Vatutin	Refers to the automation of human intellectual activities such as learning, thinking, decision-making, and problem-solving (Vatutin, 1978).
3	Richardson, Craig	A new attempt on how to make computers think and imbue machines with intelligence (Richardson & Craig, 1985).
4	Akerkar	AI studies human intellectual behavior through the utilization of computer models (Akerkar, 2014).
5	Andrew	Considers AI as a discipline that studies how to enable machines to perform tasks that humans would do, and notes that the concept of AI evolves over time with the advancement of computer science (Andrew, 1991).
6	Seng and Mason	AI is an unprecedented innovative machine technology that performs human-like tasks through computational means (Seng & Mason, 2021).
7	Neumann	AI involves designing computer programs to enable machines to perform human-like intelligent tasks without human intervention during execution (Neumann, 2010).
8	Winston	Research and development in theories, methodologies, technologies, and application systems for simulating, extending, and expanding human intelligence constitute a new technical science (Winston, 1992).

No.	Author	Viewpoint
9	Aghion et al.	Understands AI as "the capability of machines to mimic human intelligent behavior" or "the capability of agents to achieve goals in a broad environment" (Aghion et al., 2017).
10	Korinek and Stiglitz	View AI as an automated process, believing that it is a long-term, sustained automation process. This automation involves using computers to implement human cognitive functions, i.e., "the effects produced by human cognitive thinking through computers" (Korinek & Stiglitz, 2018).

With advancements in computing power and data processing technology, AI has gradually shifted from symbolism to data-driven methods. In the 1980s, machine learning emerged as a significant branch of AI, garnering widespread attention. Machine learning employs statistical methods to enable computers to learn from and make predictions based on data, categorized into three types: supervised learning, unsupervised learning, and reinforcement learning (Sarker, 2021b). Supervised learning involves training and prediction using labeled data, with typical applications including image and speech recognition. Unsupervised learning, on the other hand, uses unlabeled data for clustering and dimensionality reduction, commonly applied in customer segmentation and recommendation systems (Hastie et al., 2005). Reinforcement learning optimizes strategies through a reward system, extensively used in gaming and autonomous driving. Entering the 21st century, deep learning has become a crucial subfield of machine learning, performing complex pattern recognition through multi-layer neural networks. Notable models in deep learning include Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which have achieved groundbreaking progress in fields like image processing, natural language processing, and speech recognition (Torfi & Fox, 2020). For instance, LeCun et al. (1998) introduced LeNet-5, achieving significant success in handwritten digit recognition, becoming a classic example of deep learning applications. The evolution of AI is not only reflected in the advancements of algorithms and models but also accompanied by exponential growth in computing resources and data scales. Krizhevsky et al. (2012) introduced AlexNet, which achieved breakthrough results in the ImageNet image classification competition, marking the practical era of deep learning. Since then, deep learning technologies have been widely applied to various real-world problems, such as Google's AlphaGo defeating top human players in Go, demonstrating AI's powerful capability in complex decision-making. In recent years, AI technologies have further integrated with emerging technologies like the Internet of Things (IoT), Big Data, and Cloud Computing, expanding their application scenarios. For example, Smart Manufacturing utilizes AI to optimize production processes and enhance efficiency; Smart Cities employ AI for traffic management, environmental monitoring, and public safety management, improving the level of intelligence in urban administration (Phuyal et al., 2020). The development of AI has evolved from symbolism to machine learning and then

to deep learning. Each developmental stage has propelled the progress of AI theory and applications, demonstrating immense potential and value in increasingly diverse fields. In the future, with continuous technological advancement and deeper interdisciplinary integration, AI will play a significant role in various fields, driving comprehensive development in society and the economy.

Humanity's creative innovations of production tools during the handicraft era led to the creation of machines. Technically, a machine represents an integration of simple tools, which collectively generate substantial productive capacity. The primary difference between tools and machines lies in the changed relationship between means of production and producers across different modes of production. During the handicraft era, producers used tools to manufacture goods, where the worker was the subject and held a dominant position; however, in the industrial era, the worker becomes an object, subordinate to the machine that dictates the production process.

As AI technologies continue to develop and their applications intensify, AI, as a representation of advanced productive forces, will objectively drive the progress of social productivity and even lead to changes in the relations of production. The development of AI technology will increasingly enhance machine intelligence, initially replacing some simple labor and ultimately substituting human intellectual labor, fully realizing the replacement of labor.

The use of AI technology in machines also reflects the intelligence and technologization of production itself, which will significantly propel the development of human science and technology. From this perspective, machines are the material crystallization of human intelligence. With the widespread application of AI technology, machines continuously improve. Consequently, workers, as subordinates to machines, require progressively lower levels of skills and knowledge in the production process, thereby lowering the threshold for workers, yet overall social production efficiency is steadily increasing. To some extent, the use of machines has driven the division of labor in society and the globalization of production, with AI technology intensifying this process. AI can make machines and production processes more intelligent, applying machines to replace production workers who were once part of a localized workforce, which, while increasing production efficiency, also intensifies social division of labor. This will cause some industries to gradually exit the historical stage, while others may emerge as necessary. Additionally, the intelligence of machines promotes the intensification of capital, and the continuous concentration of capital leads to an expansion of production scale. Intelligence could also enable products to venture into the global market, intensifying the trend

toward globalization of production and the economy.

The application of AI technology in manufacturing strengthens the job replacement effect of machines, constantly changing the boundary between simple and complex labor. What was previously considered complex labor may later be regarded as simple, leading to an increasing number of workers being replaced. AI technology represents advanced production technology, which, while causing the demise of some outdated industries, also gives rise to many new types of industries. For instance, the Fourth Industrial Revolution has liberated most humans from strenuous physical labor but has also resulted in job losses. With the continuous development and expansion of the tertiary sector, it has now become an important part of the national economic system.

In summary, AI can be categorized into three types: anthropomorphic behavior that simulates outcomes, anthropomorphic thinking that simulates brain operations, and unrestricted simulation known as generalized intelligence. These categories show a trend of increasing technical requirements, but the era of hyper-connectivity, boundless communication, and generalized intelligence will be the long-term direction for the development of AI. To date, there is no unified definition of AI. Based on the perspective of this study, it is believed that humans use AI technology to explore human intelligence greatly and create technological outcomes and intelligent machines, using technological innovation to enhance human wisdom and efficiency, thus solving problems more effectively. In this era of information explosion, traditional businesses face numerous challenges and pain points, including increased operating costs, consumer demand for higher services, and environmental management. At this stage, AI transitions from specialized to general AI, driven by the joint development and application of data and algorithms, pushing application scenarios continuously forward.

The development of AI technology has profoundly impacted various industries and social levels, affecting production efficiency, employment patterns, decision-making processes, and more. AI significantly enhances production efficiency through automation and intelligent technologies. For instance, in smart manufacturing, AI is used to optimize production lines and predict faults, effectively reducing downtime and production costs (Phuyal et al., 2020). In agriculture, AI technologies are employed for crop monitoring and pest control, increasing agricultural productivity and yield (Wolfert et al., 2017). These applications have substantially boosted productivity across industries, driving economic growth. While AI technology enhances production efficiency, it also raises concerns about employment. AI and automation may reduce job positions, particularly in repetitive and low-skilled work. However, AI also creates new job opportunities, such as data scientists and machine learning engineers, positions

that require high-level skills. Research by the McKinsey Global Institute indicates that by 2030, AI could contribute approximately $13 trillion to global economic activity (Lamarre et al., 2023). This economic growth will generate new employment opportunities and demands for professional transitions.

In sectors like healthcare and finance, AI assists decision-making processes through big data analytics and predictive models. AI plays a critical role in medical diagnostics and treatment recommendations, improving accuracy and treatment outcomes (Jacobs, 2021). For example, AI technologies can analyze a vast array of medical images, helping doctors detect diseases earlier and increasing treatment success rates. In finance, AI is used for risk management and market forecasting, helping financial institutions better handle market volatility and risks) (Davenport & Ronanki, 2018). These applications not only enhance the efficiency and accuracy of decisions but also reduce risks and costs. As AI technology becomes more widely adopted, societal and ethical issues have also garnered widespread attention. Challenges in data privacy, algorithmic bias, and transparency exist with AI. To ensure fairness and transparency in AI technology, it is crucial to develop appropriate regulations and policy frameworks to ensure that technological applications adhere to ethical standards (Cowls et al., 2019). For instance, the decision-making processes of AI algorithms need to be transparent to avoid discriminatory outcomes due to biases. Protecting data privacy is also vital, ensuring that user data is not misused. The development of AI technology requires workers to acquire new skills and knowledge, prompting transformations in the fields of education and training. Many countries and regions enhance the skill levels of their workforce to adapt to the AI-driven economic transformation by promoting STEM education and professional training (West & Allen, 2018). For example, educational institutions are adjusting curricula to include more AI-related content to cultivate the skilled talents needed for the future. This not only aids individual career development but also promotes the overall economic transformation and upgrading. Governments play a crucial role in advancing the development of AI. Through investing in fundamental research, crafting policies and regulations, and promoting international cooperation, governments facilitate the innovation and application of AI technology. For example, the "New Generation Artificial Intelligence Development Plan" released by the Chinese government clarifies strategic goals and implementation paths for AI development. This policy support has ensured the rapid advancement of AI technology, driving the intelligent transformation of various industries.

The development of AI technology has profoundly impacted various industries and social levels, driving improvements in production efficiency, changes in employment patterns,

optimization of decision-making processes, and addressing social and ethical issues. As AI technology continues to evolve, its future impact will be even more profound and widespread.

2.1.2 Applications of core AI technologies in manufacturing

In recent years, AI technologies have made significant progress, particularly in fields such as machine learning, deep learning, computer vision, natural language processing, generative adversarial networks, and reinforcement learning. These technologies have been widely applied in intelligent manufacturing, healthcare, finance, and other areas.

Machine learning and deep learning serve as foundational technologies for AI. Machine learning utilizes algorithms to learn and make predictions from data and is extensively used in image recognition, speech recognition, and natural language processing (Sarker, 2021a). Deep learning, a method that mimics the way humans acquire certain types of knowledge, is essentially an automated predictive analysis method. While traditional machine learning algorithms are linear, deep learning algorithms are stacked in an increasingly abstract and complex hierarchical structure. Programs using deep learning undergo a similar process, where each algorithm in the hierarchy applies non-linear transformations to its inputs and uses what it has learned to create a statistical model as output. This iterative process continues until the output reaches an acceptable level of accuracy, with the data passing through multiple processing layers that derive deep insights from the labels. Deep learning, through multi-layer neural networks, has made breakthroughs in complex pattern recognition, especially in image and speech recognition (LeCun et al., 2015). For example, convolutional neural networks (CNNs) are used in medical imaging to detect diseases and enhance diagnostic accuracy (Y. Chen et al., 2020). In intelligent manufacturing, AI technologies are employed to optimize production lines and perform fault prediction, effectively reducing downtime and production costs (Phuyal et al., 2020).

Computer vision is a technology designed to enable computers to understand and process visual information and is extensively applied in autonomous driving, medical image analysis, and industrial quality inspection. Computer vision uses one or more cameras, analog-to-digital conversion (ADC), and digital signal processing (DSP), with the generated data sent to a computer or robot controller. The complexity of computer vision is comparable to speech recognition. While the human eye is sensitive to electromagnetic wavelengths between 390 to 770 nanometers, cameras can detect a broader range of wavelengths, including infrared (IR), ultraviolet (UV), or X-ray wavelengths. Binocular (stereoscopic) machine vision requires computers with advanced processors. This depth perception involves high-resolution cameras,

substantial random-access memory (RAM), and AI programming. It is used in various applications, from signature recognition to medical image analysis, focusing on machine-based image processing. Computer vision, often confused with machine vision, automates object detection and classification through image processing and pattern recognition, enhancing the automation level of production lines (Krizhevsky et al., 2012). For instance, in intelligent manufacturing, computer vision is employed for product quality inspection and automated assembly, significantly improving production efficiency and product quality (L. Yang & Liu, 2020).

Natural Language Processing (NLP) aims to facilitate natural interaction between computers and human language, finding applications in voice assistants, translation systems, and text analysis. NLP enables computer programs to understand human language. Developing NLP applications is challenging because computers traditionally require highly structured programming languages or limited clear speech commands for interaction. However, human speech is often imprecise and ambiguous, with structures dependent on complex variables like slang, regional dialects, and social context. Most NLP research focuses on search, particularly enterprise search. Machines interpret key elements of human language sentences that may correspond to specific features in datasets, returning answers. NLP technologies enhance human-computer interaction convenience in voice assistants like Siri and Alexa by understanding and responding to voice commands (Hirschberg & Manning, 2015). In intelligent manufacturing, NLP is used to analyze and process vast amounts of text data, such as production reports and customer feedback, to optimize production processes and improve customer satisfaction (Radziwill & Benton, 2017).

Generative Adversarial Networks (GANs) are deep learning models used for generating new data. GANs operate through adversarial training between two neural networks—a generator and a discriminator—to produce images that closely resemble real ones (Goodfellow et al., 2014). The generator creates images from noise, while the discriminator attempts to differentiate between generated and real images. Through this adversarial process, the generator eventually produces highly realistic images (Sabuhi et al., 2021). In manufacturing, GANs are used to simulate and optimize production processes, reducing experimental costs and time. By generating virtual samples, enterprises can minimize the production of physical prototypes, enhancing research and development efficiency.

Reinforcement Learning (RL) is a machine learning method that learns optimal strategies through interaction with the environment. It optimizes decision-making processes through trial-and-error and reward mechanisms (Sutton & Barto, 1998). RL is widely applied in game AI,

robotic control, and autonomous driving. For instance, AlphaGo employed RL techniques to defeat top human players in Go (Silver et al., 2016). In intelligent manufacturing, RL is used to optimize production line scheduling and robotic path planning, improving production efficiency and flexibility by continually adjusting and optimizing operational strategies (Paturi & Cheruku, 2021).

Edge AI refers to AI technologies running on edge devices rather than relying on cloud computing. It reduces latency and enhances data processing efficiency by handling data on local devices (W. Shi et al., 2016). Edge AI has extensive applications in Internet of Things (IoT) devices, smart homes, and industrial automation. Particularly in intelligent manufacturing, Edge AI technologies are used for real-time monitoring and optimization of production equipment, enhancing the responsiveness and reliability of production lines (Satyanarayanan, 2017). By processing data locally, Edge AI reduces data transmission time and cloud processing loads, improving the overall efficiency and security of the system.

Core AI technologies play a crucial role in sectors such as intelligent manufacturing, healthcare, and finance. These technologies not only improve production efficiency and product quality but also drive the intelligent transformation and upgrading of various industries. As AI technology continues to advance, its applications will become more widespread and penetrate deeper, continuing to have a profound impact on various sectors. AI technology applications are primarily concentrated in specific areas, fundamentally based on machine learning to achieve capabilities in knowledge representation, speech-to-text conversion, natural language processing, predictive systems, local search, expert systems, audio signal processing, computer vision, and more. These are applied in collaborative robots, intelligent agents, biometric face and gesture recognition, smart products, intelligent automation, recommendation systems, as well as voice, text, and video recognition, image analysis, and personalized applications. Specific application areas include autonomous driving, spam filtering, voice recognition, logistics planning, autonomous planning and scheduling, machine translation, and robotics technology, among others. The details of AI technology and applications are illustrated in Figure 2.1.

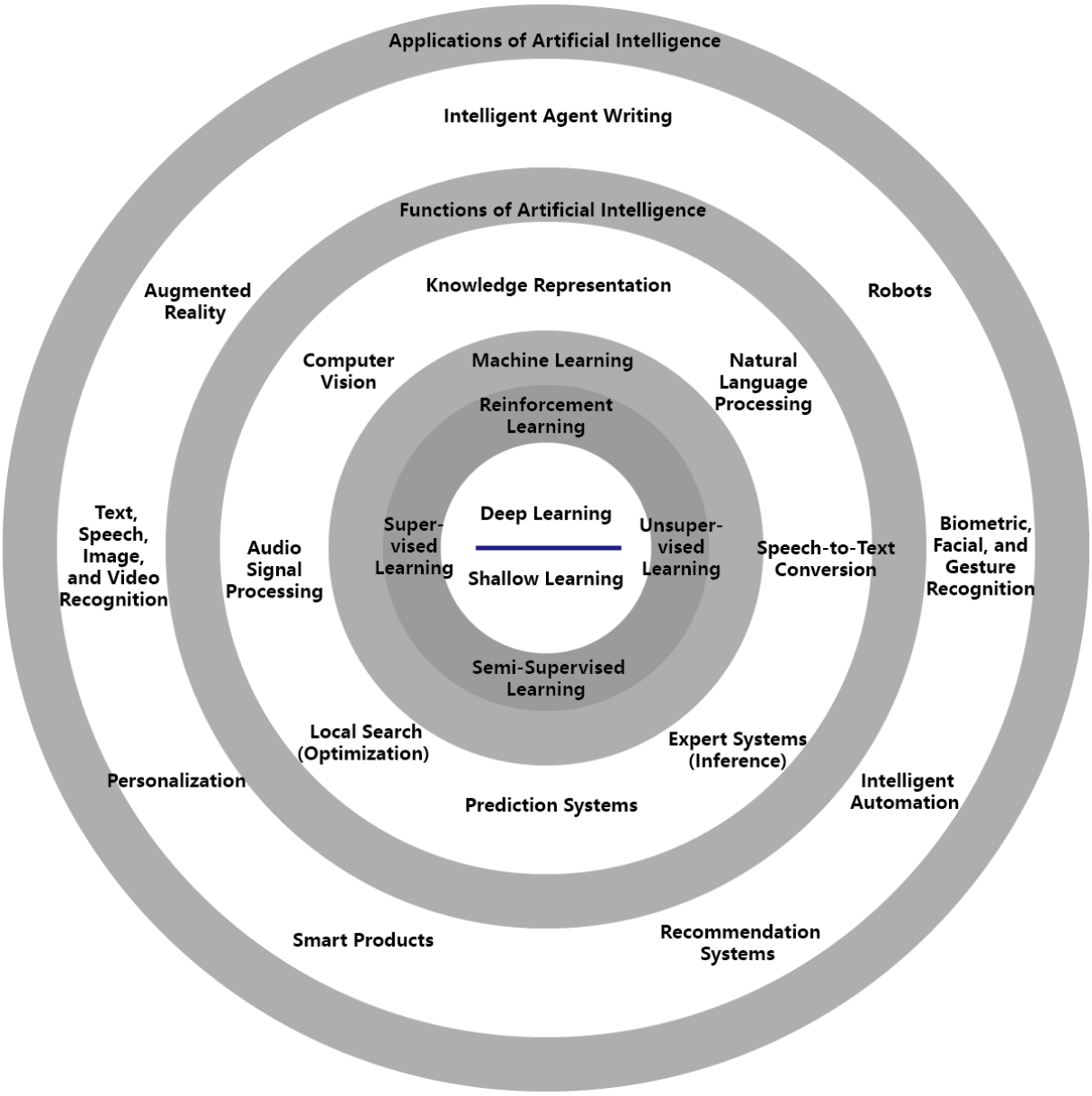


Figure 2.1 A visual representation of the status of AI technology and its applications

In China, the development of AI technology is mainly focused on three levels: foundational research, technological development, and applications (see Table 2.2). Foundational research focuses on cloud platforms, chips, data, and visual sensors. Technological advancements are mainly in computer vision, voice and natural language processing, and machine learning. Application areas are primarily in manufacturing, transportation, security, healthcare, education, finance, and new retail sectors. This text specifically explores the role and mechanism of AI technology in high-end equipment manufacturing.

Table 2.2 Summary of domestic and international perspectives on intelligent manufacturing

Category	Representative Scholar/Institution	Viewpoint
International	Smart Manufacturing Leadership Coalition (SMLC) (2009)	Defined Smart Process Manufacturing as an integrated, knowledge-based, model-using enterprise where all operations are explicit and are conducted based on optimal information and a broad array of performance metrics to execute predictively.
	SMLC (2011)	Defined intelligent manufacturing as manufacturing that enables the enhanced application of Advanced Intelligent Systems (AIS), dynamic real-time response to product demands, and real-time optimization of the manufacturing process and supply chain network.
	General Electric (GE) (2012)	Merged the outcomes of the industrial revolution, such as machinery, units, physical networks, with intelligent devices, intelligent networks, and intelligent decisions from the Internet revolution, terming it the “Industrial Internet.” Proposed that the concept of the "Industrial Internet" is essentially the same as intelligent manufacturing and can be mutually referenced.
	German Industry 4.0 Group (2013)	Asserted that the essence of Industry 4.0 includes the integrated application of Cyber-Physical Systems (CPS) in manufacturing and logistics industries, as well as the application of the Internet of Things and service technologies in industrial production processes, which will impact business models, value creation, and work organization.
	Kusiak (2018)	Understood intelligent manufacturing as the integration of current and future manufacturing assets with sensors, computational platforms, communication technologies, data-intensive modeling, control, simulation, and predictive engineering, utilizing technologies like Networked Physical Systems, Internet of Things, cloud computing, service-oriented computing, AI, and data science.
Domestic	Twelfth Five-Year Plan for the Development of Intelligent Manufacturing Technology (2014)	Defined intelligent manufacturing as information manufacturing under the condition of ubiquitous sensing throughout the product and production lifecycle. Intelligent manufacturing is the deep integration of information technology and intelligent technology, achieved through intelligent perception, human-machine interaction, and intelligent decision-making and execution technologies, encompassing processes including design and manufacturing.
	2015 Action Plan for Intelligent Manufacturing Pilot Demonstration	Defined intelligent manufacturing as advanced manufacturing processes, systems, and models based on new-generation information technology, covering the entire product lifecycle, with capabilities for deep self-awareness, intelligent optimization, precise control, and self-execution.

Category	Representative Scholar/Institution	Viewpoint
	National Intelligent Manufacturing Standard System Construction Guide (2015 Edition)	Explained intelligent manufacturing from three dimensions: lifecycle, system level, and intelligent functionality. The standard system for intelligent manufacturing is composed of basic general standards, key technical standards, and key industry standards.
	Intelligent Manufacturing Development Plan (2016-2020)	Pointed out that intelligent manufacturing is established on the basis of the integration of a new generation of information and communication technology and advanced manufacturing technology, and covers activities such as design, production, management, and service, with functionalities like self-awareness, self-learning, self-decision, self-execution, and self-adaptation.
	Lu (2010)	Stated that intelligent manufacturing is an integrated intelligent system consisting of human experts and intelligent machines that collaboratively perform intelligent activities such as analysis, judgment, and decision-making in the manufacturing process.
	An (2016)	Pointed out that intelligent manufacturing not only refers to intelligent manufacturing equipment but also includes the intelligence of products, equipment, production methods, management, and services.
	Huang (2016)	Described intelligent manufacturing as the integration of new-generation information technology like big data and IoT with manufacturing technology. This allows the system to autonomously adapt to changes in the manufacturing environment, achieving optimized objectives throughout the entire lifecycle from product design to recycling, including efficient, high-quality, green, networked, and personalized manufacturing, as well as intelligent production, intelligent products, and intelligent services.

Source: Compiled from Public Information

In summary, from the definitions of intelligent manufacturing both domestically and internationally, it is evident that from a technological perspective, emphasis is placed on the integration of AI or new-generation information technologies like big data and the Internet of Things with the manufacturing industry. From a process perspective, intelligent manufacturing is highlighted as encompassing the entire industry chain and life cycle, including raw materials, design, production, logistics, sales, and recycling. From an objective standpoint, the goals are to maximize productivity, shorten manufacturing cycles, reduce energy consumption, achieve networked real-time optimized manufacturing, and enhance product quality. Thus, it can be concluded that intelligent manufacturing is currently defined mainly from a technological viewpoint, while its relationship with the rapidly evolving new industrial revolution has not been extensively analyzed.

Internationally, scholars' research on intelligent manufacturing mostly revolves around

intelligent design, intelligent management, intelligent production, and intelligent services. From the perspective of intelligent design, X. Xu (2009) suggested integrating existing design databases and computer-aided design automation technologies with the product research and development of manufacturing enterprises. This allows information technology to be fully utilized during the enterprise design stage, aiding in the realization of intelligent design processes in manufacturing enterprises. Lu et al. (2020) emphasized the importance of digitalization in manufacturing enterprises during the design process. The design process in manufacturing enterprises is carried out using computer-aided equipment and machines, while digital devices monitor and provide early warnings about the design processes, thus supporting the development towards intelligent design. In the context of industrial intelligence, the flexibility of enterprises becomes notably significant; the flexibility of manufacturing enterprises is closely related to the environments they operate in and their design processes (Bi et al., 2014). Possik et al. (2022) used system assessment methods to simulate and analyze the interrelationships among production layout, production scheduling, and job assignments in manufacturing enterprises. They proposed that the system design goals of discrete manufacturing enterprises are to enhance production flexibility through improved design levels, and noted that a fundamental framework of intelligent manufacturing involves human-machine collaboration. Alexopoulos et al. (2020) demonstrated that the implementation of Digital Twins (DT), integrating cyberspace and physical space, can contribute to intelligent manufacturing, and that AI applications based on machine learning (ML) are considered among the most promising technologies in the manufacturing sector.

From the perspective of intelligent management, researchers have explored how AI technologies impact the manufacturing sector, focusing on aspects like the supply chain, internal and external environments, and the use and maintenance of machinery. Schuh et al. (2014) analyzed how collaborative frameworks that emphasize effective communication, collaborative cooperation, and dynamic coordination can facilitate the intelligent development of manufacturing enterprises. Effective communication involves sharing production information among all links, serving as the foundation for collaborative cooperation and dynamic coordination. Collaborative cooperation requires employees across departments to adhere to common regulations and engage in authorized cooperation across departmental boundaries, which can bring significant enterprise benefits. Dynamic coordination refers to the capability of enterprise managers to allocate resources and tasks needed for various production activities based on available information resources, allowing flexible completion of production tasks and maximizing efficiency.

Cagnin and Könnölä (2014) analyzed management methods of manufacturing enterprises during the implementation of intelligent manufacturing in some more developed regions, summarizing the crucial role of human resources in intelligent manufacturing and stressing the importance of focusing on human resources during the intelligent transformation of manufacturing. Monostori et al. (2016) discussed the mechanisms of Industry 4.0 in areas such as scheduled management, product R&D, product delivery and recovery, and production debugging. They emphasized that integrating the physical and cyber systems—including enterprise products and human resources—facilitates automatic exchange of information and autonomous decision-making through cloud computing and big data, thus enabling dynamic management of operations and enhancing resource allocation and production efficiency.

From an intelligent production perspective, Frankowiak et al. (2005) proposed integrating manufacturing technologies and information technologies, such as sensors, numerical control systems, and flexible systems, into the production process of manufacturing enterprises to facilitate a rapid and efficient transition to intelligent manufacturing. Dombrowski and Wagner (2014) focused on the psychological and capability aspects of manufacturing personnel, proposing that the goal of the fourth industrial revolution is to establish an environment of human-machine interaction and collaboration. By fully integrating machine equipment with humans, a collaborative physical information system can be formed, allowing manufacturing enterprises to achieve large-scale customized production. Ruiz et al. (2014) used empirical analysis to highlight the advantages of simulation models incorporating multi-agent systems in the production process, which can adapt simulation models to an intelligent production environment more effectively.

From the perspective of intelligent services, Tso et al. (2000) proposed enhancing the service capabilities and efficiency of manufacturing enterprises by integrating services with information technology using computers and other informational devices. Giret et al. (2016) analyzed service manufacturing systems from the aspects of standards, protocols, technology, and environment, developing a foundational framework for manufacturing enterprise system developers using the THOMAS platform and new methods. This framework, combined with intelligent systems, can enhance the service-oriented intelligence of manufacturing enterprises. Neal et al. (2019) emphasized that cyber-physical systems will be a focal point in intelligent service research. These systems not only enhance the efficiency of enterprise services but also enable accurate service predictions and risk prevention.

2.1.3 AI technology and industrial upgrading in manufacturing

The introduction of the intelligent manufacturing concept signifies the broad recognition and application of AI in industrial production. Comb (2010) proposed that digitizing the equipment manufacturing industry would significantly enhance the production efficiency of its products. Y. Liang and Liu (2013) noted that industrial robots have become indispensable in advanced manufacturing and are a critical indicator of a country's manufacturing prowess. As Western countries focus on "reindustrialization" to undergo strategic management and organizational transformation, high-end intelligent manufacturing, exemplified by industrial robots, is poised to become a primary competitive focus globally.

Miao (2014) analyzed the architectural framework of intelligent factories, suggesting that China should adopt the Industry 4.0 initiative, innovate boldly, and accelerate the transformation and upgrading of its equipment manufacturing industry. Pan et al. (2015) pointed out that the major issue for China's large but not strong manufacturing sector is the short lifespan of critical components and the production of non-competitive, low-added-value products, which challenges sustainable development. Promoting high-performance intelligent manufacturing is crucial for the healthy transformation of China’s manufacturing industry.

Schwab (2016) believes that enterprises can achieve intelligent development by applying smart technologies in business operations and production, which will increase R&D speed, shorten production cycles, and enhance profits. X. Wu (2016) argued that blending internet technologies with traditional manufacturing and adopting AI, big data, IoT, and other advanced technologies can integrate production factors with more useful resources, leading to an intelligent upgrade of industrial products.

J. Zhou (2018) stated that the new generation of intelligent manufacturing truly embodies manufacturing and will fundamentally lead and advance a new industrial revolution. J. Jiang and Dong (2018) suggested implementing intelligent transformations of equipment, building smart workshops and factories, and accelerating the cultivation of system integrators to achieve intelligent manufacturing engineering. Gong et al. (2019) discussed the intelligent manufacturing development plans of major industrial nations, analyzed the overall technological framework of smart factories, and introduced the practice of intelligent manufacturing in China.

Z. Liu and Zhang (2016) analyzed the internal and external effects of technological progress in the equipment manufacturing industry and empirically tested these effects, finding that both income and energy efficiency in the equipment manufacturing industry positively impact

technological levels bidirectionally, as does the quality of foreign investment introduced into the industry. N. He and Xia (2019) empirically determined that integration into the global value chain presents both "inhibiting effects" and "promoting effects" on technological progress in China's equipment manufacturing industry, showing a U-shaped relationship. J. Liu and Wang (2018) empirically verified that China's equipment manufacturing industry is trapped in a "low-end lock-in" dilemma, proposing that intelligent manufacturing is an essential pathway for the industry to ascend in the global value chain, and outlined its mechanisms. Y. Li (2019) moved the research on the relationship between industrial technological innovation and global value chain upgrading from unilateral impact to system coupling, identifying key factors influencing coupling evolution at different stages. C. Wang (2020) suggested that to maintain growth in the output value of intelligent products, new technological introductions and industry-academic-research cooperation should be balanced with external inputs from the government and the market. M. Li (2020) calculated the total factor productivity of Heilongjiang equipment manufacturing enterprises over different years and found through empirical analysis that the intelligent upgrading of the equipment manufacturing industry could promote technological progress and enhance productivity, proposing paths and strategies for the intelligent development of Heilongjiang’s equipment manufacturing industry.

2.1.4 AI technology and innovation performance in manufacturing

In the context of the new industrial revolution, AI is a prevailing trend in China's industrial development. From the earlier focus on informatization to the recent emphasis on digitalization, these are areas closely related to AI. Intelligence is the ultimate goal of informatization and digitalization and an inevitable trend in development. With deeper applications of AI, China's economy is expected to cultivate new growth points and dynamic energies for high-quality development (Ren & Li, 2019). Current research on the impact of AI on innovation performance in high-end manufacturing enterprises often explores both internal and external factors.

Several scholars believe that external factors such as government policies and legal frameworks can influence enterprise innovation. Y. Wang (2013) found that government subsidies could lead to a decline in innovation performance in state-owned enterprises, with these subsidies playing a negative moderating role in the relationship between R&D investment and innovation performance. Guo (2018), based on the characteristics of China's context, built a signaling mechanism model after analyzing the potential impacts of government grants on enterprise innovation. He proposed that innovation-related government grants would enhance enterprise innovation input and increase the proportion of substantial innovative outputs.

Additionally, factors like the market environment and technological environment also impact enterprise innovation. J. Zhang et al. (2014) focused on the relationship between market competition and innovation, and empirical analysis of enterprise data showed that frequent competitive activities stimulate stable growth in enterprise innovation capabilities. T. Zhong and Wang (2017) studied the impact of financial development on enterprise innovation, using multiple indicators to measure financial development. They found that the stock market had a more significant positive impact on high-quality invention patents than the banking sector.

Different internal factors have been proposed by scholars. W. Li and Yu (2015), based on data from China's industrial enterprise database, studied the impact of equity structure on enterprise innovation capability. They discovered that in private enterprises, the proportion of non-state ownership influences enterprise innovation, with both individual and legal person holdings promoting innovation capabilities in private enterprises. Enterprise size and age are also significant factors affecting innovation. Huergo and Jaumandreu (2004) found that newly established enterprises tend to have the highest enthusiasm for innovation, which tends to decrease as the enterprise ages. See and Coelli (2012) empirically analyzed data disclosed by listed enterprises and found that differences in asset size impact technological innovation efficiency. Additionally, an organization’s culture and technological capability also play roles in enterprise innovation. Hogan and Coote (2014), building on Schein's multi-layered organizational culture model, extended previous research and developed methods for assessing and managing specific elements of organizational culture. Their research identified innovation culture as key to sustaining and promoting innovative behaviors within organizations. However, the most critical factor is the structure of human capital. Kong et al. (2017) used data from Chinese listed enterprises to explore the impact of pay disparities on innovation output, finding that pay gaps significantly promoted enterprise innovation output. Y. Li and Wang (2022) discovered that salary reduction policies for executives in state-owned enterprises suppressed R&D investment in innovation for these enterprises. S. Liu et al. (2017), based on collected resume data and considering factors such as personnel mobility, constructed a social network of enterprise human capital. Their research showed that both human capital and social networks promote enterprise innovation performance.

2.2 AI and high-end equipment manufacturing in China

2.2.1 Technological innovation and China's high-end equipment manufacturing industry

In recent years, China's high-end equipment manufacturing industry has achieved significant development. According to data from the Ministry of Industry and Information Technology, in 2022, the added value of the high-end manufacturing sector increased by 7.4% year-over-year, while the equipment manufacturing sector grew by 5.6%. These figures highlight the significant role of high-end manufacturing in promoting the high-quality development of China's economy. Intelligent manufacturing is an essential component of the high-end equipment manufacturing industry. Shanghai, as the birthplace of China's high-end equipment manufacturing industry, has incorporated intelligent manufacturing into one of its six major advanced manufacturing clusters during the "14th Five-Year Plan" period (2021-2025). By 2022, the scale of the intelligent manufacturing equipment industry in Shanghai exceeded 100 billion RMB, making it one of China's largest export bases for intelligent manufacturing system integration solutions. The widespread application of intelligent manufacturing technologies not only enhances production efficiency but also reduces costs and improves the international competitiveness of China's manufacturing sector.

In international literature, from early on, scholars have investigated the impact of advanced manufacturing technology systems, automation technologies, and design technologies on the innovation capability of high-end manufacturing enterprises. Zairi (1992) suggested that the key components of advanced manufacturing technology systems, including computer-aided technologies, automation technologies, and design technologies, jointly promoted intelligent upgrading and efficiency improvement in manufacturing. da Rosa Cardoso et al. (2012) pointed out that the key to enhancing enterprises' financial performance lies in identifying and adjusting multidimensional internal factors in a timely manner, thereby accelerating the innovation process of advanced manufacturing technologies and ultimately improving overall competitiveness. Bülbül et al. (2013) investigated technological R&D investment strategies in the Turkish automotive industry and found that different investment approaches significantly affected enterprises' financial performance and scale, highlighting the importance of technological investment decisions for enterprise growth. Sainz (2015) emphasized that, to improve the quality of high-end equipment, managers must actively explore multiple technological upgrading paths, among which leveraging AI to promote automation and digital transformation constitutes an important strategy for enhancing efficiency and reducing

operational costs. Shang et al. (2020) further noted that, in pursuing customer satisfaction, high-end equipment manufacturing enterprises must not only respond flexibly to personalized demands but also continuously strengthen their technological R&D capabilities, as technological strength is closely related to both product quality and enterprises' agility to adapt to market changes.

In the Chinese literature, technological innovation has been one of the most extensively studied areas in research on high-end equipment manufacturing. B. Li and Zhou (2012) examined the mechanisms through which market innovation, institutional innovation, and technological innovation jointly influence innovation activities in aviation equipment manufacturing enterprises, revealing how these three drivers interact to shape the innovation process. W. Liu and Sun (2014) explored evaluation standards for technological and knowledge innovation, establishing a model to measure the coupling degree between these two types of innovation and validating it through case analysis. Y. Wang et al. (2022), through empirical analysis, found an inverted U-shaped relationship between innovation performance and R&D investment in China's high-end equipment manufacturing industry, indicating that technological choice and external technology do not directly determine innovation performance but instead have lagged moderating effects between R&D investment and innovation performance. Qiao (2016) suggested that China's high-end equipment manufacturing industry was at a critical stage of development and must effectively integrate technological innovation capability, cost control advantages, capital utilization efficiency, and locational advantages to strengthen core competitiveness. Lv (2018), based on an analysis of the development of high-end equipment manufacturing in Liaoning, identified bottlenecks in technological innovation and proposed innovation-driven development pathways. D. Fan and Du (2018), from an input–output perspective, analyzed the resource allocation efficiency of technological innovation in high-end equipment manufacturing, found significant differences across subsectors, and proposed countermeasures correspondingly.

In summary, existing studies consistently demonstrate that technological innovation is a key factor that both constrains and drives the development of high-end equipment manufacturing. AI, big data, and intelligent manufacturing technologies are becoming critical technological supports for improving R&D efficiency and enhancing innovation capability of enterprises. However, there is still a lack of systematic enterprise-level empirical research on how AI is embedded into the R&D systems of high-end equipment manufacturing enterprises and through which mechanisms it influences innovation performance.

2.2.2 Innovation input and output in high-end equipment manufacturing industry

Innovation input is a critical prerequisite for achieving technological progress and shaping competitive advantages in the high-end equipment manufacturing industry. Given its distinctive characteristics, including high R&D intensity, substantial capital investment, and high technological risk, innovation activities in this industry are highly dependent on R&D funding, human capital, technological platforms, and policy support. Existing studies typically examined innovation input in high-end equipment manufacturing enterprises from the perspectives of R&D intensity, human resource allocation, R&D subsidies, and policy incentives.

In international literature, Lotti and Santarelli (2001), using survey data from manufacturing enterprises in Germany and Italy, constructed regression models and identified technological innovation and R&D expenditure as key drivers of production efficiency. Nunes et al. (2012) found a prominent interaction between R&D intensity and enterprise performance in high-tech advanced equipment manufacturing industry: in enterprises with strong R&D capabilities, R&D investment was more likely to translate into performance gains, whereas in enterprises with weaker R&D capabilities, this transformation effect was weaker. These findings indicate that the effectiveness of innovation input depends not only on the scale of investment but also on enterprises' capability of absorbing and transforming technologies.

In the Chinese literature, Z. Wu et al. (2018) revealed significant relationships among R&D subsidies, R&D investment, and human resources: both R&D investment and government subsidies could enhance enterprises' innovation performance, with R&D investment serving as a key bridge linking subsidies to innovation performance; moreover, highly educated executives and highly skilled R&D personnel were found to have a moderating effect in this process by enhancing the relationship. C. Wang et al. (2017), established an organizational innovation measurement index system for high-end equipment manufacturing enterprises and found that factors such as organizational structure adaptability, human resource quality and allocation, and environmental dynamism significantly influenced enterprises' innovation capabilities. These findings suggest that in high-end equipment manufacturing enterprises, innovation input is not merely a matter of capital investment but is also closely related to talent structure, organizational mechanisms, and institutional environments.

With the development of AI technologies, some scholars have made efforts to examine the impact of digital and intelligent technologies on the structure of innovation input. On the one hand, AI increases enterprises' demand for highly skilled R&D personnel, algorithm experts, data platforms, and digital infrastructure, shifting innovation input from traditional R&D

expenditure toward a composite structure of "capital + talent + data + system platforms". On the other hand, through AI-assisted R&D, intelligent analysis, simulation optimization, and predictive decision-making, AI can improve the efficiency of innovation input, reducing trial-and-error costs. This suggests that AI not only affects the scale of innovation input but also reshapes its structure and allocation.

Existing studies have extensively demonstrated the importance of R&D investment, human resources, and policy support for innovation input in high-end equipment manufacturing. However, with the application of AI restructures innovation input and further affects enterprises' innovation performance remains to be further explored.

2.2.3 Influencing factors and development pathways of high-end equipment manufacturing industry

Existing studies on the influencing factors and development pathways of the high-end equipment manufacturing industry primarily analyzed policy support, market orientation, competitive intelligence, digital innovation ecosystems, technological capability, organizational resources, and external environmental factors.

In terms of influencing factors, international studies have indicated that technological innovation and R&D expenditure are key drivers of production efficiency and performance in high-end equipment manufacturing enterprises (Lotti & Santarelli, 2001; Nunes et al., 2012). Nsiah (2012) identified several critical drivers of manufacturing export performance, including industrial unionization, enterprise growth potential, geographic location, environmental regulations, and legal systems. Yousuf and Siddiqui (2019) further found that export tax rebate policies exhibited regional and market heterogeneity in their effects on high-end equipment manufacturing enterprises. In the Chinese literature, C. Wang et al. (2017) demonstrated that organizational structure adaptability, human resource quality, and environmental dynamism significantly influenced the innovation capability of high-end equipment manufacturing enterprises. Z. Wu et al. (2018) further emphasized that R&D subsidies, R&D investment, and highly skilled management teams played important roles in enhancing enterprises' innovation capability.

In terms of development path, Zheng and Luo (2023) emphasized that to achieve high-quality development, high-end equipment manufacturing enterprises should evolve through self-transformation, the establishment of technology transfer centers, development of independent innovation markets, and collaborative cooperation between enterprises. G. Zhou et al. (2020) highlighted that high-end equipment manufacturers must pay attention to

competitive intelligence, improving their core competitiveness by enhancing technological innovation capabilities. L. Chen et al. (2019) studied the development path of Shanghai's high-end manufacturing industry in the context of the US-China trade war, suggesting that in an uncertain international environment, Shanghai's high-end manufacturing industry should enhance its competitiveness through technological innovation and by leveraging policy support. Y. Liu and Li (2025) examined the impact of digital innovation ecosystems on the intelligent development of high-end equipment manufacturing. They found that constructing a "core-periphery" digital innovation ecosystems could significantly improve enterprises' level of intelligence. Lv (2018) used fuzzy rough set theory and multiple weighting methods to establish a comprehensive evaluation index system for assessing the sustainable innovation capability of high-end equipment manufacturing enterprises. Y. Li et al. (2018) proposed a competitiveness and industry innovation evaluation method tailored to the characteristics of high-end equipment manufacturing. and comprehensively evaluated the impact of enterprises' technical innovation capability, market demand, and policy environment on enterprise development.

In addition, some scholars have made efforts to examine the development of the high-end equipment manufacturing industry from the perspectives of new technology applications, intelligent algorithms, and digital technologies. Employing neural networks and Tobit panel regression models, Alizadeh et al. (2018) found that technological innovation played a critical role in enhancing enterprises' competitiveness. Park et al. (2020) indicated that data-driven technological innovation and integrated neural networks could significantly enhance production efficiency and product quality. Petrović et al. (2019), using linear regression and neural network models, assessed the progress of high-end equipment manufacturing in adopting new technologies and concluded that the application of advanced technology could significantly increase productivity and market responsiveness. Dungore and Patel (2021) highlighted that high-end equipment manufacturing enterprises should actively adopt AI to maintain a sustainable competitive advantage. Brandt et al. (2008) indicated that the development of China's high-end equipment manufacturing industry must rely on national strategic support, and that combining technological innovation with industrial policies could enable enterprises to achieve sustainable growth. Guan et al. (2018) studied the current status and development trends of Shenyang's high-end equipment manufacturing industry and identified government support and enterprise innovation as key driving forces. Sun and Yuan (2015) investigated the bottlenecks for the development of high-end equipment manufacturing in northern Chinese cities, as well as the corresponding countermeasures, suggesting that addressing problems such as capital shortages and technological backwardness is the essential to enhancing

competitiveness. W. Zhang et al. (2024) emphasized that the key to revitalizing the high-end equipment manufacturing industry lies in innovation, and that industrial upgrading could be achieved through technological breakthroughs. Yuan and Lv (2011) proposed that the industry's overall competitiveness could be improved through industrial clusters and technology alliances, which represents an important pathway for the development of the high-end equipment manufacturing industry.

In summary, existing studies indicate that technological innovation is one of the key factors affecting the development of the high-end equipment manufacturing industry. In addition, the development capability of enterprises, government policies, organizational structure and resources, talent resources, and external environment are also significant influencing factors. With the increasing application of AI technology, the academic and industrial communities have begun to focus on the impact of AI on the development of high-end equipment manufacturing. However, existing studies primarily focused on general manufacturing contexts, macro-level policy analysis, or case-specific analyses, whereas limited attention has been paid to how AI influences innovation performance at the enterprise level and how it further affects industrial upgrading and enterprise value through innovation performance. Hence, this study, taking enterprises in the high-end equipment manufacturing industry in Shenzhen as a sample, attempts to explore the effects and influence pathways AI technology on their development and performance, aiming to contribute to the high-quality development of high-end equipment manufacturing in Shenzhen and to provide references for other high-tech-oriented cities.

2.3 Disruptive innovation and innovation performance in high-end equipment manufacturing

2.3.1 Disruptive innovation and incremental innovation

Christensen (1997) pointed out that *disruptive innovation* and *incremental innovation* differ substantially in nature. Disruptive innovation brings revolutionary change, provides strong competitiveness to mainstream markets, and lays the foundation for long-term competitive advantage. Since the concept was introduced, scholars have analyzed and defined disruptive innovation from various perspectives. Thomond et al. (2003), from a business model perspective, argued that disruptive innovation stems from innovation in business models during market competition and strategy formulation. Through reconfiguring business logic—such as converting paid services to free models or shifting sales channels from offline to online—

enterprises can address customer pain points and even reshape consumer habits. From a product perspective, Kotelnikov (2023) proposed that disruptive innovation involves creating entirely new products or achieving significant improvements in product performance through technological transformation and product modification. Overall, research on disruptive innovation generally falls into two perspectives: technology/product and industry/market.

McDermott and O'Connor (2002) suggested that incremental innovation typically originates from incumbent and stable enterprises, where market conditions and technologies are relatively certain, while disruptive innovation involves high investment costs and greater market risks. Hall and Martin (2005) emphasized that disruptive innovation undermines the rules and vested interests of traditional industries and incumbents, thereby creating instability. Schmidt and Druehl (2008) found that the two forms of innovation differ in technological application, diffusion, and market expansion. Veryzer Jr (1998) argued that disruptive innovation diverges from incremental innovation in product development, dominant design, work processes, and resource input. Corso and Pellegrini (2007) further highlighted that disruptive innovation demands creativity, risk-taking, and exploratory capabilities, while incremental innovation relies more on continuous R&D and foundational resources. Similarly, Peng and Yang (2009) stressed that the two types of innovation differ substantially in terms of resource assets and foundational capabilities required by enterprises.

2.3.2 Disruptive innovation and dynamic capabilities

In the late 1990s, Teece et al. (1997) integrated the evolutionary economic model of the enterprise with the resource-based view, forming the strategic framework of *dynamic capabilities*. Building on this, Chinese scholars such as Jiao and Wei (2008) developed a four-dimensional structure of dynamic capabilities, including environmental sensing, organizational renewal, technological flexibility, and organizational flexibility. Xiao et al. (2016) proposed a conceptual model of co-evolutionary dynamic capabilities between enterprises and consumers, arguing that enterprises must adaptively evolve with consumers in order to guide consumer behavior, respond to consumption changes, and adjust plans in real time. K. Shen et al. (2012), from a dynamic alliance perspective, reviewed the background, evolution, and research progress of dynamic capability theory, concluding that studies should focus on capability formation, development, and its impact on performance, thereby enriching strategic management practices.

From these studies, it is evident that dynamic capabilities have been understood from two main perspectives: (a) the ability to sense and adapt to external environments, and (b) the ability

to mobilize and configure internal resources to align with strategic objectives. Accordingly, definitions and measurement approaches differ depending on the perspective. Integrating prior research, Barreto (2010) suggested that dynamic capabilities are best conceptualized as a multidimensional construct. Following this view, and drawing from the works of Teece, Pisano, Jiao, Feng, and Gao, the present study classifies dynamic capabilities into three dimensions: opportunity sensing, resource integration, and organizational reconfiguration.

2.3.3 Disruptive innovation and innovation performance

K. Chen and Yu (2009) argued that disruptive innovation is one of the most critical means for weaker enterprises to surpass powerful incumbents. J. Shi et al. (2017) constructed a model examining the relationship between disruptive innovation behaviors and market performance during the start-up and growth stages. They highlighted that innovative channels and consumer education are key mechanisms through which disruptive innovation reshapes consumer preferences and ultimately enhances enterprise performance.

Although research on the categorization of disruptive innovation remains limited, many studies have examined innovation classification more broadly from technology/product and market/business model perspectives. Garcia and Calantone (2002) suggested that innovation can arise from both technological and market changes. Benner and Tushman (2003), focusing on technology, classified innovation as incremental or radical; from a market perspective, they distinguished incremental from disruptive innovation. Govindarajan et al. (2011) further emphasized that innovation fundamentally rests on two bases—technology and market—within which radical and disruptive innovations represent the most distinctive forms.

In summary, disruptive innovation serves as a key mechanism linking technological progress and business model transformation, influencing innovation performance in several ways: shifting technological trajectories (e.g., from analog to digital, hardware to algorithms), reshaping product value propositions and customer relationships, stimulating exploratory learning and cross-boundary integration, and breaking path dependence to pursue high-performance outcomes under uncertainty. However, there is still no consensus on the classification and measurement of disruptive innovation. Most existing studies focus primarily on technological aspects, with less attention paid to the synergistic effects of business model innovation on performance. To address this gap, the present study adopts a dual-dimensional framework, distinguishing **product disruptive innovation** and **business-model disruptive innovation**, to more accurately capture the mechanisms through which disruptive innovation influences innovation performance.

2.4 Review on AI technology and high-end equipment manufacturing

This section critically evaluates existing research on AI and its influence on the high-end equipment manufacturing sector, aiming to identify the theoretical foundations and empirical gaps that underpin this study's research framework.

The influence of AI technology on the development of the manufacturing industry has received considerable attention in recent years. Numerous studies demonstrate AI's significant role in optimizing production processes, improving product quality, reducing costs, and shortening production cycles. For instance, Y. Chen et al. (2020) examined AI applications in smart manufacturing, noting substantial improvements in efficiency and quality. Similarly, J. Liu et al. (2020) provided empirical evidence from the Chinese manufacturing sector, showing that AI adoption significantly enhances total factor productivity. These findings establish a foundational understanding of AI as a productivity driver within the manufacturing domain.

Existing literature also investigates the characteristics, sub-sectors, and developmental impacts of high-end equipment manufacturing. As a leading sector characterized by technological complexity, innovation intensity, and high value-added output, it serves as the cornerstone of industrial modernization. C. H. Wang et al. (2015) emphasized that the growth of high-end equipment manufacturing relies heavily on continuous technological innovation and R&D investment. However, most current research remains at the macro level, focusing on policy and industry-wide effects, with limited attention to how AI technologies are applied and operationalized at the enterprise level. This limitation restricts the understanding of AI's micro-level mechanisms in shaping enterprise performance and innovation behavior.

Although some scholars have begun to explore the intersection of AI and high-end equipment manufacturing, research in this area remains fragmented and nascent. Damioli et al. (2021), for example, found that AI adoption enhances labor productivity, yet their work mainly emphasizes technological aspects while neglecting organizational transformation, managerial decision-making, and market expansion. Furthermore, most existing studies rely on qualitative methods or small-sample case analyses, leading to a lack of generalizable empirical evidence. As a result, the specific mechanisms through which AI affects enterprise competitiveness, innovation performance, and industrial upgrading remain insufficiently understood (X. Zhang et al., 2022).

Overall, the current literature exhibits three key limitations. First, the research perspective is relatively narrow, often focusing on single dimensions—either technological or managerial—rather than adopting a multi-level analytical framework. Second, there is a methodological gap:

the predominance of qualitative case studies limits the robustness and scalability of findings. Third, the mechanisms linking AI application to innovation performance and industrial upgrading are still underdeveloped, leaving the "black box" of how AI reshapes enterprise behavior, resource configuration, and value creation largely unexplored (Bahoo et al., 2023).

Future studies should therefore move toward multi-dimensional, data-driven investigations that integrate technological, organizational, and institutional perspectives. Combining qualitative insights with large-scale quantitative data would enable a more holistic understanding of AI's impact. Additionally, greater emphasis should be placed on sectoral heterogeneity to identify common and distinct patterns across different types of high-end equipment manufacturing, thereby informing policy formulation and enterprise strategy (L. Yang & Liu, 2020).

Beyond the AI literature, research on disruptive innovation offers complementary insights into the mechanisms of industrial transformation. Scholars have distinguished disruptive innovation from incremental innovation in terms of risk, required capabilities, and market effects (Christensen et al., 2018). While prior studies have examined the link between technological innovation and performance outcomes, they often isolate the technological dimension, overlooking the mediating role of organizational capabilities such as dynamic capabilities (Teece, 2018). Moreover, empirical analyses tend to treat product and business model innovation separately, failing to capture their combined effects within AI-enabled manufacturing contexts.

Building upon these research streams, the present study develops an integrative perspective that situates AI application within the framework of dynamic capabilities and disruptive innovation. Specifically, it investigates how AI-driven disruptive innovation—both product-oriented and business-model–oriented—affects enterprise-level innovation performance through the mediating role of dynamic capabilities. This integrative approach addresses the existing theoretical and empirical gaps, providing a foundation for the research model and hypothesis development presented in Chapter 3 and Chapter 4.

Chapter 3: Relevant Concepts and Theoretical Foundations

3.1 Economic theories of artificial intelligence (AI)

The economic study of artificial intelligence (AI) originated with Hanson (2001), who introduced the concept of machine intelligence into the neoclassical economic growth model to explore the impacts of AI technology on the macroeconomy. Hanson defined AI as machinery that can effectively substitute for human labor and analyzed its role in economic growth within his theoretical framework. Graetz and Michaels (2015) analyzed the positive effects of AI on labor productivity and economic growth using panel data from 17 countries over 15 years, further validating Hanson's theoretical implications. Their research demonstrated that the introduction of AI technology significantly enhanced labor productivity and fostered sustained economic growth. This empirical analysis strongly supported Hanson's theory and further expanded the application of AI in economics.

Nordhaus (2015) proposed, based on singularity theory, that the economy would experience explosive growth once AI development surpassed a certain threshold. He noted that as a factor of production, when AI performance reaches a certain level, it would lead to nonlinear economic growth. This perspective emphasizes the significant potential of AI to drive economic growth. This theoretical framework provides a new perspective for understanding the potential impacts of AI on future economic development. Acemoglu and Restrepo (2018) expanded Hanson's research by defining AI as machinery that effectively substitutes human labor and explored its effects on macroeconomic fluctuations. Their studies showed that AI technology could replace traditional labor forces and significantly affect macroeconomic stability and volatility by enhancing production efficiency and reducing costs. Aghion et al. (2017) further expanded the theoretical implications of AI to include technological innovation, positing that AI not only substitutes human labor but also replaces technological human capital. Aghion's research highlighted the role of AI in driving technological progress and innovation, noting that AI technology could accelerate the process of technological innovation, thereby promoting long-term economic growth.

Prettner (2019) introduced AI as a factor in his model by differentiating traditional capital from intelligent capital, analyzing the macroeconomic impacts of AI technology development.

His research showed that AI factors are embedded within capital elements in the production process, thereby enriching and enhancing the understanding of AI's theoretical implications. Prettner's work provides a new theoretical framework for understanding the role of AI in the modern economy. According to the McKinsey Global Institute, AI is expected to contribute approximately $13 trillion to global economic activity by 2030, representing a 16% cumulative increase in GDP from today, equivalent to an additional 1.2% GDP growth per year. AI drives productivity growth through various factors, including labor automation, innovation, and new competition (Lamarre et al., 2023).

Mueller (2006) demonstrated that private enterprises and university R&D activities positively impact regional economic performance. These intangible assets, such as R&D, brand value, and patents, significantly enhance the total factor productivity of enterprises in the ICT sector (Nakatani, 2021). These studies further reveal how AI, as an emerging general-purpose technology, influences economic growth and enterprise performance through various pathways (Trajtenberg, 2018).

Overall, Economic theories regarding AI (Acemoglu & Restrepo, 2018; Hanson, 2001; Romer, 1987) conceptualize AI as a factor of production that can either complement or substitute human labor, as well as a form of technological capital. These theories indicate that AI can enhance productivity and knowledge spillovers, affecting both regional and enterprise-level growth. For this study, these insights provide theoretical justification for treating AI as a key independent variable at the enterprise level, while "innovation output" (patent applications) serves as a meso-level indicator of AI's contribution to productivity and technological progress. Furthermore, Romer (1987)'s endogenous growth theory supports the inclusion of R&D investment and human capital (HR) as mediators or moderators in the proposed model.

3.2 Advanced equipment manufacturing industry

3.2.1 Equipment manufacturing and advanced equipment manufacturing

Currently, there is no universally accepted definition for the advanced equipment manufacturing industry. The concept of "equipment manufacturing industry" first appeared at the Economic Work Conference of the Central Committee of the Communist Party of China in 1998, generally understood as the industry involved in "manufacturing machinery for producing other machines". The concept of "advanced equipment manufacturing industry" was proposed by China and lacks a standardized definition internationally, exhibiting strong regional

characteristics. Abroad, related concepts mainly include “discrete manufacturing enterprises”, “high-tech enterprises”, or “advanced manufacturing enterprises”. The equipment manufacturing industry, a subset of the manufacturing sector, primarily provides production equipment and facilities necessary for the expansion of various economic sectors. It is the core of industry and a pillar of national economic growth. In 1998, the Central Economic Work Conference explicitly emphasized the need to vigorously develop the equipment manufacturing industry, marking its first entrance into public awareness. Although the concept of equipment manufacturing lacks a unified definition internationally, in China, the scope and connotations of the industry have been clearly defined. According to the “National Economic Industry Classification” (GB/T 4754—2002, GB/T 4754—2011), the equipment manufacturing industry includes several major categories of heavy industry.

The equipment manufacturing industry has three main characteristics: capital intensity, technology intensity, and labor intensity. First, the equipment manufacturing industry requires substantial capital investment. Costs for building factories, purchasing equipment, implementing research and development, and hiring talent are significantly high, from producing general-purpose to high-end equipment (Johnson et al., 2017). For example, manufacturing high-tech key equipment necessitates acquiring expensive machinery and constructing advanced production facilities, all requiring substantial financial support. Second, the industry heavily relies on science and technology; the production processes for its products are complex and precise. For instance, the production of integrated circuits, electronic devices, transportation equipment, and medical devices all demand high levels of scientific research strength and advanced manufacturing technologies. Continuous technological advancement is a key driver of the development of the equipment manufacturing industry. By adopting new technologies, the industry can continually enhance product quality and production efficiency (Ammar et al., 2021). Third, the production organization process in the equipment manufacturing industry is complex, often adopting job-order or project manufacturing models, which differ significantly from mass production. Therefore, the industry is highly dependent on human resources, with workers playing crucial roles in procurement, design, organizational management, assembly, and production planning adjustments (Youndt et al., 1996). This high labor intensity means that the equipment manufacturing industry not only requires a large number of skilled technicians but also professionals with high levels of management and innovative capabilities. The equipment manufacturing industry primarily encompasses the production and manufacturing of various industrial equipment, tools, machinery, instruments, and consumer goods. Its core lies in using efficient machines and equipment to produce a

variety of industrial and consumer products, thereby driving economic growth and social development (S. Liang et al., 2018). The equipment manufacturing industry involves not only the mechanization and automation of production lines but also the optimization of production processes and management of manufacturing workflows (Yan & Ma, 2019).

The advanced equipment manufacturing industry represents a higher phase of the equipment manufacturing sector, involving production processes that are high in technology content and added value. This industry typically includes aerospace equipment, rail transport equipment, intelligent manufacturing devices, marine engineering equipment, and high-tech ships. It is not only a crucial component of a nation's strategic emerging industries but also plays a key role in enhancing national competitiveness and achieving industrial upgrading (L. Chen et al., 2019; Habib et al., 2020). The products in this sector are generally characterized by high technology content, high added value, and strong market competitiveness, representing a nation’s technological level and comprehensive strength in manufacturing (Segreto & Teti, 2019). In China, the advanced equipment manufacturing industry first emerged in 2010, defined as the industry that produces high-value, technologically advanced industrial equipment. It is based on various industrial technologies, emerging technologies, and information technology, providing many advanced technologies and equipment for major industries in China, playing an invaluable role in the development of the national economy and technological progress. The definition and characteristics of this industry are mainly reflected in the following aspects:

First, wide application range. The equipment manufacturing industry covers everything from basic mechanical processing to complex electronic equipment manufacturing. Its wide application range includes agricultural machinery, construction equipment, transportation vehicles, energy equipment, and more (G. Zhou et al., 2020). This extensive application ensures the critical position of the equipment manufacturing industry in the national economy. It involves a large amount of machinery and electronic equipment in the production process and many services and support systems related to industrial manufacturing, such as production line design and optimization, and process management and control.

Second, technology-intensive. Although the equipment manufacturing industry includes a lot of traditional mechanical processing, with technological advancements, modern equipment manufacturing increasingly relies on advanced technologies and processes, such as CNC technology, laser processing, and robotics (Kravets, 2020). The application of these technologies not only improves production efficiency but also significantly enhances product quality and precision. For example, CNC technology allows for more precise machining of complex parts, while robotics technology improves safety and efficiency in assembly and

handling hazardous procedures.

Third, capital-intensive. The equipment manufacturing industry usually requires substantial capital investment, including production equipment, research and development expenses, and infrastructure construction. This makes it a capital-intensive industry, requiring enterprises to have strong financial capabilities (Park et al., 2020). The acquisition of high-end equipment and technology, construction of production facilities, and development of R&D activities all require substantial financial support. The intensive investment in capital is not only reflected in hardware equipment but also includes continuous investment in technology research and innovation.

Fourth, labor-intensive. Despite the gradual shift of modern equipment manufacturing towards automation and intelligence, traditional equipment manufacturing processes still require significant labor input. Especially in stages that require precision machining and assembly, human labor remains indispensable (Brown et al., 2020). Workers are involved not only in production but also in equipment maintenance, operation, and quality control. Therefore, the equipment manufacturing industry depends not only on technology and capital but also requires a large number of skilled workers and engineers.

The advanced equipment manufacturing industry builds upon the foundations of equipment manufacturing by further enhancing technological content and added value. Its definition and characteristics are mainly reflected in the following aspects:

First, high technological content. The advanced equipment manufacturing industry involves the production of products that are high in precision, complexity, and reliability. These products usually require advanced design, precise manufacturing processes, and stringent quality control. For example, aerospace equipment demands extremely high precision and reliability, capable of stable operation under harsh environmental conditions (Bock & Linner, 2015). High technological content is not only reflected in the design and manufacturing processes but also in technological innovations and breakthroughs during the research and development stages.

Second, high added value. Products in the advanced equipment manufacturing industry typically possess high added value. This is reflected not only in the technological sophistication and market competitiveness of the products but also in their economic benefits. Products of the advanced equipment manufacturing industry are usually priced higher, yet their high added value brings greater profits to enterprises (Johnson et al., 2017). For example, intelligent manufacturing equipment integrates advanced information technology, smart technology, and manufacturing technology, achieving automation, digitization, and intelligence in production

processes, significantly enhancing production efficiency and product quality (L. Chen et al., 2019).

Third, innovation-driven. The development of the advanced equipment manufacturing industry highly depends on technological innovation and research and development investments. Enterprises need to continually conduct technology research and process improvements to maintain their competitive edge and market position. For instance, intelligent manufacturing equipment, through the integration of advanced information, intelligence, and manufacturing technologies, achieves significant improvements in production efficiency and product quality (L. Chen et al., 2019). This innovation is not limited to the technological level but also includes innovations in management models, production processes, and service models.

Fourth, high-end links in the industrial chain. The advanced equipment manufacturing industry typically occupies the high-end links of the industrial chain, involving high-end design, precision manufacturing, and efficient services. This positions the advanced equipment manufacturing industry prominently within the entire industrial chain, capable of driving the development and upgrading of upstream and downstream industries (Kravets, 2020). High-end design includes not only product research and innovation but also optimization and improvement of production processes. Efficient services encompass aspects such as after-sales service, technical support, and customer training, ensuring efficient operation and maintenance throughout the product's lifecycle.

In summary, both equipment manufacturing and advanced equipment manufacturing play significant roles in driving economic growth and industrial upgrading. Through continuous innovation and technological advancement, these sectors are becoming vital pillars of modern industry and providing new impetus for global economic development. As technology progresses and market demands evolve, both equipment manufacturing and advanced equipment manufacturing are poised to face broader development prospects.

3.2.2 Definition and characteristics of high-end equipment manufacturing enterprises

(1) Five categories division

As a pillar and leading industry of the national economy, the high-end equipment manufacturing industry encompasses multiple critical areas. According to the 2010 “Decision of the State Council on Accelerating the Cultivation and Development of Strategic Emerging Industries”, the high-end equipment manufacturing industry is defined as one of the seven major strategic emerging industries. Specifically, it primarily includes five major fields: aviation equipment, satellite and applications, rail transport equipment, marine engineering equipment,

and intelligent manufacturing equipment. Here is a detailed introduction to these five categories:

(a) Aviation equipment

Aviation equipment is a strategic industry for the country, representing national technological and economic strength. China's aviation equipment manufacturing industry has made significant progress in recent years, especially in the design and manufacture of large aircraft. Aviation equipment includes various types of aircraft, engines, avionics, and other critical systems. According to forecasts by the International Air Transport Association (IATA), China is expected to become the world's largest aviation market in the coming years, largely due to strong government support and rapidly growing market demand.

China's aviation equipment manufacturing industry has achieved important breakthroughs in projects such as the C919 large passenger aircraft and the ARJ21 regional jet, showcasing rapid progress in the field of high-end aviation equipment manufacturing. The C919, China's first independently developed mainline civilian aircraft in accordance with international mainstream airworthiness standards, has received a large number of orders since its first flight. The ARJ21, China's independently developed regional jet, has also been put into commercial use and has performed well in the domestic market. Additionally, the Aviation Industry Corporation of China (AVIC) has made significant achievements in areas such as unmanned aerial vehicles and helicopters, particularly in military drones, possessing strong international competitiveness. According to data from the Civil Aviation Administration of China, as of 2020, China's civil aviation transport turnover reached 131.3 billion ton-kilometers, an increase of 7.2% year-over-year, ranking second globally. By 2025, the market size of China's aviation equipment manufacturing industry is expected to reach 200 billion RMB. Furthermore, with the advancement of the "Belt and Road" initiative, the share of China's aviation equipment manufacturing in the international market continues to expand, further enhancing its global competitiveness.

(b) Satellite and applications

The satellite applications industry is highly interconnected, directly related to smart cities, digital Earth, and cloud computing. In recent years, China's satellite manufacturing and application industry has developed rapidly, especially in the field of satellite navigation systems. The BeiDou Navigation Satellite System is one of China's significant breakthroughs in the global navigation satellite system arena, having been widely used in various civilian and military applications.

Satellite and its applications include the design, manufacturing, launching, and ground application systems of satellites. The BeiDou Navigation Satellite System, a global navigation

satellite system independently developed by China, provides positioning, navigation, and timing services worldwide. The applications of the BeiDou system cover transportation, agriculture, forestry, fishing, water resources, meteorology, telecommunications, public safety, and more, playing a significant role in enhancing China's technological strength and international influence. In recent years, China's manned space station project, lunar exploration program, and the second-generation BeiDou Navigation Satellite System have driven rapid development in the satellite manufacturing and application industry. For instance, the BeiDou-3 global satellite navigation system officially began services in 2020, marking China as the third country, after the United States with GPS and Russia with GLONASS, to independently own a global navigation satellite system. By 2025, the market size of China's satellite navigation industry is expected to reach 400 billion RMB.

(c) Rail transit equipment

Rail transit is a vital infrastructure for national development, significantly impacting the national economy and societal progress. Rail transit equipment includes high-speed railways, subways, light rails, and related signal systems, traction equipment, braking systems. In recent years, China’s rail transit equipment manufacturing industry has seen substantial development, particularly in high-speed railway construction. As of the end of 2020, China’s operational high-speed railway mileage exceeded 38,000 kilometers, accounting for two-thirds of the global high-speed railway total. CRRC Corporation Limited, as the world's largest rail transit equipment manufacturer, has achieved significant accomplishments in high-speed trains, urban rail vehicles, and rail construction machinery. China’s high-speed rail technology has been exported to several countries, such as Indonesia, Thailand, and Russia, further enhancing the international influence of China’s rail transit equipment. According to data released by China Railway Corporation, in 2020, the national railway completed 3.57 billion passenger trips and 4.35 billion tons of freight. The rail transit equipment manufacturing industry has developed a comprehensive industrial chain, significantly enhancing various segments from train manufacturing to signal systems, track construction, and operation maintenance. By 2030, the market size of China’s rail transit equipment is expected to reach 1 trillion RMB.

(d) Marine engineering equipment

Marine engineering equipment, mainly used for exploration and extraction in offshore oil and gas fields, is an essential part of the high-end equipment manufacturing industry. The Chinese government places high importance on the development of marine engineering equipment, focusing on developing key equipment such as large underwater systems and operation equipment. According to the “Notification on the Issuance of the Marine Engineering

Equipment Industry Innovation Development Strategy (2011-2020)", the marine engineering equipment industry is the material and technological base for the exploitation and utilization of marine resources.

In recent years, China's marine engineering equipment manufacturing industry has made significant progress in technological innovation and application expansion. For example, China successfully developed the "Blue Whale 2" deep-sea drilling platform, capable of drilling at water depths of 1500 meters, greatly enhancing China's capabilities in deep-sea oil and gas resource development. According to data released by China National Offshore Oil Corporation, by 2020, China's offshore oil production totaled 51.3 million tons, an increase of 5.5% year-over-year. By 2030, the market size of China's marine engineering equipment is expected to reach 500 billion RMB.

(e) Intelligent manufacturing equipment

Intelligent manufacturing equipment is one of the key directions of China's high-end equipment manufacturing industry. It includes CNC machine tools representing basic manufacturing, industrial robots, new sensors, intelligent control systems. In recent years, China's intelligent manufacturing equipment industry has made significant progress, especially in the fields of CNC machine tools and industrial robots. According to the "Twelfth Five-Year Development Plan for Intelligent Manufacturing Equipment Industry", China's intelligent manufacturing equipment industry will continue to rapidly develop in the coming years, with industry sales revenue expected to exceed 3 trillion RMB by 2025. Intelligent manufacturing equipment not only includes core key technologies such as new sensors and instruments, industrial robots but also encompasses the intelligent and green transformation of manufacturing and production processes. China's intelligent manufacturing equipment industry also occupies an important position in the global market. For example, industrial robots are increasingly used in automobile manufacturing, electronic product assembly, and other fields, improving production efficiency and product quality. According to data from the International Federation of Robotics (IFR), in 2019, China's industrial robot sales reached 140,500 units, accounting for 36.2% of global sales, maintaining its position as the world's largest industrial robot market for seven consecutive years.

In summary, the five categories division provides a clear framework and direction for understanding and analyzing China's high-end equipment manufacturing industry. By focusing on the development of key areas such as aviation equipment, satellites and applications, rail transit equipment, marine engineering equipment, and intelligent manufacturing equipment, China is poised to secure a competitive advantage in the global market for high-end equipment

manufacturing.

(2) Eight categories division

In the Thirteenth Five-Year Plan for the Economic and Social Development of the People's Republic of China, the high-end equipment manufacturing industry is divided into eight key areas. These areas cover the core directions of advanced manufacturing technology, aiming to enhance the overall level of China's manufacturing industry and strengthen international competitiveness. In the first four years of the "Twelfth Five-Year Plan", the added value of China's equipment manufacturing industry grew by an average of 13.2% annually, which was 2.7 percentage points faster than the growth rate of large-scale industries. By 2015, the equipment manufacturing industry accounted for 31.8% of the added value of large-scale industries, an increase of 3.8 percentage points from 2008; the industry's main business income exceeded 30 trillion RMB, ranking first in the world for five consecutive years. These achievements laid a solid foundation for further development of the high-end equipment manufacturing industry during the "Thirteenth Five-Year Plan" period.

(a) Aerospace equipment

Aerospace equipment is a crucial indicator of a nation's technological strength and strategic capabilities. China has made significant advancements in the aerospace industry, including the development and production of civilian and military aircraft and various spacecraft. In recent years, China has successfully developed the C919 large passenger aircraft and achieved significant breakthroughs in space exploration, such as the successful landing of the Chang'e-4 probe on the far side of the moon, marking the advanced level of China's aerospace equipment. According to data from "China Aviation News", in 2019, the total revenue of China's aviation industry reached 875 billion RMB, an increase of 8% from 2018. In 2019, China successfully conducted the maiden flight of the Long March 5B rocket and launched the manned space station project. These achievements indicate that China has strong international competitiveness in the field of aerospace equipment.

(b) Marine engineering equipment and high-tech ships

Marine engineering equipment and high-tech ships are key to the exploration of marine resources. China has achieved significant results in areas such as deep-sea drilling platforms and subsea mineral exploration equipment. For example, the independently developed deep-sea drilling platform "Blue Whale 2" has demonstrated leading technological capabilities in deep-sea oil exploration. Meanwhile, significant progress has been made in the development and manufacturing of high-tech ships, advancing the marine engineering equipment industry. According to the "2020 China Marine Economy Statistical Bulletin", the total output value of

China’s marine engineering equipment manufacturing industry reached 400 billion RMB in 2020. In recent years, China has built several advanced marine engineering vessels, such as the 3000-meter deep-sea operation support vessel and the world's first intelligent unmanned ship, significantly enhancing the efficiency and safety of marine resource development.

(c) Advanced rail transit equipment

Rail transit equipment includes high-speed trains, subway vehicles, and maglev trains. China has the longest high-speed railway operating mileage in the world, and its high-speed rail technology has been exported to several countries. For example, the Fuxing high-speed train, with a speed of up to 350 km/h, represents China’s leading position in the field of rail transit equipment. According to the “China Railway Yearbook”, as of the end of 2020, China’s high-speed railway operating mileage exceeded 38,000 kilometers, accounting for two-thirds of the global total. The technological level of China’s rail transit equipment continues to improve, forming a complete industry chain. The export volume of rail transit equipment has been increasing year by year; in 2019, China's rail transit equipment exports reached 8 billion USD, an increase of 12% from 2018.

(d) High-end CNC machine tools

High-end CNC (Computer Numerical Control) machine tools are the core of intelligent manufacturing. China’s technological level in CNC machine tools has continuously improved, finding wide application across various manufacturing industries. Through the promotion of high-precision CNC equipment and intelligent production lines, the automation and intelligence levels of China’s manufacturing industry have significantly enhanced. According to the China Machine Tool & Tool Builders’ Association, in 2020, the market size of CNC machine tools in China reached 100 billion RMB, an increase of 5% from 2019. The application of high-end CNC machine tools not only improves the production efficiency of the manufacturing industry but also advances the indigenization of critical components. For instance, the development and application of high-speed machining centers and five-axis linkage machine tools have substantially enhanced precision manufacturing capabilities in sectors such as aerospace and automotive manufacturing.

(e) Robotic equipment

Robotic equipment is widely used in industrial manufacturing, medical, and service sectors. China’s technological level in industrial robots has continually risen, driving the automation and intelligence of the manufacturing industry. In recent years, the prevalence of industrial robots in China has significantly increased, with installations exceeding 150,000 units in 2018, ranking first globally. According to data from the International Federation of Robotics (IFR),

in 2020, the market size of industrial robots in China reached 5 billion USD, accounting for 25% of the global market share. The development of robotic equipment also includes service robots and specialized robots. Service robots are extensively used in fields such as medical care, elderly care, and education, while specialized robots demonstrate their critical value in emergency response and military applications.

(f) Modern agricultural machinery equipment

Modern agricultural machinery equipment includes agricultural machinery and intelligent agricultural equipment. With the advancement of agricultural modernization, intelligent and automated agricultural equipment is widely used in China. For example, the promotion and application of unmanned tractors and automated harvesters have improved agricultural production efficiency and reduced labor intensity. According to the China Agricultural Machinery Industry Association, in 2020, the market size of modern agricultural machinery equipment in China reached 200 billion RMB. The development of modern agricultural machinery not only enhances agricultural production efficiency but also promotes rural economic development. The widespread adoption of intelligent agricultural equipment allows for refined management and scientific decision-making in various stages of agricultural production.

(g) High-performance medical machinery

High-performance medical machinery is an essential equipment category in the healthcare industry, encompassing advanced diagnostic, therapeutic, and monitoring devices. China has made significant advancements in the field of medical machinery, enhancing the level of medical services. For instance, high-performance CT scanners, MRI machines, and surgical robots have been widely utilized in both domestic and international markets. According to data from the China Association for Medical Devices Industry, in 2020, the market size of high-performance medical machinery in China reached 100 billion RMB, growing by 10% from 2019. The development of high-performance medical machinery not only improves the quality of medical services but also promotes the indigenous innovation of medical devices. For example, domestically produced surgical robots have excelled in complex surgeries such as cardiac and neurosurgery, gradually replacing imported equipment.

(h) Advanced chemical engineering equipment

Advanced chemical engineering equipment is a crucial component of the high-end equipment manufacturing industry. This category includes large-scale petrochemical equipment, fine chemical equipment, and new energy devices. China has achieved notable success in technological innovation and industrial application in this field, driving the modernization and

efficiency of the chemical industry. According to data from the China Chemical Equipment Association, in 2020, the market size of advanced chemical engineering equipment in China reached 150 billion RMB. The development of advanced chemical engineering equipment includes areas such as new materials equipment and environmental protection devices. For instance, the research and application of high-efficiency catalyst production equipment and waste gas treatment devices have significantly enhanced the environmental standards and economic benefits of chemical production.

Through the detailed introduction of these eight categories of high-end equipment manufacturing, it is evident that China has made substantial progress in the field of high-end equipment manufacturing, particularly in areas such as aerospace, marine engineering, and rail transit, forming a well-developed industrial chain and modern industrial clusters. With continuous technological advancements and policy support, China's high-end equipment manufacturing industry is expected to continue its rapid development, driving high-quality growth of the national economy.

In summary, the characteristics of the advanced equipment manufacturing industry—high technology intensity, long product lifecycles, and complex supply chains—imply that AI's impact extends beyond production automation to encompass design, quality control, and after-sales service throughout the product lifecycle. Accordingly, this study measures AI application breadth across production, design, and after-sales functions, examining its effects on innovation output (Inv) and industrial upgrading (IUI). Moreover, industry-specific characteristics justify the inclusion of human capital structure (HR) and government support (Gov) as key mediating or moderating variables, since talent and policy support are critical drivers in this sector.

3.3 Innovation performance theory

The concept of technological innovation originates from innovation theory, and in some studies, technological innovation performance is also referred to as innovation performance. Schumpeter and Nichol (1934) were among the first to propose the concept of "innovation", defining it as the process of recombining production factors and conditions to achieve excess profits. This includes five forms: new products, new processes, new markets, new organizations, and new materials. With the rise of the new technological revolution, scholars began to focus on how technological innovations promote economic growth, thereby enriching and expanding research on technological innovation and its performance.

Freeman (1997) viewed technological innovation as a multi-linked process, involving

research and development, management, design, production, and marketing aspects in the introduction of new products or processes. Stoneman and Ireland (1983) considered that the first application of a scientific invention and the creation of profit within the economic sector constitutes technological innovation. The OECD's "Oslo Manual" clearly defines innovation as industrial technological innovation, including new products and processes as well as significant technological changes in products and processes.

Technological innovation performance is an important metric for evaluating the effectiveness of technological innovation implementation. Drucker (1993) noted that technological innovation performance is difficult to define directly; it represents a combination of all innovation elements and is a comprehensive reflection of the outcomes of innovation. Hagedoorn and Cloodt (2003) suggested that the input and output efficiency and benefits displayed by an enterprise during its technological innovation activities can be considered as the enterprise's technological innovation performance.

As innovation theory has deepened, research on technological innovation performance has become richer and more extensive. Especially in the context of technological and industrial revolutions, scholars have increasingly recognized the crucial role of technological innovation in regional economic transformation, industrial upgrading, and enterprise development. Thus, more research has focused on an in-depth exploration of technological innovation and its performance outcomes. Past studies have mainly divided the external influences on enterprise technological innovation performance into two levels: external environmental factors and internal organizational factors.

External environment factors are crucial for the survival, development, and innovation of enterprises. The dynamism of the environment promotes innovation cooperation among enterprises while also introducing innovation risks. A highly dynamic market environment stimulates enterprise value creation and generates additional innovation profits (York & Venkataraman, 2010). Research by Bai et al. (2019), which surveyed 505 high-tech enterprises over three consecutive years, showed that institutional environments like tax incentives positively impact enterprise technological innovation, whereas government R&D subsidies have a crowding-out effect on enterprise technological innovation performance. Wen et al. (2020) believe that enterprises can effectively enhance their technological innovation performance by engaging in technology standard research and diffusion through standard alliances, leveraging the innovative resources obtained through network embedding within the alliance.

Internal organizational factors are also a focal point of scholarly attention, including

enterprise strategy, resources, capabilities, organizational routines, culture. Organizational strategy is a crucial consideration in the process of enterprise technological innovation (Shoham & Fiegenbaum, 2002). S. Zhang and Chen (2022) discussed the factors affecting technological innovation performance from a dynamic capabilities perspective. Furthermore, the impact of internal organizational changes, represented by organizational routines and culture, on enterprise technological innovation performance has also gained widespread attention.

The literature indicates that innovation performance can be measured through patents (applications or grants) and new product sales. Given the long commercialization cycles typical in high-end equipment manufacturing, this study uses the number of patent applications (log-transformed) as the primary dependent variable (Inv) and includes patent grants for robustness checks, capturing both the intensity and willingness of enterprise-level R&D output. Additionally, innovation performance is influenced by both external (policy, institutional environment) and internal (human capital, organizational capability) factors, providing theoretical support for treating HR and Gov as mediators in the model.

3.4 Economic growth theory

Economic growth theory is one of the theoretical foundations for the development of the high-end equipment manufacturing industry. Studying the characteristics and conditions of economic growth is crucial for understanding the development of this industry. Economic growth refers to the increase in the total volume of goods and services produced within an economic system over a certain period. Economic growth primarily relies on natural resource reserves, the accumulation of physical capital, enhancement of human capital, technological progress, and institutional environments (Domar, 1946; Harrod, 1939).

The Harrod-Domar model, proposed independently by Harrod (1939) and Domar (1946), was one of the beginnings of modern economic growth theory, explaining that the economic growth rate depends on the level of savings and the capital-output ratio. The model posits that high levels of savings lead to more funds available for investment, thereby increasing the capital stock and promoting economic growth (Domar, 1946; Harrod, 1939). However, the model's limitation is that it assumes technological progress has no impact on economic growth and focuses only on capital accumulation and savings rates.

Romer (1987) introduced the endogenous growth theory, which internalizes technological progress, asserting that knowledge and technology are key drivers of economic growth. In Romer's model, economic growth depends not only on capital and labor inputs but also on

improvements in human capital and technology levels. Romer's AK model, represented through a production function, shows that technological progress determines the increase in the variety of intermediate products, which in turn directly affects economic growth. This highlights that technological innovation and knowledge spillovers are crucial for sustaining long-term economic growth.

Moreover, modes of economic growth can be divided into extensive and intensive types. Extensive economic growth relies on increasing the quantity of production factors to expand production scale, characterized by high resource consumption, high costs, and difficult-to-guarantee product quality. In contrast, intensive economic growth achieves economic expansion by improving the quality and efficiency of production factors, offering advantages such as low resource consumption, controlled costs, and high product quality, thus achieving higher economic benefits (Hagemann & Scazzieri, 2009; Yoshida, 1900).

In the development of the high-end equipment manufacturing industry, technological innovation and policy support are considered key factors. K. Gao et al. (2022) used the DEMATEL-ISM model to analyze the impact of technology levels and organizational management on military equipment maintenance capabilities, emphasizing the importance of technological advancement in enhancing productivity and management efficiency. Yi et al. (2020) examined the impact of government R&D subsidy policies on innovation efficiency, finding that policy support significantly enhances an enterprise's technological innovation capabilities.

According to the development of China's manufacturing industry, particularly with Shenzhen as the hub of high-tech manufacturing, its economic growth mode demonstrates the practical application of the aforementioned theories. Shenzhen has achieved rapid development in high-end manufacturing through policy support, technological innovation, and capital accumulation. Shenzhen's success is largely due to its investments in technological innovation and knowledge accumulation, as well as government support in R&D and industrial policy. This model has not only improved the production efficiency and product quality of Shenzhen's manufacturing industry but also fostered rapid regional economic growth, serving as a model for the modernization of China's manufacturing industry (Y. Chen et al., 2020; Y. Liu et al., 2018).

In summary, economic growth theory underscores the significant roles of technological progress, capital accumulation, and policy support in driving economic growth. The development of the high-end equipment manufacturing industry relies on technological innovation and policy support to achieve long-term stable economic growth. Drawing from

Shenzhen's practical experience, it is evident that through strengthening technological innovation and policy support, the high-end equipment manufacturing industry can sustain continuous economic growth and industrial upgrading. Endogenous growth theory emphasizes the decisive role of technological progress and human capital in driving long-term growth, which positions enterprise-level innovation activities (R&D, patents) as critical mechanisms for generating value. This study incorporates Tobin's Q as a dependent variable to examine whether innovation output (Inv) translates into market value, reflecting the extent to which capital markets reward technological capital, consistent with both Tobin's Q theory and the endogenous growth framework.

3.5 Industrial upgrading theory

Industrial upgrading theory is a crucial framework for understanding the development of the high-end equipment manufacturing industry. It involves rationalizing and elevating the industrial structure, including improvements in production factors, structural optimization, enhancement of product quality, increased production efficiency, and upgrading of industrial chains. Industrial upgrading is not limited to the transformation of the existing industrial structure but also includes progression to higher levels of industrial forms, transitioning from labor-intensive to capital-intensive and knowledge-intensive industries.

At the macro level, industrial upgrading represents a shift in a country's economic growth model, primarily reflected in the enhanced efficiency of resource allocation and the optimization of industrial structures. The 17th-century classical political economist William Petty was among the first to note the varying impacts of different industrial structures on the national economy. He observed that commercial income exceeded industrial income, which in turn exceeded agricultural income (Gollin et al., 2016). In 1940, Colin G. Clark, building on Petty's research, proposed the "Petty-Clark Theorem", which posits that as national income increases, labor shifts from the primary sector (agriculture) to the secondary sector (industry) and subsequently to the tertiary sector (services) (Glaeser et al., 1992). Kuznets (1955) further studied the evolution of industrial structures and introduced the "Kuznets Rule": the income and labor share of the agricultural sector gradually decline, the income share of the industrial sector rises, and the income and labor share of the service sector continuously increase.

The "Flying Geese Theory" proposed by Japanese scholar Kaname Akamatsu in 1935 describes the dynamic changes in the industrial structure of developing countries. He theorized that developed countries initially lead in certain industries; as technology matures and

production factors change, the industrial competitiveness of these countries weakens and gradually shifts to other less developed countries. These countries, in turn, upgrade their industrial structures by introducing and absorbing advanced technologies (Kojima, 2000). This theory has been further expanded and applied to understand the dynamic evolution of global industrial chains. Hirschman and Sirkin (1958) introduced the industry linkage benchmarks, which determine the interdependence of national production sectors in product supply and demand relationships through linkage coefficients, forming the basis of the "leading sector theory". Hirschman's research emphasized the importance of certain key sectors in driving overall economic growth.

At the micro-level, industrial upgrading is achieved through internal technological advancements, optimization of management models, and enhancement of product quality within enterprises. Enterprises increase the added value of their products through technological innovation, thereby enhancing their market competitiveness and economic benefits. In studying the industrial structures of developing countries, Hollis Chenery used regression analysis to find that the development of manufacturing is significantly influenced by per capita GNP, demand scale, and investment rate, which is crucial for understanding the evolution of modern manufacturing (Morrison, 2008).

Overall, industrial upgrading theory emphasizes that technological progress, capital accumulation, and policy support play vital roles in promoting economic growth. By integrating these concepts with the development strategies of sectors such as high-end equipment manufacturing, nations and enterprises can achieve sustainable economic growth and industrial advancement.

Modern research further emphasizes the central role of technological innovation in industrial upgrading. For example, Croitoru (2012) in his theory of Innovation and Growth, points out that industrial upgrading is achieved through the process of technological innovation and the phasing out of old products. Technological innovation not only improves the industrial structure but also enhances production efficiency and product quality, leading to advanced industrial development. With the growth of the global digital economy, digital technologies such as big data and AI increasingly play a role in promoting the digital transformation and value chain upgrading of traditional industries. These technologies not only optimize production processes but also drive the development of emerging industries, enhancing the overall added value of industries (Gu, 2024). Specifically, in the development of high-end equipment manufacturing in China and Shenzhen, policy support and technological innovation are key drivers of industrial upgrading. Shenzhen, as a representative of China's high-tech

manufacturing industry, has transformed from a labor-intensive to a technology and knowledge-intensive industry through proactive industrial policies and innovation-driven strategies. Shenzhen's success demonstrates that technological innovation and policy support play a significant role in enhancing industrial added value and competitiveness. This model not only improves production efficiency and product quality but also promotes rapid regional economic growth, becoming a model for the modernization of China's manufacturing industry (J. Yang, 2014; G. Zhang & Lee, 2021).

In summary, industrial upgrading theory emphasizes enhancing industrial added value and competitiveness through technological innovation, management optimization, and policy support. Technological innovation is considered a core mechanism for increasing industrial value-added and optimizing industrial structure. The development of the high-end equipment manufacturing industry relies on these factors to achieve sustained economic growth and industrial upgrading. The practical experience of China and Shenzhen demonstrates that strengthening technological innovation and policy support enables continuous economic growth and industrial advancement. Building on this theoretical foundation, the present study uses industrial structure rationalization (TL) and industrial advancement ratio (TS) as measures of industrial upgrading (IUI), allowing an assessment of whether enterprise-level innovation output can accumulate into structural improvements at the industry level—facilitating the transformation from low-end manufacturing to high-end design, precision manufacturing, and service-oriented production.

3.6 Technological innovation and industrial upgrading theory

The theory of technological innovation and industrial upgrading explores the pivotal role of technological progress in promoting the upgrading of industrial structures. This theory was initially proposed by British scholars John A. Cantwell and Paz Estrella Tolentino in the 1980s, based on the phenomenon of rapidly increasing direct investments from developing countries into developed nations. The core ideas of this theory are: first, the industrial structure upgrading in developing countries indicates a steady improvement in their enterprises' technological capabilities, a result of long-term accumulation; second, the enhancement of technological capabilities in enterprises from developing countries is closely linked to the growth in foreign direct investment, exhibiting predictable trends across industries and regions. Technological innovation serves as the main driver for industrial upgrading, as pointed out by Schumpeter in his 1934 theory of Innovation and Growth, which states that technological innovation promotes

economic growth and industrial structural upgrading through “creative destruction”. This process includes the introduction of new products, new processes, or new business models, phasing out old production methods to achieve recombination of production factors and optimal resource allocation (Minsky, 1990).

In the context of the modern economy, technological innovation is not limited to improvements within a single industry but also includes cross-industry and cross-regional technology diffusion and application. Lee and Gereffi (2021) studied the cross-industry value chain of the smartphone industry and found that technological innovation not only enhances the competitiveness of a single industry but also promotes the upgrading and optimization of the entire industry chain. Furthermore, innovations in digital technology and green technology also play a significant role in industrial upgrading. Digital technology drives the transformation of traditional manufacturing to intelligent manufacturing by enhancing production efficiency and product quality. Research indicates that digital technology has become a new engine for manufacturing upgrading, achieving production process optimization and value chain enhancement through data-driven innovation (Fu, 2022). Green technology innovation, driven by environmental regulations, promotes the rationalization and high-quality development of industrial structures (Yu et al., 2023). According to China's actual conditions, technological innovation plays a key role in promoting industrial upgrading and economic growth. China’s rapid industrialization process relies on technological innovation and accumulation. With government policy support and proactive enterprise innovation, China has made significant progress in high-end equipment manufacturing, with Shenzhen serving as a typical case study. Studies show that China has transitioned from labor-intensive to technology-intensive and knowledge-intensive industries through technological innovation, effectively enhancing industrial added value and international competitiveness (Jin & Lee, 2020; Y. Liu & Madni, 2024).

In summary, theories linking technological innovation and industrial upgrading emphasize technology diffusion and value chain as key mechanisms for industrial advancement. In high-end equipment manufacturing, AI promotes industrial upgrading by enhancing enterprise-level innovation performance, and AI, in conjunction with policy and organizational capabilities, strengthens innovation conversion efficiency via dynamic capabilities (sensing, integration, reconfiguration). These theoretical insights directly support the role of dynamic capabilities as a mediator in the model.

This chapter reviews the economic theory of AI, characteristics of the high-end equipment manufacturing industry, innovation performance theory, economic growth and industrial

upgrading theories, and the mechanisms linking technological innovation to industrial upgrading. Based on these theoretical foundations, this study constructed the following conceptual chain: AI (enterprise-level) → Innovation Performance (patent applications/grants) → Industrial Upgrading (TL, TS) and Enterprise Value (Tobin's Q), with human capital structure (HR) and government support (Gov) acting as mediators between AI and innovation performance. Considering that although macro-level panel data analysis enables identifying the effects of AI, it cannot reveal the mechanism through which enterprises' internal capability reconfiguration shapes performance. Therefore, this study further proposed a micro-level analytical pathway of "disruptive innovation – dynamic capabilities – innovation performance". Accordingly, this study established a two-step research framework of "macro-level empirical identification – micro-level mechanism extension", providing as a unified theoretical foundation for the empirical analyses in Chapters 4 and 5.

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Chapter 4: Empirical Study on Impact of AI Technology on the Development of the High-End Equipment Manufacturing Industry

Building on the preceding theoretical analysis and literature review, this study first conducted an empirical study at the macro level. Considering that the impact of artificial intelligence (AI) technology on the development of the high-end equipment manufacturing industry is not limited to enterprise innovation, but may further extend to industrial upgrading and enterprise value, we used panel data from listed high-end equipment manufacturing enterprises in Shenzhen from 2010 to 2023 to construct regression models to comprehensive test the potential direct effects, mediating effects, and extended effects. The primary objective of this chapter is to examine whether AI technology significantly influences the development of high-end equipment manufacturing enterprises and to identify the key outcome variables and influencing pathways. To this end, the chapter focuses on testing the impact of AI on enterprise innovation performance and further analyzes the mediating effects of human capital structure and government support, as we as the extended effects of innovation performance on industrial upgrading and enterprise value. The findings provide an empirical foundation for subsequent analysis of the underlying mechanisms from the perspective of enterprises' internal capabilities.

4.1 Research model and hypotheses

In the context of globalization, China's manufacturing industry faces several challenges, including outdated technological capabilities, dependence on foreign core technologies, overcapacity, and severe environmental pollution. This extensive growth model has become unsustainable, necessitating urgent reforms. To achieve high-quality development, traditional manufacturing must undergo transformation and upgrading to enhance competitiveness and innovation capacity. The application of emerging technologies, such as artificial intelligence (AI), is critical in this regard.

Innovation theory suggests that enterprise innovation stems from the generation of new combinations, which include the adoption of new technologies. As a newly introduced general-purpose technology, AI is not only regarded as an essential foundational resource for enterprises

but also as an advanced form of information technology. Built upon big data and cloud computing technologies, AI further evolves with characteristics like deep learning, which enhances enterprises' dynamic capabilities (McAfee & Brynjolfsson, 2017).

AI not only brings the general advantages of information technology but also possesses unique technical features that can improve enterprises' innovation capacity in various ways (Autor, 2015; Furman & Seamans, 2019). Studies have shown that AI technology promotes technological progress and increases R&D efficiency through knowledge production. Digital technologies add depth and diversity to enterprise innovation, influencing production organization, resource allocation, and supply methods, thus enabling an intelligent transformation of manufacturing technologies (Agrawal et al., 2018). On the demand side, innovation emphasizes user value, and digital technologies drive iterative innovation through generational development (Cockburn et al., 2018). Information technologies in smart manufacturing facilitate information exchange between enterprises and external partners, reducing costs and improving innovation performance (C. M. Chen et al., 2015).

In Shenzhen's high-end equipment manufacturing industry, the application of AI technology has significantly enhanced innovation outcomes. For example, the adoption of intelligent production equipment and systems has led to notable improvements in product development, production efficiency, and quality control. The integration of big data and AI technologies enables enterprises to predict market demand more accurately, optimize production processes, and improve overall innovation performance (Rammer et al., 2022). Furthermore, government support in Shenzhen, including policies and funding for AI technologies, has substantially fostered technological innovation (J. Liu et al., 2020).

Based on the above analysis, this study proposes the following hypothesis:

H1: AI application significantly promotes enterprises' innovation performance.

4.1.1 The impact pathways of AI on innovation performance in manufacturing enterprises

From an external perspective, the Chinese government has been strongly supporting the integration of AI with manufacturing by introducing numerous related policies. These policies can be categorized into functional industrial policies and selective industrial policies. Selective industrial policies are typically designed to support strategic and emerging industries, aiming to shorten the development timeline of industrial structures and facilitate the rapid growth of these industries. For instance, the governments of the United States and the United Kingdom have implemented various measures to promote the integration of AI and manufacturing, such as direct subsidies, tax incentives, and financial support (Lamarre et al., 2023; Yu et al., 2023).

Functional industrial policies, on the other hand, indirectly foster innovation by improving infrastructure, investing in science and technology, and developing human capital. These policies create favorable internal conditions for innovation while establishing a supportive external environment. Studies show that industrial policy, as an essential government intervention in economic operations, influences resource allocation, drives economic development, and enhances spillover effects through macroeconomic regulation. For example, the UK government has introduced a new national defense AI strategy to promote AI applications in the military sector, thereby boosting innovation capacity and efficiency (Kinkel et al., 2022). Similarly, the US government has supported AI adoption in the public sector through organizations like Google Public Sector, leveraging AI and machine learning tools to advance digital transformation, which indirectly supports innovation in manufacturing.

In Shenzhen, the government has taken various initiatives to facilitate the integration of AI technology with manufacturing. Policies such as direct subsidies and tax incentives have supported the application of AI in high-end equipment manufacturing. These measures not only provide financial support but also create a conducive innovation environment through infrastructure improvements and technological investments. In 2021, Shenzhen's government invested 5 billion RMB in AI research and applications, significantly advancing AI technology adoption in the manufacturing sector (Office of Information Disclosure of the People's Government of Shenzhen Municipality, 2021).

From an internal perspective, the application of AI significantly impacts the human capital structure of enterprises. The adoption of AI increases the demand for highly skilled employees, optimizing the human capital structure within organizations. Research has demonstrated that advancements in information technology substantially raise the proportion of highly skilled labor in enterprises (Ghobakhloo et al., 2024). Related studies predict that the development of AI will increase the supply of skilled labor, enhance labor structure optimization, and drive technological innovation in enterprises (Tekic & Koroteev, 2019).

High-end equipment manufacturing enterprises in Shenzhen have significantly improved their innovation performance with the aid of AI technologies. The application of intelligent production equipment and systems has resulted in substantial advancements in product development, production efficiency, and quality control. Statistics show that in 2022, R&D expenditures accounted for 8% of sales revenue in Shenzhen's high-end equipment manufacturing sector, far exceeding the national average of 3.5% (Shenzhen Municipal Bureau of Statistics, 2023). This high level of R&D investment, supported by government policies and AI applications, has enabled remarkable progress in technological innovation.

Furthermore, Shenzhen prioritizes the recruitment and training of highly skilled talent, using various training and incentive measures to increase the proportion of skilled labor. For example, Shenzhen hosts multiple high-skill talent training programs annually, attracting a large pool of technical professionals. These initiatives not only expand the talent base of enterprises but also optimize human capital structures, thereby enhancing overall innovation capabilities. By 2022, the proportion of highly skilled workers in Shenzhen's labor force reached 12%, surpassing the national average of 7% (Shenzhen Municipal Bureau of Statistics, 2022).

In summary, the pathways through which AI influences innovation performance in manufacturing enterprises include government policy support and the optimization of human capital within enterprises. Governments promote the integration of AI and manufacturing through various policy measures, providing financial and environmental support for enterprises. Meanwhile, enterprises adopt and apply AI technologies to optimize their human capital structures and enhance technological innovation capabilities. Together, these pathways drive improvements in innovation performance in manufacturing enterprises.

Based on the above analysis, this study proposes the following hypotheses:

H2: AI application influences enterprises' innovation performance by optimizing human capital structure.

H3: AI application significantly influences enterprises' innovation performance through increased government subsidies.

4.1.2 The impact of AI technology advancement on high-end equipment manufacturing enterprises

In recent years, technological innovation has been widely regarded as a key driver for industrial upgrading. Schumpeter's theory of economic development emphasizes that innovation can drive economic growth and industrial structural upgrading through the process of "creative destruction" (Schumpeter & Nichol, 1934). Innovation not only generates new products and processes but also facilitates technological progress and efficiency improvement in existing industries.

The development of the digital economy and AI has accelerated this process. Studies indicate that the application of digital technologies, such as big data and AI, significantly enhances manufacturing enterprises' productivity and product quality, thereby promoting industrial upgrading (Y. Jiang & Zheng, 2021). By leveraging intelligent production systems and data-driven decision-making processes, enterprises can utilize resources more efficiently, reduce waste, optimize production processes, and improve overall productivity (X. Li et al.,

2025).

Furthermore, the application of AI in manufacturing fosters collaboration and integration across the industrial chain. Intelligent manufacturing systems not only improve the efficiency of individual enterprises but also enhance the operational efficiency of the entire supply chain through optimization and coordination (X. Gao & Feng, 2023). This collaborative effect promotes technological advancements in individual enterprises while driving technological upgrades and structural optimization across the industry (S. L. Wang et al., 2023).

Existing research also highlights the critical role of government policies in advancing the integration of AI technology with manufacturing. The Chinese government has actively promoted the application of AI in manufacturing through various policy supports and financial investments. These policies include R&D funding, tax incentives, and innovation rewards, which significantly boost technological innovation and industrial upgrading (B. Qian, 2023). In addition to providing necessary financial support, these policies also create an optimized innovation environment and enhance enterprise competitiveness, accelerating the rapid development of the high-end equipment manufacturing sector.

As the center of high-end equipment manufacturing in China, Shenzhen has significantly improved enterprise innovation capabilities and industrial standards through the vigorous integration of AI technology and manufacturing. With policy support and financial investments, the Shenzhen government has established multiple AI R&D centers and laboratories, fostering technological innovation and industrial upgrading in high-end equipment manufacturing. In 2021, Shenzhen's investment in AI technology R&D and applications reached 5 billion RMB, greatly advancing the adoption of AI in the manufacturing sector (Office of Information Disclosure of the People's Government of Shenzhen Municipality, 2021).

Shenzhen's high-end equipment manufacturing enterprises have achieved intelligent and automated production processes through the adoption of advanced AI technologies, resulting in significant improvements in productivity and product quality. These advancements enable these enterprises to maintain a competitive edge in the international market. Based on the above analysis, the following hypothesis is proposed:

H4: AI application promotes industrial upgrading by enhancing enterprises' innovation performance.

AI technology significantly impacts the value of high-end equipment manufacturing enterprises. By improving operational efficiency, product quality, and overall competitiveness, AI technology increases enterprise value. Multiple studies have shown that AI-driven productivity improvements have a crucial impact on enterprise value. By applying AI

technology, enterprises can optimize production processes, reduce costs, and enhance product quality, thereby increasing market competitiveness (X. Gao & Feng, 2023).

Additionally, AI accelerates innovation management in manufacturing. Haefner et al. (2021) found that AI significantly promotes technological innovation, positively impacting enterprise value. By utilizing AI technology, enterprises can optimize R&D processes, shorten the time-to-market for new products, and improve product quality and functionality, thus strengthening market competitiveness.

AI technology also significantly enhances enterprises' financial performance. Studies indicate that AI improves operational efficiency and profitability, thereby boosting enterprise value. For instance, high-end equipment manufacturing enterprises in Shenzhen have achieved substantial progress in product R&D, production efficiency, and quality control through the application of intelligent production equipment and systems. In 2022, the R&D investment of Shenzhen's high-end equipment manufacturing enterprises accounted for 8% of their sales revenue, significantly higher than the national average of 3.5% (Shenzhen Municipal Bureau of Statistics, 2023). This high level of R&D investment has not only enhanced their technological innovation capabilities but also significantly increased their market value and financial performance.

Based on the above analysis, the following hypothesis is proposed:

H5: AI application enhances enterprise value by improving innovation performance.

The proposed model diagram is as shown in Figure 4.1.

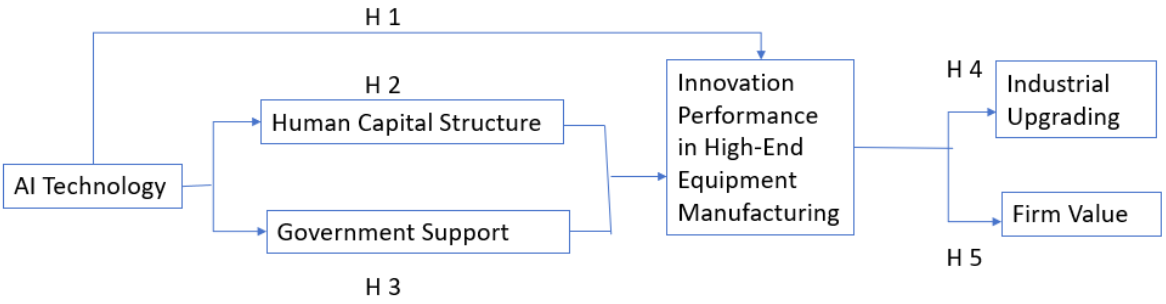


Figure 4.1 Conceptual model

4.1.3 Model construction

To test the hypotheses proposed in this study and explore the relationship between AI and the innovation performance of high-end equipment manufacturing enterprises in Shenzhen, the following regression models are constructed:

$$\mathbf{Inv_{i,t}} = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1}\mathbf{AI_{i,t}} + \boldsymbol{\alpha_2}\mathbf{Size_{i,t}} + \boldsymbol{\alpha_3}\mathbf{Age_{i,t}} + \boldsymbol{\alpha_4}\mathbf{Growth_{i,t}} + \boldsymbol{\alpha_5}\mathbf{Cr_{i,t}} + \boldsymbol{\alpha_6}\mathbf{Crl_{i,t}} + \sum \mathbf{Year} + \boldsymbol{\varepsilon_{i,t}} \quad (4.1)$$

I represents the enterprise. t Represents the year. α_0 is the constant term. α_1-α_7 are coefficients of the independent variables in the model, representing their respective impacts on the dependent variable. $\varepsilon_{i,t}$ is the random disturbance term capturing unobservable factors affecting the dependent variable.

This study also explores the impact pathways of AI on innovation performance by constructing mediating effect models for human capital structure and government support, based on Model (1) using the stepwise regression method.

$$\mathbf{Inv_{i,t}} = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1}\mathbf{AI_{i,t}} + \boldsymbol{\alpha_2}\mathbf{HR_{i,t}} + \boldsymbol{\alpha_3}\mathbf{Size_{i,t}} + \boldsymbol{\alpha_4}\mathbf{Age_{i,t}} + \boldsymbol{\alpha_5}\mathbf{Growth_{i,t}} + \boldsymbol{\alpha_6}\mathbf{Cr_{i,t}} + \boldsymbol{\alpha_7}\mathbf{Crl_{i,t}} + \sum \mathbf{Year} + \boldsymbol{\varepsilon_{i,t}} \quad (4.2)$$

$$\mathbf{Inv_{i,t}} = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1}\mathbf{AI_{i,t}} + \boldsymbol{\alpha_2}\mathbf{Gov_{i,t}} + \boldsymbol{\alpha_3}\mathbf{Size_{i,t}} + \boldsymbol{\alpha_4}\mathbf{Age_{i,t}} + \boldsymbol{\alpha_5}\mathbf{Growth_{i,t}} + \boldsymbol{\alpha_6}\mathbf{Cr_{i,t}} + \boldsymbol{\alpha_7}\mathbf{Crl_{i,t}} + \sum \mathbf{Year} + \boldsymbol{\varepsilon_{i,t}} \quad (4.3)$$

By constructing Regression Model 4, the study examines the impact of innovation performance on industrial upgrading in the high-end equipment manufacturing sector.

$$\mathbf{IUI_{i,t}} = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1}\mathbf{AI_{i,t}} + \boldsymbol{\alpha_2}\mathbf{Inv_{i,t}} + \boldsymbol{\alpha_3}\mathbf{Size_{i,t}} + \boldsymbol{\alpha_4}\mathbf{Age_{i,t}} + \boldsymbol{\alpha_5}\mathbf{Growth_{i,t}} + \boldsymbol{\alpha_6}\mathbf{Cr_{i,t}} + \boldsymbol{\alpha_7}\mathbf{Crl_{i,t}} + \sum \mathbf{Year} + \boldsymbol{\varepsilon_{i,t}} \quad (4.4)$$

By constructing Regression Model 5, the study examines the impact of innovation performance on the enterprise value of high-end equipment manufacturing enterprises.

$$\mathbf{TobinQ_{i,t}} = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1}\mathbf{AI_{i,t}} + \boldsymbol{\alpha_2}\mathbf{Inv_{i,t}} + \boldsymbol{\alpha_3}\mathbf{Size_{i,t}} + \boldsymbol{\alpha_4}\mathbf{Age_{i,t}} + \boldsymbol{\alpha_5}\mathbf{Growth_{i,t}} + \boldsymbol{\alpha_6}\mathbf{Cr_{i,t}} + \boldsymbol{\alpha_7}\mathbf{Crl_{i,t}} + \sum \mathbf{Year} + \boldsymbol{\varepsilon_{i,t}} \quad (4.5)$$

4.2 Research design

4.2.1 Sample selection and data sources

This study investigates the impact of AI technology on the innovation performance of high-end equipment manufacturing enterprises. The primary data are sourced from the CSMAR Wind Financial Terminal, patent data from the China Research Data Service Platform (CNRDS), and policy documents from the official websites of central and provincial authorities.

The initial sample includes high-end equipment manufacturing enterprises registered in Shenzhen that continuously operated between 2010 and 2023. Further sample refinement was conducted based on the following criteria:

(1) Exclusion of enterprises with significant missing data on key indicators.

(2) Exclusion of enterprises classified as ST, *ST, or PT.

After applying these criteria, a final sample of 222 listed high-end equipment manufacturing enterprises was selected, comprising 1,584 data observations.

4.2.2 Variable measurement

(1) Enterprise Innovation Performance (Inv)

Existing literature measures enterprise innovation performance using two primary indicators: total patent applications or patent grants and sales revenue from new products. Since Chinese enterprises are not required to disclose new product sales revenue in their annual reports, this study uses patent data for measurement.

Cai and Zhang (2015) highlight that the core of AI's creative features lies in its ability to improve R&D efficiency. X. Zhou et al. (2012) argued that technological innovation is a result of resource input and efficiency. They pointed out that using patent grants as an indicator might fail to capture the true innovation level of enterprises, as granting requires rigorous examination and associated costs. Patent applications, however, provide a more authentic reflection of an enterprise's innovation capabilities.

To eliminate the influence of extreme values, following the methodology of F. Zhong and Leng (2022) and Y. Zhang, Yuan, et al. (2023), this study constructs the dependent variable by taking the natural logarithm of total invention patent applications plus one. For robustness checks, the total number of all patent applications is also used as an alternative measure of innovation performance.

(2) AI Technology (AI)

Existing studies often use the frequency of AI-related terms in enterprise reports as a proxy variable for AI technology adoption. Keywords in annual reports can reflect an enterprise's managerial philosophy and strategic direction, making text analysis a scientifically valid method to measure AI's application in R&D.

However, this method has limitations. In the context of China's push for intelligent manufacturing, enterprise reports may include exaggerated claims about AI applications. Conversely, some enterprises heavily apply AI technology but provide limited disclosure in their reports. These factors can lead to measurement bias. To address this issue, following Y. Zhang and Li (2022), this study constructs a composite indicator of AI by combining two dimensions: the frequency of AI-related keywords in annual reports and the level of enterprise investment in AI. This approach provides a more comprehensive and objective measurement of

AI adoption at the micro-enterprise level. The specific calculation formula is as follows:

$$\boldsymbol{AI = \beta_0 + \beta_1 AI_{Invest} + \beta_2 AI_{Text}} \quad (4.6)$$

(3) Human Capital Structure (HR)

The relationship between human capital and innovation performance has been the subject of extensive empirical research, yet the findings remain inconclusive.

J. Wang and Wang (2016) analyzed the impact of employee education levels on enterprise innovation performance using data from the Second China Economic Census Yearbook. They measured education levels as the proportion of employees with various educational backgrounds within an industry. Their study found that higher employee education levels and longer years of schooling positively correlate with improved innovation performance.

Conversely, some empirical studies suggest that human capital investment does not always have a significant positive relationship with innovation performance. For example, Feng (2010) measured the innovation performance of high-tech enterprises using patent output and new product output. The study found no significant relationship between R&D personnel investment and innovation output. Cao (2010) conducted an empirical analysis of China's electronics and communications equipment manufacturing industry. They investigated the relationship between R&D personnel input and performance output. The results indicated that R&D personnel investment had varied effects on different performance metrics. For instance, increasing R&D personnel investment reduced the share of new product sales but increased main business revenue.

To evaluate the human capital structure of enterprises more comprehensively, this study uses two indicators:

Average Years of Education (EDU): Reflecting the overall educational attainment of employees.

Proportion of High-End R&D Personnel (RD): Measuring the share of advanced R&D personnel within the workforce.

These indicators collectively assess the human capital structure in enterprises.

$$\boldsymbol{HR = \beta_0 + \beta_1 EDU + \beta_2 RD} \quad (4.7)$$

(4) Government Support (Gov)

Currently, government support for AI technology in high-end equipment manufacturing primarily involves direct subsidies and tax incentives. These policies not only provide financial assistance to enterprises but also create a conducive innovation environment through infrastructure development and technological investments.

To quantify government support, most studies use government subsidies as the primary

evaluation metric. However, findings on the relationship between government subsidies and innovation performance are mixed. Y. Yang et al. (2015) analyzed the impact of government subsidies on enterprises with different ownership structures using industrial enterprise data. The study found that subsidies have a stronger positive effect on innovation performance in private enterprises compared to state-owned enterprises. Conversely, F. Li et al. (2017) examined the effects of industrial policies on the innovation and financial performance of Chinese photovoltaic enterprises. The study revealed that during the rapid expansion and adjustment phase of China's photovoltaic industry, government subsidies significantly improved financial performance but had no significant impact on innovation performance. As market and policy environments stabilized, subsidies began to significantly promote both innovation and profitability.

In this study, government subsidies are adopted as the primary proxy for government support to analyze their influence on the innovation performance of high-end equipment manufacturing enterprises.

(5) Industrial Structure Upgrading

Industrial structure upgrading includes two dimensions:

a) Rationalization of Industrial Structure (TL): Reflects the degree of coordination among industries and the efficiency of resource utilization. The Theil Index is used as the measure for this aspect.

b) Advancement of Industrial Structure (TS): Captures the evolutionary process of industrial structure, measured by the proportion of high-end equipment manufacturing output to the total output of all manufacturing industries.

The specific formulas are as follows:

$$\mathbf{TL} = \sum_{\mathbf{i=1}}^{\mathbf{n}} \left(\frac{\mathbf{Y_i}}{\mathbf{Y}}\right) \mathbf{ln}\left(\frac{\mathbf{Y_i}}{\mathbf{L_i}} \Big/ \frac{\mathbf{Y}}{\mathbf{L}}\right) \tag{4.8}$$

$$\mathbf{TS} = \frac{\mathbf{Y_H}}{\mathbf{Y_2}} \tag{4.9}$$

These metrics comprehensively assess the rationalization and advancement of industrial structure, providing a quantitative basis for analyzing the impacts of AI technology and policy interventions on industrial upgrading.

(6) Enterprise Value

R&D Activities and Enterprise Value

R&D activities are crucial sources of competitive advantage for enterprises, with investments in R&D-intensive enterprises yielding higher economic returns. Patents, as the ultimate outcomes of R&D, provide enterprises with significant benefits upon successful

application and disclosure. These benefits include enhancing the ability to absorb external knowledge, signaling effects that attract valuable research inputs such as high-quality talent, enabling sales of newly developed products to customers, measurement of enterprise Value.

Enterprise value can be measured using Metrics based on the book value of various asset types, such as Return on Equity (ROE), Return on Assets (ROA), Net Profit Margin, Earnings Per Share (EPS). However, financial indicators have limitations. They are subject to quarterly or annual fluctuations. Book profits can be artificially adjusted, undermining insights into long-term enterprise development. These overcome the limitations of financial metrics and focus on long-term enterprise growth.

Proposed by American economist James Tobin in 1969, Tobin's Q ratio is a widely used metric for evaluating enterprise value. It is defined as the ratio of the market value of an enterprise's stock to its replacement cost, with the following implications:

Q > 1: The market value exceeds the replacement cost, encouraging managers to expand through organic growth.

Q < 1: The market value is less than the replacement cost, motivating managers to pursue expansion through acquisitions.

It is a relative metric, allowing comparisons across enterprises of varying sizes and types. Tobin's Q integrates internal and external data, avoiding the short-term and manipulable nature of financial metrics. By combining assets and market value, Tobin's Q reflects market recognition of an enterprise's assets, encouraging management to adopt a long-term perspective, conducive to sustainable development.

(8) Control Variables

Drawing on previous studies on enterprise innovation performance, this study includes the following control variables to account for enterprise-specific and structural factors that might influence innovation outcomes. These variables are selected and measured as shown in the Table 4.1.

Table 4.1 Variables of this study

Type	Variable	Code	Explanation
Dependent Variable	Innovation performance	Inv	The natural logarithm of the total number of patent applications plus 1
	Industry upgrade	IUI	Industrial structure rationalization (TL) and industrial structure upgrading (TS)
	Enterprise value	TobinQ	The ratio of the market value of stocks to the replacement cost
Independent Variable	AI technology	AI	The frequency of AI keywords in annual reports and the level of AI investment of enterprises

Type	Variable	Code	Explanation
Mediator	Human capital structure	HR	The average number of years of education per capita (EDU) and the proportion of high-end R&D personnel (RD)
	Government support	Gov	The amount of government subsidies
Control Variable	Enterprise size	Size	The natural logarithm of the total assets of enterprises
	Enterprise age	Age	The natural logarithm of the difference between the sample year and the year of establishment of the enterprise
	Growth potential	Growth	The growth rate of total assets
	Current asset ratio	Cr	Current assets divided by total assets
	Equity concentration	Crl	The shareholding ratio of the largest shareholder
	Year	Year	Dummy variables

4.3 Data analysis results

4.3.1 Descriptive statistical analysis

The descriptive statistical analysis of all variables is presented in Table 4.2. The mean value of the innovation performance indicator (Inv) is 5.253, indicating that high-end equipment manufacturing enterprises in Shenzhen demonstrate strong performance in patent applications. A standard deviation of 1.133 reveals significant variation in innovation performance among enterprises, with a wide range between the minimum and maximum values, highlighting the leading position of certain enterprises in innovation capability.

Table 4.2 Descriptive statistics of variables

Variable	Sample	Mean	SD	Min	Max
Inv	1584	5.253	1.133	3.032	8.985
IUI	1584	0.751	0.153	0.287	1.193
TobinQ	1584	1.332	0.629	0.762	3.539
AI	1584	5.467	2.041	0.000	9.892
HR	1584	2.387	0.378	1.562	2.974
Gov	1584	2.813	0.891	1.238	4.622
Size	1584	10.512	2.237	7.736	15.075
Age	1584	2.435	0.751	1.288	4.862
Growth	1584	0.126	0.087	-0.053	0.458
Cr	1584	3.627	0.188	3.261	3.974
Crl	1584	0.756	0.145	0.438	0.961

The mean value of industrial upgrading (IUI) is 0.751, reflecting a generally balanced performance by most enterprises in terms of rationalization and sophistication of industrial structures. A standard deviation of 0.153 suggests relatively minor differences among enterprises in industrial upgrading, yet the gap between the minimum and maximum values still

points to some enterprises holding a leading edge.

The mean value of enterprise value (TobinQ) is 1.332, showing that the market value of high-end equipment manufacturing enterprises in Shenzhen generally exceeds their asset replacement costs. A standard deviation of 0.629 indicates substantial fluctuations in enterprise value, with a maximum of 3.539 signifying high market recognition for certain enterprises, whereas a minimum value of 0.762 implies significant market challenges for others.

The mean value of AI technology (AI) is 5.467, suggesting a high frequency of AI mentions in annual reports and significant levels of AI application among these enterprises. However, a standard deviation of 2.041 indicates considerable disparities in AI technology adoption. While some enterprises have not yet engaged with AI (minimum value = 0), others have achieved a leading position in intelligent manufacturing (maximum value = 9.892).

The mean value of human capital structure (HR) is 2.387, reflecting a high average educational attainment per employee and a substantial proportion of high-end R&D personnel among these enterprises. A standard deviation of 0.378 shows some variation in human capital structure among enterprises, though the overall level is relatively close, with limited differences between the minimum and maximum values.

The mean value of government support (Gov) is 2.813, indicating that most enterprises receive subsidies or support from the government. A standard deviation of 0.891 reveals some degree of variation in the amounts of support received by different enterprises.

4.3.2 Regression analysis

Based on the regression models constructed earlier, the study hypotheses are validated as follows:

Using STATA 17.0, a regression analysis is conducted to examine the impact of AI technology on innovation performance (see Table 4.3). This step tests the direct relationship between AI implementation and enterprises‘ innovation capabilities. Subsequently, a mediation effect analysis is performed to explore the roles of human capital structure and government support in the relationship between AI technology and innovation performance. This involves testing whether and how these two factors mediate the influence of AI on innovation outcomes. Finally, regression analysis is carried out to assess the effect of innovation performance on industrial upgrading and enterprise value, providing insights into how innovation contributes to broader enterprise-level outcomes.

Table 4.3 Regression analysis results

Variable	Model 1 Inv	Model 2 Inv	Model 3 Inv	Model 4 IUI	Model 5 TobinQ
AI	0.213***				
HR		0.312***			
Gov			0.145**		
Inv				0.387***	0.355*
Size	0.258**	0.240*	0.221*	0.207*	0.185
Age	-0.134*	-0.125	-0.118	-0.109	-0.102
Growth	0.098	0.089	0.082	0.076	0.068
Cr	-0.172**	-0.160**	-0.149**	-0.136**	-0.127**
Crl	0.097*	0.091*	0.085*	0.078*	0.071*
N	1584	1584	1584	1584	1584
Adj_R2	0.682	0.671	0.659	0.641	0.625

Note: Significance Levels: *** p < 0.01, ** p < 0.05, * p < 0.10

The regression results in Model (1) indicate that the regression coefficient of AI technology (AI) is 0.213, which is significant at the 0.01 level. This finding suggests that AI application has a significant positive impact on enterprise innovation performance, thereby validating Hypothesis H1. Specifically, the adoption of AI technology provides enterprises with multiple innovation advantages. AI enhances automation and intelligence in R&D activities, reducing repetitive tasks and enabling the efficient development of new products and technologies. This efficiency gain is directly reflected in the increase in patent applications, demonstrating tangible improvements in innovation capabilities. For Shenzhen's high-end equipment manufacturing enterprises, AI adoption not only improves product quality and production efficiency but also opens new business opportunities and markets. Applications in precision manufacturing and intelligent testing allow enterprises to respond rapidly to market demands, introducing technologically advanced products and gaining a competitive edge. Overall, the regression results of Model (1) highlight that investments in AI technology not only enhance quantitative innovation indicators, such as patent applications, but also fundamentally transform enterprises' innovation capabilities and approaches. This underscores the pivotal role of AI in modern enterprise innovation. Policymakers are also provided with valuable insights, suggesting that encouraging and supporting the application of AI technology could be a crucial avenue to fostering enterprise innovation.

In Model (2), the regression coefficient of human capital structure (HR) is 0.312, significant at the 0.01 level, indicating a significant positive impact on innovation performance. Higher levels of education and a greater proportion of R&D personnel significantly enhance enterprises' innovation capabilities. This result may also suggest that enterprises aiming to strengthen AI-driven innovation are actively recruiting highly educated and skilled talent. Shenzhen, as a hub for high-caliber talent, enables high-end equipment manufacturing enterprises to heavily rely

on skilled professionals. The city boasts a substantial pool of highly educated and skilled individuals, particularly in engineering, computer science, and AI fields. The accumulation and utilization of talent directly drive enterprise innovation activities. The proportion of high-end R&D personnel is crucial for improving innovation performance, as skilled technical talent enables enterprises to undertake complex R&D projects and maintain a competitive edge in the industry. Optimizing human capital structure is thus critical for high-end equipment manufacturing enterprises in Shenzhen to sustain innovation momentum.

In Model (3), the regression coefficient of government support (Gov) is 0.145, significant at the 0.05 level, indicating a positive effect of government subsidies on enterprise innovation performance. The greater the government support received, the higher the innovation performance of enterprises. Government policies, such as financial subsidies and tax incentives, reduce R&D costs, encouraging enterprises to allocate more resources toward innovation activities. However, the impact of government support is less pronounced compared to AI technology and human capital structure. This may be attributed to certain limitations or delays in the allocation and utilization of subsidies. For instance, enterprises might divert portions of the subsidies to non-R&D activities, or an over-reliance on government support could undermine intrinsic innovation motivation, leading to a limited improvement in innovation performance.

In Model 4, the regression coefficient of innovation performance (Inv) on industrial upgrading (IUI) is 0.387, significant at the 0.01 level. This result indicates that innovation performance has a significant positive impact on industrial upgrading. For Shenzhen's high-end equipment manufacturing sector, industrial upgrading is closely linked to enterprise innovation performance. Enterprises with strong innovation capabilities are better positioned to drive the rationalization and advancement of industrial structures, facilitating the transition from traditional manufacturing to intelligent manufacturing. By continuously engaging in technological innovation, enterprises in Shenzhen improve overall manufacturing efficiency and increase the added value of their products. Through this process, the sector is progressively shifting from low-value-added processing and manufacturing to high-tech, high-value-added production. Therefore, Hypothesis H4 is supported, confirming that innovation performance significantly promotes industrial upgrading in Shenzhen's high-end equipment manufacturing industry.

In Model 5, the regression coefficient of innovation performance (Inv) on enterprise value (TobinQ) is 0.355, significant at the 0.1 level. While this result suggests a positive relationship between innovation performance and enterprise value, the lower significance level (0.1)

warrants cautious interpretation. In the context of Shenzhen's high-end equipment manufacturing sector, this finding requires careful consideration due to several factors.

First, the time lag of innovation investment plays a role. Innovation activities often take time to produce measurable outcomes. The period between R&D efforts and market realization of new products can be considerable. As a result, current innovation performance may not yet be fully reflected in the market value of enterprises. This is particularly true in high-end equipment manufacturing, where technological innovation involves complex development and testing processes, which may not yield immediate increases in enterprise value.

Second, the risks and uncertainties associated with innovation must be considered. While innovation enhances competitiveness, it also involves significant risks. Failed projects or poor market responses can result in substantial financial losses, potentially decreasing enterprise value. External factors such as market acceptance of new technologies and regulatory changes may also affect the realization of innovation outcomes, delaying the translation of innovation performance into enterprise value.

Third, market expectations and competitive pressures are important considerations. The high-end equipment manufacturing sector in Shenzhen faces intense competition. When multiple enterprises engage in similar innovations, market share gains from such efforts may be limited, restricting the associated increase in enterprise value. Additionally, discrepancies between investors' expectations of an enterprise's innovation capabilities and actual outcomes can lead to volatility in enterprise value. In capital markets, heightened expectations that fail to materialize could result in declining valuations, even if enterprises perform well in innovation.

Fourth, financial constraints and pressures are another factor. Innovation in high-end equipment manufacturing typically requires substantial financial investment. Over-reliance on external financing can increase financial strain. High debt levels or liquidity issues may offset the gains from innovation, preventing expected increases in enterprise value.

Lastly, the conversion of innovation outcomes into business value is a critical determinant. The extent to which innovation outcomes can be successfully commercialized depends on factors such as marketing, supply chain management, and customer service. Any shortcomings in these areas during the marketization of innovation results may prevent improved innovation performance from translating into actual growth in enterprise value.

From the perspective of control variables, enterprise size (Size) and equity concentration (Crl) are positively correlated with innovation performance, while current asset ratio (Cr) and enterprise age (Age) show significant negative correlations with innovation performance. These results suggest that larger enterprises and those with higher equity concentration are better

positioned to enhance innovation performance. Expanding enterprise size appropriately provides additional resources and support for innovation activities. Meanwhile, higher equity concentration improves decision-making efficiency and reduces potential conflicts arising from overly dispersed ownership, thereby promoting innovation. Additionally, increased R&D investment plays a critical role in improving innovation performance. On the other hand, higher current asset ratios may negatively impact innovation performance, highlighting the need for enterprises to allocate idle funds effectively. Instead of accumulating excessive current assets, enterprises should invest these resources in innovation projects to strengthen innovation capacity and core competitiveness. Finally, as enterprises age, they may experience organizational rigidity and declining innovation incentives. Therefore, maintaining flexibility and innovation vitality throughout an enterprise's growth is essential for sustaining innovation development.

4.3.3 Mediation effect testing

The Bootstrap method is employed to evaluate the direct and indirect effects of AI on enterprise innovation performance through human capital structure (HR) and government support (Gov) as mediating variables (see Table 4.4).

Table 4.4 Mediation effect testing of human capital structure and government support

Pathway	Effect Type	Effect Value	Standard Error	Bootstrap 95% CI	
				L L C I	U L C I
AI → Human Capital Structure → Innovation Performance	Direct Effect	0.134	0.045	0.048	0.294
	Indirect Effect	0.079	0.043	0.008	0.076
AI → Government Support → Innovation Performance	Direct Effect	0.168	0.042	0.086	0.286
	Indirect Effect	0.045	0.037	0.002	0.019

In the pathway with human capital structure (HR) as the mediator, the direct effect of AI on innovation performance is 0.134, with a standard error of 0.045, and the indirect effect is 0.079, with a standard error of 0.043. The Bootstrap 95% confidence intervals for both effects do not include zero, indicating statistical significance. This result demonstrates that AI technology indirectly improves innovation performance by enhancing the human capital structure, such as increasing employees' educational levels or attracting high-end R&D talent. Therefore, Hypothesis H2 is supported.

In the pathway with government support (Gov) as the mediator, the direct effect of AI on innovation performance is 0.168, with a standard error of 0.042, and the indirect effect is 0.045,

with a standard error of 0.037. Again, the Bootstrap 95% confidence intervals for both effects do not include zero, confirming significance. This indicates that AI also indirectly enhances innovation performance by leveraging government support. Thus, Hypothesis H3 is supported.

Overall, AI technology not only directly promotes enterprise innovation performance but also enhances it indirectly through two pathways: improving human capital structure and securing government support. These findings highlight the critical role of AI technology in modern enterprises and its synergistic effect with human capital and government policies in driving innovation.

4.3.4 Testing for endogeneity

To address potential endogeneity issues, such as reverse causality between AI application and enterprise innovation performance or omitted key variables, this study adopts a strategy using lagged AI application data as instrumental variables. Specifically, AI application data lagged by one and two periods are employed as instrumental variables, and the instrumental variable (IV) approach is applied. The regression results are shown in Table 4.5.

Table 4.5 Endogeneity test

Variable	One period lag	Two period lag
L_AI	0.235***	
LL_AI		0.362***
Size	0.218**	0.195*
Age	-0.112*	-0.098
Growth	0.081	0.073
Cr	-0.154**	-0.139**
Crl	0.089*	0.084*
N	1584	1584
Adj_R2	0.658	0.642

In the one-period lagged model, the regression coefficient of lagged AI application (L_AI) is 0.235, significant at the 0.01 level. This indicates that AI technology investments made in the previous period have a significant positive impact on current innovation performance. Such improvements are specifically reflected in measurable outcomes like an increase in patent applications or other innovation metrics. In the two-period lagged model, the regression coefficient of lagged AI application (LL_AI) is 0.362, also significant at the 0.01 level. This suggests that earlier AI technology investments have an even stronger impact on innovation performance. This finding highlights the cumulative effect of AI application, where its influence on innovation becomes more substantial over time.

These results underscore the role of AI technology as a key driver of innovation performance in the high-end equipment manufacturing industry. The cumulative impact of AI

investments validates Hypothesis H1 and demonstrates that sustained AI application significantly enhances an enterprise's innovation outcomes over time.

4.3.5 Robustness testing

To further verify the robustness of the regression results, this study adopts an alternative measure for the dependent variable, innovation performance. Specifically, the original indicator of patent applications is replaced with the number of patents granted, and the variable is logarithmically transformed for quantification. The calculation formula is as follows:

$$\mathbf{Inv_S = Ln(P + 1)} \tag{4.10}$$

where PPP represents the number of patents granted.

Using this revised indicator, regression analysis is conducted again to test the consistency and robustness of the findings (see Table 4.6).

Table 4.6 Model robustness test results

Variable	Model 1 Inv_S	Model 2 Inv_S	Model 3 Inv_S	Model 4 IUI	Model 5 TobinQ
AI	0.245***				
HR		0.310***			
Gov			0.150**		
Inv_S				0.379***	0.348*
Size	0.221**	0.215*	0.198*	0.207*	0.188
Age	-0.115*	-0.108	-0.103	-0.111	-0.097
Growth	0.082	0.076	0.072	0.070	0.065
Cr	-0.161**	-0.154**	-0.149**	-0.142**	-0.131**
Crl	0.091*	0.087*	0.082*	0.088*	0.073*
N	1584	1584	1584	1584	1584
Adj_R2	0.672	0.658	0.645	0.663	0.648

Based on the regression results after replacing the dependent variable, the following observations can be made:

In Model 1, the regression coefficient of AI is 0.245, significant at the 0.01 level. This indicates that AI technology has a significant positive impact on enterprise innovation performance. Even after replacing the measure of innovation performance, the influence of AI remains significant, underscoring its critical role in enhancing enterprises' innovation capabilities.

In Model 2, the regression coefficient of human capital structure (HR) is 0.310 and significantly positive. This shows that HR has a significant positive impact on innovation performance. After substituting the dependent variable, the effect of HR remains robust, highlighting the importance of high-end talent and human capital in driving enterprise innovation performance.

In Model 3, the regression coefficient of government support (Gov) is 0.150, significant at the 0.05 level. This suggests that government support continues to have a positive impact on enterprise innovation performance. Even with a different measure of innovation performance, government support remains a crucial driver of enterprises' innovation activities.

In Model 4, the regression coefficient of innovation performance on industrial upgrading is 0.379 and highly significant (***). This indicates that innovation performance has a significant positive effect on industrial upgrading. Sustained innovation enables enterprises to optimize their industrial structures and achieve higher levels of industrial upgrading.

In Model 5, the regression coefficient of innovation performance on enterprise value is 0.348, significant at the 0.05 level. This demonstrates that innovation performance enhances enterprise market value, with enterprises gaining greater market recognition and valuation through their innovation activities.

These results are consistent with those obtained before replacing the dependent variable, confirming the robustness of the findings. The relationships between AI application, human capital structure, government support, innovation performance, industrial upgrading, and enterprise value remain stable and reliable across different measures of innovation performance.

4.4 Chapter summary

This chapter presented the empirical analysis of the proposed research model, testing the direct, indirect, and extended effects of AI application in Shenzhen's high-end equipment manufacturing enterprises. The results from descriptive statistics confirmed significant heterogeneity among enterprises in innovation performance, AI adoption, human capital structure, and government support. Regression analysis demonstrated that AI exerts a strong positive effect on innovation performance, thereby validating the central hypothesis. Furthermore, mediation testing revealed that AI indirectly enhances innovation performance through two key pathways: the optimization of human capital structure and the strengthening of government support. These findings highlight the dual role of AI as both a direct driver of innovation and an enabler of external and internal conditions that foster innovation.

Beyond innovation, this chapter also investigated AI's extended effects. Innovation performance was shown to significantly promote industrial upgrading, confirming that AI contributes to structural transformation through innovation-driven mechanisms. Similarly, innovation performance positively affected enterprise value, although the statistical significance was weaker, suggesting that the translation of innovation into enterprise value may

involve time lags, risks, and market uncertainties. Robustness checks, including alternative measures of innovation output and lagged instrumental variables, consistently supported the stability and reliability of the findings.

In summary, the empirical evidence strongly supports most of the proposed hypotheses, with only partial support for the effect of AI on enterprise value (see Table 4.7). This outcome underscores the complexity of value realization in high-end equipment manufacturing, where innovation advantages must overcome external market and financial constraints before being fully reflected in enterprise valuation. Overall, the findings affirm AI's pivotal role in enhancing innovation capabilities, optimizing structural pathways, and driving high-quality development in Shenzhen's high-end equipment manufacturing sector. However, although macro-level panel data analysis effectively identified "whether" and "to what extend" AI is effective, it could not explain the specific organizational mechanisms through which enterprises translate technological applications into innovation performance. In particular, the impact of AI within enterprises is often not directly reflected in performance improvement, but is indirectly realized through processes such as product innovation, business model innovation, resource reconfiguration, and the upgrading of organizational capabilities. Accordingly, building on the findings of the macro-level study, the next chapter will extend the analysis to the perspective of internal enterprise mechanisms.

Table 4.7 Research hypotheses and results

Hypothesis	Statement	Result
H1	AI application significantly promotes enterprises' innovation performance.	Supported
H2	AI application significantly influences enterprises' innovation performance by optimizing human capital structure.	Supported
H3	AI application significantly influences enterprises' innovation performance through increased government subsidies.	Supported
H4	AI application promotes industrial upgrading by enhancing enterprises' innovation performance.	Supported
H5	AI application enhances enterprise value by improving innovation performance.	Partially Supported

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Chapter 5: Extended Study: Impact of Disruptive Innovation and Dynamic Capabilities on Innovation Performance

5.1 Research questions

Chapter 4, based on macro-level panel data analysis, verified the impact of artificial intelligence (AI) technology on the innovation performance of high-end equipment manufacturing enterprises and its extended effects, revealing the important role of AI in promoting enterprise development. However, macro-level empirical analysis primarily addressed whether AI exerts an effect, while the specific mechanisms through which this effect is realized within enterprises require further in-depth exploration. Accordingly, building on the preceding findings, we further extended the analysis to an internal enterprise perspective, forming a two-step research logic of "macro-level empirical identification – micro-level mechanism extension".

In the digital economy era characterized by rapid technological advancement and market dynamics, the ability of enterprises to enhance their core competitiveness through continuous technological and organizational innovation has become a key determinant of sustainable development. Distinct from incremental innovation, disruptive innovation, characterized by disruptive value propositions, lower initial performance, and cost advantages, often reshapes industry competition landscape, posing significant challenges to existing market leaders. For high-end equipment manufacturing enterprises, the impact of AI is not limited to its use as a technological tool; it also fundamentally reshapes product forms, value creation processes, and organizational operation modes. Therefore, disruptive innovation can be regarded as an essential manifestation of enterprises' responses to the impact of AI and efforts to achieve innovation breakthroughs.

However, disruptive innovation does not inherently lead to high performance. Whether enterprises can effectively absorb, integrate, and reconfigure emerging resources in response to disruptive changes depends on their dynamic capabilities. Dynamic capabilities emphasize an enterprise's ability to sense opportunities, integrate resources, and reconfigure organizational structures in dynamic environments. They determine not only whether enterprises can respond promptly to external technological shocks, but also whether innovation activities can be effectively translated into performance improvements. Therefore, from the perspective of

disruptive innovation and dynamic capabilities, this chapter aims to systematically explore how enterprises can achieve improvements in innovation performance by enhancing their internal capabilities in environments with high uncertainty.

Based on this background, this study aims to address the following research questions (RQs):

RQ1: Does disruptive innovation significantly influence enterprise innovation performance, and in what direction?

RQ2: Do dynamic capabilities play a mediating role between disruptive innovation and innovation performance, and is this mediation full or partial?

RQ3: Do different dimensions of dynamic capabilities, such as sensing, integrating, and reconfiguring, exert differential effects in the mediating pathways?

5.2 Research hypotheses

5.2.1 Disruptive innovation and innovation performance

Disruptive innovation is generally regarded as an important form of innovation through which enterprises disrupt existing technological paths, market boundaries, and value creation models. Classical studies suggest that disruptive innovation is not merely incremental improvement of existing products and services, but rather involves the reconstruction of existing competitive landscape through new technological solutions, new market entry pathways, or business model innovation, which can generate new growth opportunities for enterprises. As indicated by Christensen (1997), disruptive innovation often originates outside mainstream markets, but it may eventually reshape existing market structures as technologies improve and market acceptance increases. Tushman and Nadler (1986) also pointed out that disruptive innovation could drive capability upgrading and competitive advantage reconfiguration within enterprises.

In the context of digitalization and the rapid advancement of AI, the effect of disruptive innovation in enhancing enterprise performance has received increasing empirical support. Y. Li et al. (2024) found that the application of AI technologies could significantly promote enterprise innovation by increasing knowledge diversity, breaking organizational routines, and improving resource allocation efficiency, with a particularly strong effect on disruptive innovation. Y. He and Xiong (2025), using a sample of manufacturing enterprises, further demonstrated that AI applications significantly enhanced enterprise innovation performance, indicating that technology-driven innovation transformation can be effectively translated into

enterprise performance improvements. J. Shen and Wang (2025) also showed that AI resources significantly promoted ambidextrous innovation performance, suggesting that the integration of new technological elements could increase the likelihood of generating high-value, disruptive innovations. K. Chen et al. (2025), from the perspective of new-quality productive forces, indicated that AI applications could reconstruct innovation paradigms and drive productivity upgrading within enterprises, thereby enhancing sustainable competitive advantage.

For high-end equipment manufacturing enterprises, the significance of disruptive innovation is particularly prominent. On the one hand, product disruptive innovation, through the introduction of new knowledge, new technologies, and new product forms, can break path dependence on existing technologies and enhance product performance and market competitiveness. On the other hand, business-model disruptive innovation, by reshaping value propositions, customer interaction modes, and cost structures, can help enterprises develop new profit mechanisms and gain growth opportunities. Given the characteristics of end equipment manufacturing industry, namely, high technological complexity, long R&D cycles, and intense market competition, enterprises that achieve disruptive innovation in products or business models are more likely to gain significant advantages in both financial performance and development performance.

Based on the above findings, we propose the following hypotheses:

H1: Disruptive innovation positively affects enterprises' innovation performance.

H1a: Product disruptive innovation positively affects enterprises' financial performance.

H1b: Product disruptive innovation positively affects enterprises' development performance.

H1c: Business-model disruptive innovation positively affects enterprises' financial performance.

H1d: Business-model disruptive innovation positively affects enterprises' development performance

5.2.2 Disruptive innovation and dynamic capabilities

Dynamic capabilities theory emphasizes that, in rapidly changing environments, enterprises must continuously sense opportunities, acquire and integrate resources, and reconfigure organizational structures to sustain competitive advantage. Existing studies have primarily treated dynamic capabilities as antecedents of innovation activities. However, recent research suggests that the relationship between disruptive innovation and dynamic capabilities is not

unidirectional but may involve continuous interaction and co-evolution. Teece (2007) pointed out that in dynamic environments, whether competitive advantage can be sustained depends on an enterprise's ability to sense opportunities, integrate resources, and reconfigure organizational structures. Similarly, Eisenhardt and Martin (2000) indicated that dynamic capabilities are essentially manifested in the continuous renewal and reconfiguration of an enterprise's resource base.

Recent studies provided more specific evidence for this relationship. Y. Zhang, Li, et al. (2023), from the perspective of knowledge management, found that enterprises' meta-knowledge development capabilities were not directly translated into disruptive innovation, but through the chain effect of knowledge transfer and dynamic capabilities, indicating a strong coupling between capabilities and innovation practices. Hou et al. (2024) further pointed out that, under conditions of uncertainty in innovation ecosystems, the realization of disruptive innovation would rely on the mediation of dynamic capabilities, especially cognitive and non-cognitive capabilities, which provide critical support for innovation behaviors. Ganguly et al. (2022) found that absorptive capacity could promote disruptive innovation through organizational agility, suggesting that the more disruptive the innovation, the higher the requirements for enterprises' resource reconfiguration and organizational responsiveness. C. Wu et al. (2025), through their study of startups in a digital era, showed that enterprises could continuously strengthen dynamic marketing capabilities by leveraging digital resources to construct technological chains, platform structures, and value ecosystems, thereby driving sustained disruptive innovation.

The above studies suggest that in pursuing disruptive innovation, enterprises do not merely "utilize" existing dynamic capabilities but also continuously reinforce and reshape their capabilities in the process. Specifically, product disruptive innovation is often accompanied by changes in technological routes, knowledge renewal, and the reconfiguration of R&D processes, which will enhance enterprises' capabilities in opportunity sensing, resource integration, and organizational reconfiguration. In contrast, business-model disruptive innovation involves the redesign of business processes, organizational structures, and value networks, and thus is more likely to directly enhance organizational reconfiguration capability, while also driving the evolution of opportunity sensing and resource integration capabilities.

Based on the above findings, we propose the following hypotheses:

H2: Disruptive innovation positively influences dynamic capabilities.

H2a: Product disruptive innovation positively influences opportunity sensing capability.

H2b: Product disruptive innovation positively influences resource integration capability.

H2c: Product disruptive innovation positively influences organizational reconfiguration capability.

H2d: Business-model disruptive innovation positively influences opportunity sensing capability.

H2e: Business-model disruptive innovation positively influences resource integration capability.

H2f: Business-model disruptive innovation positively influences organizational reconfiguration capability.

5.2.3 Mediating effect of dynamic capabilities

Dynamic capabilities represent a fundamental basis for enterprises to adapt to environmental changes and may also serve as a critical bridge through which disruptive innovation is translated into innovation performance. Teece et al. (1997) pointed out that dynamic capabilities determine an enterprise's ability to integrate, build, and reconfigure resources in rapidly changing environments, thereby influencing the formation of competitive advantage. C. L. Wang and Ahmed (2007) further suggested that dynamic capabilities essentially support enterprises' continuous innovation and performance improvement, serving as an important mediator linking innovation activities and performance.

Lai et al. (2023) indicated that data-driven dynamic capabilities of manufacturing enterprises were not static; instead, they are gradually developed and evolve through the continuous interaction of data acquisition, analytical utilization, and organizational response. This suggests that, when facing new technologies and emerging contexts, enterprises must rely on dynamic capabilities to integrate dispersed information, technologies, and resources into actionable innovation activities. Shao et al. (2024) further found that digital knowledge management could significantly promote technological innovation in manufacturing enterprises through dynamic capabilities, indicating the key mediating role of dynamic capabilities in translating knowledge elements into innovation performance. In addition, X. Xu et al. (2023), from a risk prevention perspective, suggested that digitalization could enhances enterprises' ability to cope with complex environments and resist risks primarily due to the activation of dynamic capabilities. This implies that, under conditions of uncertainty, enterprises' dynamic capabilities not only facilitate risk management but also support the effective implementation of innovation activities. Y. Fan et al. (2025), drawing on digital affordance theory, found that regional digital environments significantly influenced both disruptive and incremental innovation in manufacturing enterprises, and that enterprises' ability to identify and exploit

external digital opportunities was a key condition for achieving innovation. This finding implies that innovation behaviors do not directly lead to performance outcomes; only through the identification, absorption, and transformation of opportunities via dynamic capabilities can innovation fully realize its positive effects.

In terms of the overall process of innovation performance formation, dynamic capabilities do not merely serve as auxiliary factors at a single stage, but rather function as a systemic capability mechanism that connects “innovation behavior” with the realization of “innovation value”. With respect to the research context of this study, the reason why disruptive innovation can enhance innovation performance is not that innovation activities were inherently effective; rather, it is due to the fact in the process of advancing innovation, enterprises can improve the alignment between innovation direction and market demand through opportunity sensing capability, enhance the implementation efficiency of innovation solutions through resource integration capability, and ensure the alignment of innovation activities with enterprises’ internal structures, processes, and institutional systems through organizational reconfiguration capability. Hence, different dimensions of dynamic capabilities may all mediate the relationship between disruptive innovation and innovation performance.

Based on the above research findings, we propose the following hypotheses:

H3: Dynamic capabilities mediate the relationship between disruptive innovation and innovation performance.

H3a: Opportunity sensing capability mediates the relationship between disruptive innovation and financial performance.

H3b: Resource integration capability mediates the relationship between disruptive innovation and development performance.

H3c: Organizational reconfiguration capability mediates the relationship between disruptive innovation and overall innovation performance.

Together, these hypotheses underscore that, in advancing disruptive innovation, enterprises that activate and deploy their dynamic capabilities will markedly improve the efficiency of innovation conversion and, ultimately, elevate innovation performance. To conclude, the model developed in this chapter is presented in Figure 5.1.

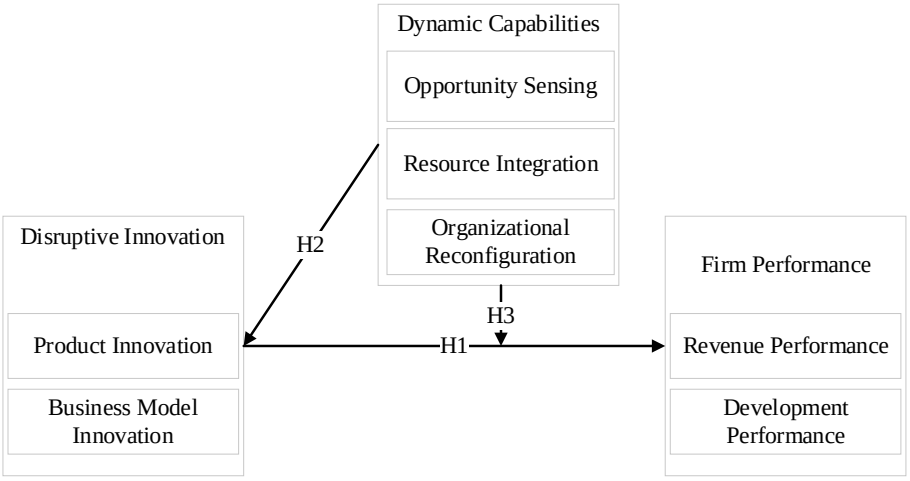


Figure 5.1 The mediating effect of dynamic capabilities in the relationship between disruptive innovation and innovation performance

5.3 Research design

This study measured the following key constructs: disruptive innovation (independent variable), dynamic capabilities (mediators), and enterprise innovation performance (dependent variable). We primarily used established scales adapted to the research context of this study. All items were measured on a 5-point Likert scale.

5.3.1 Enterprise innovation performance

Drawing on J. Gao et al. (2004) on performance indicators for technological innovation; Xie et al. (2006) on market orientation and organizational performance; J. Chen and Chen (2006) on evaluation systems for technological innovation performance; Richard et al. (2007) and Lunnan and Haugland (2008) on the distinction between financial and development performance; Newbert (2008) on the dimensionality of innovation performance; Y. Chen and Chen (2009) on how open innovation promotes innovation performance; and X. Qian et al. (2010) on network position, absorptive capacity, and innovation performance, the construct is operationalized as subjective financial performance and subjective development performance tailored to this study's sample (Table 5.1).

Table 5.1 Scale for enterprise innovation performance

Dimension	Item
Financial Performance	The enterprise outperforms peers in return on investment.
	The enterprise outperforms peers in return on assets.
	Sales volume of core products/business has increased markedly.
	Market share of core products/business has increased markedly.
	The enterprise maintains a healthy financial cash flow position.
Development Performance	The enterprise is better at improving customer satisfaction.
	The enterprise shows stronger potential to attract new customers.
	The number of employee suggestions implemented grows year by year.
	Top management is highly satisfied with business results.
	Average employee productivity exceeds that of competitors.

5.3.2 Disruptive innovation scale

The literature on disruptive innovation is largely descriptive (Christensen, 1997) and often distinguishes between radical and disruptive innovation (Govindarajan & Ramamurti, 2011; Tellis, 2006). Building on Zhao et al. (2009) on disruptive vs. sustaining innovation under ambidextrous organizations; J. Wang and Chen (2010) on disruptive innovation, producer services, and latecomer advantages; and C. Zhang and Chen (2011) on choice of innovation modes, and adapting measurement approaches for breakthrough innovation (K. Z. Zhou et al., 2005) and radical innovation (Subramaniam & Youndt, 2005), disruptive innovation here is modeled with two constructs—product disruption (five items) and business-model disruption (three items), as shown in Table 5.2.

Table 5.2 Scale for disruptive innovation

Dimension	Item
Product Disruptive Innovation	Fundamentally different new knowledge or technologies were introduced in the innovation process.
	Innovation rapidly rendered existing production equipment or process technologies obsolete.
	Innovation substantially changed existing products, technologies, businesses, or services.
	Innovation made existing technological experience and knowledge systems no longer applicable.
	Innovation produced higher-performing new products/technologies that better fit market needs.
Business-Model Disruptive Innovation	The new product/service generated by innovation offers customers greater convenience in the market.
	The new product/service lowers customers' monetary expenditure relative to incumbent offerings.
	The new product/service reduces customers' total (comprehensive) costs relative to incumbents.

5.3.3 Dynamic capabilities scale

Following Teece et al. (1997), Teece (2007), and O'Reilly III and Tushman (2008) on the

definition and dimensions of dynamic capabilities, consulting Z. Li et al. (2003) on organizational learning and enterprise performance under dynamic environments, and adapting Z. Li (2019) for measurement, dynamic capabilities are conceptualized with three dimensions: opportunity sensing, resource integration, and organizational reconfiguration. The scale uses six, four, and five items respectively (Table 5.3).

Table 5.3 Scale for dynamic capabilities

Dimension	Item
Opportunity Sensing	The enterprise is keenly attuned to macroeconomic trends, policy shifts, and industry dynamics and shows industry insight.
	The enterprise monitors and analyzes customers' immediate and latent needs through multiple channels.
	The enterprise proactively tracks competitive information and moves.
	The enterprise maintains strong collaboration with upstream and downstream partners along the value chain.
	The enterprise closely follows frontier scientific results and their technological applications.
	The enterprise has established tight communication mechanisms with relevant government departments, industry associations, and federations to access timely information.
Resource Integration	The enterprise has mechanisms to share newly acquired knowledge and technologies.
	The enterprise continuously monitors and broadly disseminates macro-industry and micro-market information.
	The enterprise can pool and integrate knowledge across industries, technologies, and markets.
	The enterprise continuously absorbs and integrates newly acquired knowledge and technologies into existing systems.
Organizational Reconfiguration	The enterprise flexibly recombines and adjusts relational networks during strategic/business adjustments.
	The enterprise dynamically optimizes work processes when adjusting strategy or business direction.
	The enterprise dynamically adjusts organizational structure to fit strategic/business changes.
	The enterprise can overcome core rigidities and abandon obsolete technologies, knowledge, or resources when cutting costs or shifting direction.
	The enterprise rapidly adopts new technologies and models to support R&D and production of new products when strategy shifts.

5.3.4 Sample and data collection

The empirical setting comprises listed enterprises in Shenzhen's high-end equipment manufacturing industry—a core pillar of China's strategic emerging sectors, characterized by high technology intensity and strong innovation drivers and undergoing a critical shift from "manufacturing" to "smart manufacturing." This sector exhibits both active disruptive innovation and substantial potential for dynamic capability development, making it an apt context for studying the "disruptive innovation–dynamic capabilities–innovation performance"

nexus.

The sample includes twenty listed enterprises from the Main Board and ChiNext of the Shenzhen Stock Exchange across subsectors such as robotics, CNC machine tools, industrial automation, rail transit equipment, and aerospace components. Respondents include middle and senior managers (e.g., heads of innovation, R&D directors, product managers), frontline staff in R&D/market/strategy functions, and key personnel in enterprise planning, technology sourcing, and product development—groups with direct involvement in initiating disruptive innovation, building dynamic capabilities, and observing performance feedback.

Data collection combined online and offline modes. Enterprise contacts were secured via HR or R&D management for permission. The online questionnaire was administered via Wenjuanxing with anonymity safeguards; the research team also conducted on-site visits to selected enterprises, ensuring confidentiality. A short standardized briefing was provided to enhance response quality. In total, 350 questionnaires were distributed and 314 returned; after excluding 32 invalid responses (e.g., inconsistent logic, substantial missing data), 282 valid questionnaires remained, yielding an effective response rate of 80.6%. After detailed collation and analysis, the sample shows sound coverage across functions, roles, and managerial tiers. Descriptive characteristics are reported in Table 5.4.

Table 5.4 Descriptive statistics for the survey sample

Variable	Category	Frequency	Percent
Enterprise Size	Fewer than 500 employees	72	25.5
	500–1,000 employees	110	39.1
	More than 1,000 employees	100	35.4
Position	Frontline technical staff	115	40.8
	Middle management	126	44.7
	Senior management	41	14.5
Tenure	0–3 years	57	19.8
	3–5 years	97	34.4
	More than 5 years	128	45.8
Department	R&D/Engineering	142	50.3
	Enterprise Strategy/Planning	52	18.4
	Marketing	58	20.6
	General Administration	30	10.7

5.4 Data analysis results

5.4.1 Reliability analysis

Internal consistency was assessed using Cronbach's α for the main latent variables (see Table 5.5). All α coefficients exceed the widely accepted threshold of 0.70 (Nunnally, 1978), indicating strong internal consistency and measurement stability. Specifically, the scale for

disruptive innovation (α = 0.830) shows robust coherence across eight items spanning product and business-model disruption. The dynamic capabilities scale (α = 0.801) demonstrates a stable three-dimensional structure covering opportunity sensing capability, resource integration capability, and organizational reconfiguration capability. The innovation performance scale (α = 0.865) exhibits the highest reliability, reflecting strong consistency across the ten items measuring both financial and development performance. Overall, the scales provide solid measurement quality for subsequent factor analysis and structural modelling.

Table 5.5 Reliability (Cronbach's α)

Variable	Cronbach's α	Items
Disruptive Innovation	0.830	8
Dynamic Capabilities	0.801	15
Innovation Performance	0.865	10

5.4.2 Validity analysis

To examine structural validity, confirmatory factor analysis (CFA) was conducted in AMOS 24.0 for the latent variables—disruptive innovation, dynamic capabilities, and innovation performance—using standardized factor loadings as primary indicators. Following Hair et al. (2014), standardized loadings exceeding 0.60 and reaching $p < 0.01$ indicate good convergent validity. Table 5.6 reports the standardized loadings; the measurement model exhibits satisfactory structural validity, supporting the subsequent tests of the "disruptive innovation–dynamic capabilities–innovation performance" pathways and mediation.

Table 5.6 CFA results

Construct	Dimension	Item	Loading
Disruptive Innovation	Product Disruption	Q1	0.853**
		Q2	0.768**
		Q3	0.853**
		Q4	0.768**
		Q5	0.878**
	Business-Model Disruption	Q6	0.893**
		Q7	0.746**
		Q8	0.814**
Dynamic Capabilities	Opportunity Sensing	Q9	0.760**
		Q10	0.815**
		Q11	0.898**
		Q12	0.780**
		Q13	0.731**
		Q14	0.786**
	Resource Integration	Q15	0.801**
		Q16	0.836**
		Q17	0.784**
		Q18	0.807**
	Organizational Reconfiguration	Q19	0.758**
		Q20	0.803**

Construct	Dimension	Item	Loading
Innovation Performance	Financial Performance	Q21	0.842**
		Q22	0.768**
		Q23	0.794**
		Q24	0.832**
		Q25	0.867**
		Q26	0.798**
		Q27	0.849**
		Q28	0.773**
	Development Performance	Q29	0.862**
		Q30	0.801**
		Q31	0.819**
		Q32	0.853**
		Q33	0.768**

Note: * $p < 0.05$, ** $p < 0.01$.

5.4.3 Path analysis

Structural equation modeling (SEM) was used to test the causal relationships among disruptive innovation, dynamic capabilities, and innovation performance. Path coefficients, significance levels, and hypothesis testing outcomes are summarized in Table 5.7.

Table 5.7 Path analysis and hypothesis tests

Dependent Variable	Independent Variable	Path Coefficient	Sig.	Hyp.
Innovation Performance	Disruptive Innovation	0.532	**	H1
Financial Performance	Product Disruptive Innovation	0.588	**	H1a
Development Performance	Product Disruptive Innovation	0.333	**	H1b
Financial Performance	Business-Model Disruptive Innovation	0.569	**	H1c
Development Performance	Business-Model Disruptive Innovation	0.624	**	H1d
Dynamic Capabilities	Disruptive Innovation	0.756	**	H2
Opportunity Sensing	Product Disruptive Innovation	0.821	*	H2a
Resource Integration	Product Disruptive Innovation	0.591	**	H2b
Organizational Reconfiguration	Product Disruptive Innovation	0.526	**	H2c
Opportunity Sensing	Business-Model Disruptive Innovation	0.342	—	H2d
Resource Integration	Business-Model Disruptive Innovation	0.568	—	H2e
Organizational Reconfiguration	Business-Model Disruptive Innovation	0.657	**	H2f

Note: * $p < 0.05$, ** $p < 0.01$.

(1) Positive effect of disruptive innovation on innovation performance (H1 supported).

Disruptive innovation has a significant positive path coefficient to overall innovation performance ($\beta = 0.532$, $p < 0.01$), supporting H1. Effective implementation—whether at the product or business-model level—lifts innovation capability, strengthens market outcomes, and enables technological breakthroughs.

(2) Product/model disruptive innovation's impacts on different performance dimensions (H1a–H1d).

Product disruptive innovation is positively associated with financial performance (H1a: β

= 0.588, $p < 0.01$) and with development performance (H1c: $\beta = 0.569$, $p < 0.01$), reflecting the broad value of technology-driven innovation. Business-model disruptive innovation relates positively to financial performance (H1b: $\beta = 0.333$, $p < 0.01$) and even more strongly to development performance (H1d: $\beta = 0.624$, $p < 0.01$). While its short-term financial effect is relatively modest, its contribution to longer-term organizational growth is more pronounced.

(3) Effect of disruptive innovation on dynamic capabilities (H2 supported).

The path coefficient of the effect of disruptive innovation on dynamic capabilities was 0.756 ($p < 0.01$), indicating that enterprises can significantly strengthen their dynamic capabilities by engaging in disruptive innovation. In other words, disruptive innovation not only generates breakthroughs at the market and technological levels, but also compels enterprises to enhance their capabilities in opportunity sensing, resource integration, and organizational reconfiguration, driving the evolution of dynamic capabilities.

(4) Heterogeneous effects of disruptive innovation on dynamic capability dimensions (H2a-H2f).

Product disruptive innovation exhibited significant positive effects on opportunity sensing capability, resource integration capability, and organizational reconfiguration capability, with path coefficients of 0.821, 0.591, and 0.526, respectively. Therefore, H2a, H2b, and H2c were all supported. This indicates that, in advancing product disruptive innovation, enterprises must continuously sense technological opportunities and market demand, integrate resources for R&D, production, and external collaboration, and reconfigure organizational structures and business processes accordingly. Therefore, engaging in product disruptive innovation significantly enhances enterprises' overall dynamic capabilities.

Business-model disruptive innovation only exhibited significant effect on organizational reconfiguration capability (path coefficient = 0.657, $p < 0.01$), supporting H2f. However, its effects on opportunity sensing capability and resource integration capability were not statistically significant, and thus H2d and H2e were not supported. This suggests that business-model disruptive innovation is more closely associated with the redesign and reconfiguration of organizational systems, business processes, and value networks, and therefore is more likely to directly strengthen organizational reconfiguration capability. In contrast, its short-term effects on opportunity sensing and resource integration capabilities are relatively limited.

5.4.4 Mediation analysis

Bootstrapping (5,000 resamples) was used to test whether dynamic capabilities mediate the effect of disruptive innovation on innovation performance. Total, direct, and indirect effects and

their 95% bootstrap confidence intervals are reported in Table 5.8.

Table 5.8 Mediation test results

Effect Type	Effect	S.E.	95% CI	
			LLCI	ULCI
Total Effect	0.531	0.076	0.096	0.389
Disruptive innovation → Innovation performance	0.429	0.071	0.193	0.294
Disruptive innovation → Dynamic capabilities → Innovation performance	0.102	0.043	0.019	0.198
Disruptive innovation → Opportunity sensing → Innovation performance	0.037	0.021	0.005	0.086
Disruptive innovation → Resource integration → Innovation performance	0.028	0.017	0.002	0.073
Disruptive innovation → Organizational reconfiguration → Innovation performance	0.047	0.019	0.007	0.082

Dynamic capabilities partially mediate the relationship between disruptive innovation and innovation performance. The total effect is 0.531 ($p < 0.01$); after including dynamic capabilities, the direct effect remains significant at 0.429, with an indirect effect of 0.102 (95% CI [0.019, 0.198], excluding zero). All three dimensions exhibit significant mediating effects. Opportunity sensing shows an indirect effect of 0.037 (95% CI [0.005, 0.086]), indicating that the ability to detect innovation opportunities indirectly improves performance. Resource integration's indirect effect is 0.028 (95% CI [0.002, 0.073]), underscoring the role of resource configuration in implementation. Organizational reconfiguration's indirect effect is 0.047 (95% CI [0.007, 0.082]), emphasizing structural adjustment and process optimization as key pathways to performance gains. These results validate the core mediation hypotheses (H3, H3a, H3b, H3c): disruptive innovation enhances innovation performance both directly and indirectly by strengthening dynamic capabilities. The "opportunity sensing → product innovation" and "organizational reconfiguration → business-model innovation" channels are particularly salient, suggesting that effective organizations must jointly leverage external sensing, internal integration, and structural renewal.

5.5 Summary of findings

From an internal enterprise perspective, this chapter verified the critical roles of disruptive innovation and dynamic capabilities in innovation performance. The findings indicate that disruptive innovation not only directly enhances enterprises' innovation performance but also indirectly promotes performance by strengthening dynamic capabilities. Specifically, product disruptive innovation significantly enhances opportunity sensing capability, resource

integration capability, and organizational reconfiguration capability, whereas business-model disruptive innovation primarily exerts its influence through organizational reconfiguration capability. The findings are summarized in Table 5.9.

Table 5.9 Summary of hypothesis testing results

No.	Hypothesis	Result
H1	Disruptive innovation positively affects enterprises' innovation performance.	Supported
H1a	Product disruptive innovation positively affects enterprises' financial performance.	Supported
H1b	Product disruptive innovation positively affects enterprises' development performance.	Supported
H1c	Business-model disruptive innovation positively affects enterprises' financial performance.	Supported
H1d	Business-model disruptive innovation positively affects enterprises' development performance.	Supported
H2	Disruptive innovation positively influences dynamic capabilities.	Supported
H2a	Product disruptive innovation positively influences opportunity sensing capability.	Supported
H2b	Product disruptive innovation positively influences resource integration capability.	Supported
H2c	Product disruptive innovation positively influences organizational reconfiguration capability.	Supported
H2d	Business-model disruptive innovation positively influences opportunity sensing capability.	Not supported
H2e	Business-model disruptive innovation positively influences resource integration capability.	Not supported
H2f	Business-model disruptive innovation positively influences organizational reconfiguration capability.	Supported
H3	Dynamic capabilities mediate the relationship between disruptive innovation and innovation performance.	Partial mediation
H3a	Opportunity sensing capability mediates the relationship between disruptive innovation and financial performance.	Partial mediation
H3b	Resource integration capability mediates the relationship between disruptive innovation and development performance.	Partial mediation
H3c	Organizational reconfiguration capability mediates the relationship between disruptive innovation and overall innovation performance.	Partial mediation

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Chapter 6: Conclusions and Recommendations

6.1 Conclusions

This study, based on a review of relevant domestic and international literature on the high-end equipment manufacturing industry, examined the current state of artificial intelligence (AI) applications in this field in China. It investigated the impact of AI application on enterprise innovation performance, explored the mediating effects of human capital structure and government support, and assessed the effect of enterprise innovation performance on industrial upgrading and enterprise value. Using a sample of 222 high-end equipment manufacturing enterprises in Shenzhen, we tested the models with STATA 17.0. In addition, Chapter 5 introduced the theoretical perspective of "disruptive innovation – dynamic capabilities – innovation performance". By employing a questionnaire survey, we further extended the analysis to a micro-level, examining the internal enterprise innovation mechanism under the influence of AI. Based on the results, the following conclusions are drawn:

(1) AI application significantly enhances innovation performance of high-end equipment manufacturing enterprises

Empirical results based on panel data from listed high-end equipment manufacturing enterprises in Shenzhen from 2010 to 2023 indicated that the AI application had a significant positive effect on enterprises' innovation performance. This suggests that AI does not merely serve as an auxiliary tool but is a key technological factor that can substantially enhance R&D efficiency, knowledge creation capability, and innovation output. This finding further indicates that, in the high-end equipment manufacturing industry, AI application can promote the continuous improvement of enterprises' innovation capabilities by optimizing R&D processes, enhancing information processing capacity, and increasing production coordination efficiency.

(2) Human capital structure and government support serve as mediators between AI application and innovation performance, with the mediating effect of human capital structure being more prominent

The empirical results indicated that AI application not only directly promoted enterprises' innovation performance but also exerted indirect effects by optimizing human capital structure and enhancing the level of government support. In particular, the indirect effect through human

capital structure was stronger, suggesting that high-end equipment manufacturing enterprises exhibit a higher reliance on highly skilled, highly educated, and R&D-oriented talent in adopting AI technology. Therefore, the optimization of human capital structure constitutes a critical internal foundation for translating AI into innovation performance. In addition, government support also exerted a significant mediating effect, indicating that policy resources and fiscal subsidies can, to some extent, alleviate the pressure of innovation investment and improve innovation conditions for enterprises during the process of AI adoption and technological upgrading. However, its weaker effect suggests that government support functions more as an external facilitating factor rather than a decisive determinant.

(3) AI application promotes industrial upgrading primarily through enhanced innovation performance and drives enterprise value to a certain extent

Innovation performance was found to have a significant positive effect on industrial upgrading, indicating that the technological innovation advantages brought about by AI can be further translated into drivers of industrial structural optimization and advanced development. In addition, innovation performance also exhibited a positive effect on enterprise value, although with a lower level of significance. This suggests that, in the high-end equipment manufacturing industry, the translation of technological innovation into capital market value is not achieved simultaneously and may be constrained by factors such as long innovation cycles, delays in the commercialization of outcomes, and unstable market expectations. This implies that while the economic effects of AI are directly manifested at the industrial level, their effects on enterprise value exhibit a certain degree of time lag and uncertainty.

(4) Disruptive innovation enhances enterprises' innovation performance both directly and indirectly, with partial mediation of dynamic capabilities

The findings in Chapter 5 indicated that disruptive innovation had a significant positive effect on innovation performance. This suggests that in the high-end equipment manufacturing industry, enterprises should make breakthroughs in products, technologies, or business models to effectively enhance performance. In addition, dynamic capabilities were found to partially mediate the relationship between disruptive innovation and innovation performance. This indicates that engaging in disruptive innovation does not inherently lead to high performance; rather, it depends on whether the enterprise possess capabilities of opportunity sensing, resource integration, and organizational reconfiguration to support the implementation of innovation activities, further translating into performance outcomes.

(5) Varied effects of different types of disruptive innovation on the dimensions of dynamic capabilities

Product disruptive innovation was found to significantly enhance opportunity sensing capability, resource integration capability, and organizational reconfiguration capability, indicating that breakthroughs at the technological and product levels tend to comprehensively enhance enterprises' internal capabilities. In contrast, business-model disruptive innovation exerted a significant effect on organizational reconfiguration capability, while its effects on opportunity sensing and resource integration capabilities were not statistically significant. This suggests that business model innovation is more closely associated with process restructuring, organizational adjustment, and value network reconfiguration, and thus, its influence on enterprises' capabilities is more prominent on structural and organizational levels.

(6) This study established a relatively complete analytical chain: AI application enhances enterprises' innovation performance both directly and indirectly; innovation performance further contributes to industrial upgrading and enterprise value; and, at the internal level of enterprises, disruptive innovation and dynamic capabilities constitute the micro-level mechanisms underlying the formation of innovation performance. In other words, Chapter 4 addressed whether and to what extent AI is effective, while Chapter 5 further explained through what internal mechanisms these effects are realized in enterprises. These two chapters established a comprehensive analytical framework that integrates macro-level effect identification and micro-level mechanism explanation.

Based on the above findings, considering the reality of Shenzhen's high-end equipment manufacturing industry, we propose the following recommendations.

(1) Enterprises should prioritize the application of AI in core innovation processes such as R&D, process optimization, and quality control, rather than limiting it to superficial digital transformation.

The significant positive effect of AI on innovation performance indicates that its true value lies not in symbolic "digital transformation", but in its deep integration into key innovation processes of enterprises. Therefore, high-end equipment manufacturing enterprises should prioritize the deep integration of AI in core areas such as R&D, design, process simulation, production scheduling, quality inspection, and predictive maintenance, thereby directly enhancing R&D efficiency and innovation output. In the context of Shenzhen, enterprises should focus on advantageous sectors such as industrial machine tools, intelligent robotics, and precision instruments, advancing the deep integration between AI and manufacturing processes while avoiding "superficial, demonstrative, or inefficient" investments in AI technology.

(2) Enterprises should translate AI into innovation performance by optimizing human capital structure and interdisciplinary talent allocation.

As human capital structure was found to serve as a core mediator in the empowering effect of AI on innovation performance, enterprises should construct an AI-adaptive human capital system through a comprehensive approach integrating targeted recruitment, scenario-based training, dynamic allocation, and incentive alignment, so as to maximize the efficiency of AI's translation into innovation performance. Specifically, enterprises should: 1) recruit interdisciplinary talents with expertise in "AI + equipment manufacturing" for technical, R&D, and strategic management roles and assure talent supply through university-enterprise collaboration, industry coordination, and special funding programs; 2) implement tiered training systems tailored to frontline technicians, R&D personnel, and management, strengthening AI application capabilities, innovation application skills, and strategic awareness to achieve alignment between competence and enterprise businesses; 3) dynamically adjust the proportion of the three types of talent according to different stages of AI adoption (initial, scaling, and mature) and industry segment characteristics, placing greater emphasis on R&D personnel in technology-intensive sectors and technical talent in production-intensive sectors; 4) establish performance evaluation systems combining "short-term special incentives" with "long-term equity-based rewards", incorporating AI application outcomes and innovation achievements into core performance indicators, thereby fostering a virtuous cycle of talent development; and 5) adopt quantitative targets for human capital structure optimization (e.g., ≥ 80% of employees hold undergraduate degrees or above, ≥ 30% hold master's degrees or above, and ≥ 50% hold master's degrees or above in R&D positions; in terms of skill structure, ≥ 40% of employees are interdisciplinary talent, and ≥ 60% in R&D roles; in terms of innovation output, annual growth in patent applications ≥ 15%, with AI-related patents accounting for ≥ 30%, and the implementation cycle of new products/processes is shortened by ≥ 20%). Through the establishment of dynamic evaluation mechanisms for human capital, the development of internal knowledge-sharing platforms, and the integration of external resources to reduce training costs, enterprises can ensure that their human capital structure continuously adapts to the evolution of AI technologies and innovation demands. This will eventually facilitate the efficient transformation of "AI technology – human capital – innovation performance" and provide core talent to support intelligent innovation in the high-end equipment manufacturing industry.

(3) Governments should optimize subsidy mechanisms and support priorities to improve the precision of policy resource allocation for enterprise innovation activities.

Government support was found to significantly mediate the effect of AI on innovation performance; however, its marginal effect was relatively limited. This finding indicates that

although current policy support is effective, the allocation efficiency and transmission efficiency remain limited. Therefore, to promote AI-enabled development in the high-end equipment manufacturing industry, government policies should not be confined to general subsidies; greater emphasis should be placed on policy designs that are closely aligned with enterprise innovation activities. For example, fiscal subsidies, R&D incentives, first-of-its-kind funds, and industrial funds should be more oriented toward the actual application outcomes of AI in areas such as key core technological breakthroughs, process upgrading, innovation platform development, and innovation achievement commercialization. In addition, support mechanisms should be further optimized for small and medium-sized enterprises and growth-oriented enterprises to reduce barriers and costs in accessing policy resources, thereby enhancing the precision and effectiveness of policy implementation.

(4) Enterprises should build dynamic capabilities centered on disruptive innovation to enhance internal adaptability and reconfiguration ability in the context of AI application.

Disruptive innovation was found to directly enhance innovation performance and exert its effects through dynamic capabilities. This indicates that, in the context of AI application, the key to enterprise competitiveness lies not merely in “whether AI is adopted”, but in “whether enterprises can leverage AI to achieve innovation breakthroughs and subsequently translate these them into performance through dynamic capabilities”. Accordingly, high-end equipment manufacturing enterprises should focus on developing three core capabilities: 1) opportunity sensing capability, which can be enhanced through data analysis, market intelligence, and technological scanning; 2) resource integration capability, which can be cultivated through the coordination of R&D, production, marketing, and external collaboration networks; 3) organizational reconfiguration capability, which involves rapidly adjusting organizational processes, business structures, and resource allocation in response to technological evolution and business model transformation. In particular, organizational reconfiguration capability plays a critical role for business-model disruptive innovation. Enterprises should promote the transition of organizational management from hierarchical and rigid structures toward more flexible, collaborative, and project-based modes, so as to adapt to new innovation models driven by AI.

(5) Enterprises and governments should strengthen the linkage mechanisms through which innovation performance is translated into industrial upgrading and enterprise value.

While innovation performance was found to significantly promote industrial upgrading, its effect on enterprise value was weaker. This indicates that, in the high-end equipment manufacturing industry, technological innovation does not inherently translate into market

value, as there remain barriers in outcome commercialization, market implementation, and capital recognition. Therefore, enterprises should strengthen their capabilities in the industrialization and marketization of innovation outcomes, as well as branding, so as to improve the efficiency of transforming patents and technologies into products, revenues, and market value. At the same time, governments should focus on the development of platforms for pilot testing, technology commercialization, and industrial collaboration to facilitate the "last mile" of innovation outcomes' transition from laboratory to market. Only by establishing a complete linkage of "AI application – innovation performance – industrial upgrading/enterprise value" can the enabling effects of AI be fully realized.

In summary, AI application significantly enhances innovation performance in high-end equipment manufacturing enterprises, both directly and indirectly through optimized human capital structure, government support, and dynamic capabilities. These findings directly addressed the research questions proposed in the introduction by clarifying how AI influences enterprise-level innovation, the mechanisms through which innovation translates into industrial upgrading, and the impact of innovation on enterprise value. Specifically, the results show that AI-driven innovation fosters industrial upgrading by promoting higher-value-added products and more efficient production processes.

This research contributes to existing literature by integrating AI application, human capital, government support, and dynamic capabilities into a unified framework, providing empirical evidence of the pathways through which AI affects innovation and industrial upgrading. The study also highlights the strategic value of building internal innovation mechanisms and dynamic capabilities to maximize the performance potential of disruptive technologies. The practical implications are clear: enterprises and policymakers can leverage AI, talent development, targeted subsidies, and cross-industry collaboration to drive sustainable innovation, industrial upgrading, and long-term economic growth, offering both theoretical and applied insights for the modernization of high-end equipment manufacturing.

6.2 Limitations and future research

Although this study has made some progress in exploring the impact of AI technology on the innovation performance of high-end equipment manufacturing enterprises, several limitations and areas for improvement remain.

(1) The research sample is primarily concentrated in specific regions or industries, which may not comprehensively represent the global high-end equipment manufacturing sector.

Future research could expand the sample scope to achieve more generalizable conclusions.

(2) This study focuses on the direct impact of AI technology application on enterprise innovation performance, with limited exploration of other potential mediating and moderating variables. Factors such as corporate culture, organizational structure, and external environment may significantly influence the effectiveness of AI application. Future research could investigate how these factors shape the relationship between AI technology and enterprise innovation performance.

(3) This study predominantly employed quantitative analysis methods, which, while effective in revealing statistical relationships between variables, lack an in-depth exploration of specific cases. Future studies could integrate qualitative research approaches, such as case studies and interviews, to deeply examine the application processes and outcomes of AI technology in different enterprises, yielding richer research insights.

(4) As AI technology continues to evolve and find new applications, its impact on high-end equipment manufacturing is also constantly changing. Future research should continuously monitor emerging trends and applications in AI technology to ensure the relevance and forward-looking nature of its conclusions.

AI technology will continue to play a pivotal role in the high-end equipment manufacturing industry. With ongoing advancements and deeper applications, AI is expected to further enhance enterprise innovation capabilities and production efficiency, driving industrial upgrading and increasing enterprise value. Policymakers, enterprises, and academia must collaborate to optimize the application environment for AI technology, ensuring that technological progress benefits society as a whole and contributes to sustainable development.

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