Thesis for the degree of Doctor of Philosophy

Research on the Influence Mechanism of Technological Innovation investment and Technological Alliances on Business Performance of Enterprises

—Focus on listed companies in China

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Abstract

As a result of the turbulent global economic environment, firms must accelerate technological innovation to cope with intense competition. However, with the rapid diffusion and penetration of knowledge, the shortening of the development cycle of new technologies, and the fact that product structures are becoming increasingly complex, the complexity of enterprises' innovation activities is also increasing, causing them to consider improving the speed of product development through the establishment of technological alliances with other enterprises and the adoption of cooperative technological innovation. Cooperative technology alliances for technological innovation have become one of the important modes of innovation and an important means for enterprises to improve their innovation performance.Therefore it is particularly important to explore the relationship between technological innovation, technology alliances and firm performance. At present, academics usually only use technological innovation and a single dimension of enterprise performance for correlation test, the research angle is relatively single. Moreover, in the existing research, a large number of literatures only focus on whether the enterprises have technological alliances or not, while the type and degree of technological alliances are not well quantified.

Therefore, this study is based on resource base theory, organizational learning theory and technological innovation theory. It divides technological innovation inputs

into technological innovation capital inputs and technological innovation human capital inputs. Innovatively using the factor analysis method, multiple indicators are constructed to evaluate the business performance of enterprises based on solvency, profitability, turnover capacity, growth capacity and market value. Meanwhile, the word frequency method is used to quantify the degree of technological alliance of enterprises. Finally, a fixed-effect model is used to conduct correlation analysis.

The main findings are as follows: (1) Both technological innovation capital investment and technological innovation human capital investment are positively correlated with business performance. This is consistent with the results of previous studies. technological innovation capital investment helps to expand the knowledge base and skills of enterprises and enhance their innovation ability. By researching new fields, firms are able to accumulate expertise, cultivate professionals, form a unique innovation culture, and promote organizational learning and growth. At the same time, technological innovation capital investment prompts firms to explore new market opportunities and discover and fulfill potential consumer needs. As for technological innovation human capital investment, enterprise technological innovation human capital investment realizes a significant positive impact on enterprise performance through various aspects of human resource management theory. Through well-designed recruitment, training, motivation, and career development strategies, firms not only improve their technological innovation capabilities, but also enhance employee-organizational bonding, which drives innovation and growth, thus achieving significant positive performance impacts.(2)The interaction between technology alliances and technological innovation investment (both capital and human) has a significant negative relationship on firm performance.The results of this study disprove what previous studies have said about the positive aspects of technology alliances.The reasons for the results may be: firstly over-reliance on technology alliances for resources leads to a weakening of the impact of firms' innovation inputs on performance; secondly, the sharing of information resources in technology alliances may provide opportunities for technological theft; and the retention of information resources and negative willingness to give in technology alliances may also contribute to their negative moderating effect.

In conclusion,This study not only challenges prevailing perceptions, but also contributes to a deeper understanding of the delicate relationship between firms' technological innovations and technological alliances, providing valuable insights into both academic and practical applications in the field.

Keyword: Investment in technological innovation; technology alliances; business performance of firms

초록

글로벌 경제 환경이 불안정하기 때문에 기업은 치열한 경쟁에 대처하기 위해 기술 혁신을 가속화해야 한다. 그러나 지식의 급속한 전파와 침투로 신기술의 개발 주기가 계속 단축되고 제품 구조가 점점 복잡해지고 기업 혁신 활동의 복잡성이 증가하고 있어 기업은 다른 기업과 기술 동맹을 구축하고 협력 기술 혁신의 방식을 채택하여 제품 개발 속도를 향상하는 방법을 고려하지 않을 수 없다. 협력 기술 혁신 동맹은 기업 혁신의 중요한 형식 중 하나가 되었으며 기업이 혁신 성과를 향상하는 중요한 수단이기도 하므로 기술 혁신, 기술 동맹 및 기업 성과 간의 관계를 논의하는 것이 특히 중요한다. 현재 학계는 일반적으로 기술 혁신과 기업 성과 간의 단일 차원만을 적용하여 상관성 검증하고 연구 각도는 비교적 단일한다. 또한 기존 연구에서 많은 문헌은 기업에 기술 동맹이 존재하는지 여부에만 초점을 맞추고 기술 동맹의 유형과 정도를 잘 정량화하지 않았다.

따라서 본 연구는 자원 기초 이론, 조직 학습 이론 및 기술 혁신 이론을 기반으로 하였다. 기술 혁신 투입을 기술 혁신 자본 투입과 기술 혁신 인적 자본 투입으로 나나누었다. 요인 분석법을 혁신적으로 적용하여 부채 상환 능력, 수익 능력, 회전 능력, 성장 능력 및 시장 가치 측면에서 기업의 경영 성과를 평가하는 여러 지표를 구축하였다. 동시에 단어 빈도 방법을 적용하여 기업의 기술 동맹 정도를 정량화하였다. 마지막으로 고정 효과 모델을 적용하여 관련 분석을 수행하였다.

주요 결론은 다음과 같다. (1) 기술 혁신 자본 투입과 기술 혁신 인적 자본 투입은 모두 기업 성과와 긍정적인 관계가 있다. 기술 혁신 자본 투자는 기업의 지식 기반과 기술을 확대하고 기업의 혁신 능력을 향상하는 데 도움이 된다. 새로운 분야에 대한 연구를 통해 기업은 전문 지식을 축적하고 전문 인재를 육성하며 독특한 혁신 문화를 형성하고 조직의 학습과 성장을 촉진할 수 있다. 동시에 기술 혁신 자본 투자는 기업이 새로운 시장 기회를 탐색하고 소비자의 잠재적 수요를 발견하고 충족하도록 촉구한다. 기술 혁신 인적 자본 투자 측면에서 기업의 기술 혁신 인적 자본 투자는 인적 자원 관리 이론의 여러 측면의 역할을 통해 기업 성과에 현저한 긍정적인 영향을 미친다. 신중하게 설계한 채용, 교육, 인센티브 및 직업 개발 전략을 통해 기업은 기술 혁신 능력을 향상할 뿐만 아니라 직원과 조직의 접착력을 강화하여 기업의 혁신과 발전을 촉진하고 현저한 긍정적인 성과를 달성했다. (2)기술 동맹과 기술 혁신 투자(자본 투자 및 인력 투자 포함) 간의 상호 작용은 기업 성과에 현저한 부정적인 관계가 있다. 이러한 결과의 원인은 첫째, 기술 동맹의 자원에 과도하

게 의존하면 기업 혁신 투입이 성과에 미치는 영향이 약해지고 둘째, 기술 동맹의 정보 자원 공유가 기술 도난의 기회를 제공할 수 있으며 기술 동맹의 정보 자원 보유 및 소극적인 기여 의지도 부정적인 조절로 이어질 수 있다.

요컨대, 본 연구는 보편적인 인식에 도전할 뿐만 아니라 기업의 기술 혁신과 기술 동맹 간의 미묘한 관계를 깊이 이해하는 데 도움이 되며 이 분야의 학술 연구 및 실제 적용에 귀중한 시사점을 제공하였다.

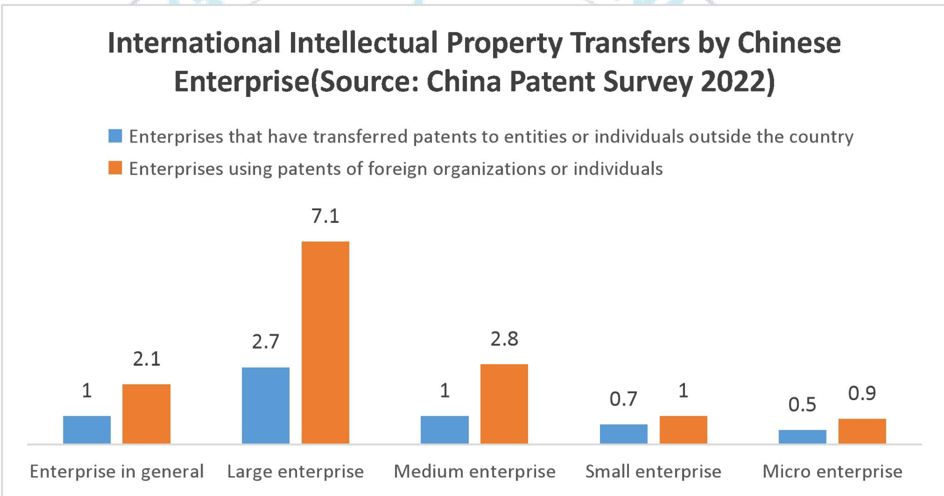
키워드: 기술 혁신 투자; 기술 동맹; 기업 경영 성과

Chapter 1. Introduction

1.1 Research background

Long critical to corporate profitability and innovative competitive advantage, technological innovation activities have long been recognized as an important part of a firm's complex innovation process and as creating value for the firm.Lin et al. (2006)[1] suggest that technological innovation is a major source of competitive advantage for companies. This is because the industry is in an era of rapid knowledge development, rapidly changing markets and technologies, increased competition, changing customer needs, rapid product obsolescence, and the emergence of new markets all require a more rapid R&D and innovation process. Investment in technological innovation also captures and maintains market share and enhances corporate profitability. In the face of a highly competitive environment, the primary goal of an organization is to maintain efficiency and productivity in order to ensure the survival of its competitive advantage.

Technological innovation holds paramount significance for enterprises, serving as a pivotal driver for enhancing competitiveness and achieving sustainable development. For enterprises aiming at long-term survival and growth, proactive measures to bolster their innovative prowess are indispensable (Zhang Liming et al., 2023)[2].In 2007, the Organization for Economic Cooperation and Development (OECDR) reported that China's overall R&D investment in 2006 surpassed Japan's and jumped to second place in the world, a noteworthy milestone. In recent years, China has maintained its position as the world's second-largest investor in total R&D and has shown a continuous upward trend, both in terms of R&D capital investment and personnel investment. R&D capital expenditure surged from RMB 1,029.841 billion in 2012 to RMB 1,567.675 billion in 2016, an average annual growth rate of about 13%. Meanwhile, R&D personnel grew from 3,247,000 person-years in 2012 to 3,878,100 person-years in 2016, an average annual growth rate of about 5%.



<Figure 1-1> International IP transfers by enterprises in 2022

Despite China's sustained increase in investment in technological innovation, the outcomes have fallen short of expectations.<Figure 1-1> visually illustrates the international IP transfers by Chinese companies.In 2022, the proportion of patents of surveyed enterprises that used patents abroad was 2.1%, which was 2.1 times the proportion of those that had licensed or transferred patents to foreign entities or individuals (1.0%). Among them, the proportion of large-sized enterprises using foreign patents is 7.1%, which is 2.6 times of the proportion of patents licensed or transferred abroad (2.7%); the proportion of medium-sized enterprises using patents from foreign entities or individuals is 2.8%, which is 2.8 times of the proportion of patents licensed or transferred abroad, both of which are relatively high. And many high and new technologies are imitating foreign technologies, the level of innovation is relatively low, and the development of some new technologies is not cutting-edge (Yu Yongze and Hu Shan, 2018)[3].And according to the Statistical Yearbook of China's High-Tech Industry (2016), China's high-tech industry is still in the middle and low end of the global value chain, mainly relying on a large number of labor inputs to support the labor productivity is only about one-eighth of that of the U.S., and the net profit margin of sales is less than 5%, which is even lower than the profit margin of some traditional industries.

However, with the rapid diffusion and penetration of knowledge, the shortening of the development cycle of new technologies, and the product structure becoming increasingly complex, the complexity of enterprise innovation activities is also increasing, and mastering all the knowledge required for innovation is becoming more and more difficult for individual firms, and the difficulty of independent innovation is dramatically increasing compared with the previous one, and the enhancement of enterprise's innovation capability is greatly restricted (Wu Shaotang et al., 2014)[4]. In addition, enterprises face great uncertainty and the challenge of limited resources in the process of innovation (Xie, Yongping and Wang, Jing, 2017)[5]. In this case, in order to better face the fast-developing market demand and make a quick response to the fierce competition, enterprises must change the way of relying solely on internal resources for innovation, and closed and independent innovation should be shifted to openness and cooperation (Wang, Jiexiang et al.,2015; Sun, Yutao and Zang, Fan,2017)[6][7]. By cooperating with other enterprises, enterprises can obtain the knowledge of other enterprises and accelerate the development of new products, which is also conducive to reducing the cost of innovation and the risk of innovation (Yang Zhangbo and Takayama Hsing,2017)[8], improving the success rate of innovation, and ultimately realizing the enterprise's strategic objectives and obtaining technological breakthroughs (Korea Won et al., 2014)[9].

In the process of cooperative innovation, the formation of technology alliances is adopted by more and more enterprises, and in order to obtain more resources, the number of alliance members has become more and more, and enterprises tend to establish alliances with more than one enterprise, in order to be able to obtain more resources, learn from partners, and improve innovation performance in this way (Lahiri and Narayanan, 2013)[10]. For example, in the process of Android development, the Open Handset Alliance (OHA) includes a number of companies such as Google, T-Mobile, HTC, Motorola, etc., which adopted the alliance to jointly develop Android in 2007. And in China, although there are also some mature technology alliances. For example: TD-SCDMA Industry Alliance, Flashlink Industry Alliance, WAPI Industry Alliance, and in December 2020, the newly established Open Wisdom Alliance. However, technical standard alliances are still in the initial development stage in China. Problems such as lack of coordination of the main parties, lack of standardization of the standard-setting process, lack of credibility, and failure of supervision and management are frequent (Zhu Bin, 2020)[11], resulting in a disconnect between the knowledge, technology and other resources and the real application of standards, and there is no effective mechanism for the formation of alliance standards yet (Li Wei, 2012)[12]. Therefore, how to effectively stimulate the standardization of vitality, the development of high-quality group standards has become the key to improve the top-level design of the standard system, and promote the alliance standardization activities.

Current research generally recognizes the importance of technological innovation investment and technological alliances in firms' business performance (Pham, Monkhouse, and Barnes, 2017; Shakeel, Kanmam, Brah, and Hassanm, 2017 ; Kiprotich, Kemboi, and Kiprop, 2015), but the mechanism of their role is research is still insufficient. Therefore, in order to more accurately and objectively determine the interaction between technological innovation investment, technology alliance and enterprise business performance, this study adopts quantitative research on the impact of technological innovation investment and technology alliance on enterprise business performance based on resource-based theory, organizational learning theory and technological innovation theory, which is conducive to enriching the theories about the relevant theories and providing guidance for enterprise development.

1.2 Significance of the research

1.2.1 Theoretical implications

Firstly, despite extensive research on open innovation theory since its inception by Henry Chesbrough, the relationship between technological innovation investment and enterprise performance remains inconclusive due to the existing limitations. Although many studies confirm that technological innovation investment has a positive contributing role to firm performance (Griliches,1979;Guth,1990;Lin et al.2006;Gong,Ziwen et al.2012)[13][14][15[16], however, there are also empirical findings that show that technological innovation investment is negatively correlated with firm performance (Hitt,1991;Tam,2008,et al.)[17][18], nonlinear (Fortune et al. 2012; Wu, Weihua et al. 2014; Chen, Jianli et al. 2015)[19][20[21], as well as having a long or short lag (Kothari et al.2002;Liang,Laixin et al.2005; Luo,Ting et al. 2009)[22][23][24]and so on.Thus, the current relationship and mechanisms between technological innovation investment and enterprise performance warrant in-depth exploration to yield more accurate and reliable conclusions.

Secondly, the mechanism underlying the impact of technology alliances on firm performance remains unclear. Existing research highlights that knowledge resources within technology alliances do not directly translate into enterprise performance (Wu Yuhao, 2021)[25]. Firms engaged in technology alliances need to internalize knowledge resources through relational learning, integration, reorganization, and secondary innovation to transform them into their capabilities and innovation performance (Blind and Mangelsdorf, 2016)[26]. While the number of papers on technology alliances has increased, most research has focused on macro and meso levels, such as the influence of technology alliances on technology standards formation, dominant design evolution, industrial innovation, and alliance performance (Wakke et al., 2015; De Vries and Verhagen, 2016; Li Dongmei et al., 2017; Zhang Lifei, 2018)[27][28][29][30]. Few studies have delved into how enterprises can deeply benefit from technology alliances at the micro level (De Vries and Veurink, 2017)[31].Based on this, this study innovatively adopts the word frequency method, which is commonly used in quantitative research on digital transformation, for quantifying the mechanism of the impact of technology alliances on firm performance.

Third， change the traditional single-dimension index, enrich and improve the evaluation method of technological innovation investment performance. Most of the traditional studies only focus on the financial investment in technological innovation and ignore the human investment, while the reason why technological innovation investment can produce performance is inseparable from the innovation efforts of enterprise technological innovation technicians.In addition, most of the traditional performance evaluation only adopts a single financial performance indicator, and due to the long cycle, high risk, and complex process of technological innovation activities, the overall performance of technological innovation activities cannot be fully reflected by a single financial indicator. In this paper, we use the factor analysis method to combine profitability, solvency, turnover, growth, and market value to measure the performance of enterprises, which can more objectively and comprehensively reflect the performance of enterprises' technological innovation investment.

Addressing these gaps, this study constructs a comprehensive relationship model encompassing technological innovation investment, technology alliances, and enterprise business performance. By considering technology alliances as moderating variables, and accounting for the synergistic effects of multiple influencing factors, this study systematically explores how enterprise business performance evolves. This approach enriches the research on enterprise innovation models significantly. On a theoretical level, the study comprehensively analyzes the causes and influencing factors of innovation in high-tech enterprises.Each variable is further divided into dimensions. This detailed empirical analysis deepens the theoretical connections among technological innovation investment, technology alliances and enterprise business performance, broadening their roles in innovation performance and transcending existing paradigms.

1.2.2 Practical implications

This study meticulously analyzes panel data from 4,096 listed firms, employing multivariate regression modeling to explore the nuanced impact of technological innovation and technological alliances on firms' business performance. This investigation occurs within the diverse landscapes of firms' internal technological strategic orientations and the dynamics of their external environments. By elucidating this regulatory mechanism, this research enhances our understanding of the intricate interplay between internal and external conditions that influence enterprise business performance. Consequently, it not only enriches the theoretical landscape in the domain of technological innovation application and business performance but also fills crucial gaps in contextualized research concerning digital transformation, market position, and the underlying mechanisms of technological innovation investment's effects on enterprise business performance.

The practical implications of this study are multifold:

Strategic Business Decision-Making: The clarified regulatory mechanisms offer valuable insights to enterprises, empowering them to make informed strategic decisions. Understanding the dynamics of technological innovation and technology alliances enables businesses to navigate complex strategic landscapes more effectively.

Enhanced Business Strategies: Armed with a deeper comprehension of the internal and external factors at play, enterprises can formulate more scientific and rational business strategies. This knowledge equips them to adapt proactively to evolving technological landscapes and market demands.

Sustainable Development: By providing a robust theoretical foundation, this study offers enterprises a roadmap for sustainable development. Informed by the research findings, businesses can align their innovation efforts and alliance strategies with long-term goals, fostering resilience and adaptability.

Scientific Resource Allocation: A nuanced understanding of the impact of technological innovation and alliances allows enterprises to allocate resources more scientifically. By focusing on areas with the most significant potential for impact, companies can optimize their resource allocation, maximizing efficiency and outcomes.

Guidance for Future Research: The findings of this study serve as a springboard for future research endeavors. Researchers and scholars can build upon this nuanced understanding of technological innovation, alliances, and business performance, exploring further dimensions and complexities in the field.

In summary, this research not only provides practical guidance to enterprises seeking sustainable growth but also offers a robust foundation for future scholarly investigations. By bridging the gap between theoretical insights and practical applications, this study contributes significantly to the evolving landscape of technological innovation investment, technology alliances, and enterprise business performance..

1.3 Research Content and Purpose

1.3.1 Content of the research

This thesis consists of seven chapters:

Chapter 1, Introduction. Introduces the current state of the research field and the problem, explaining why the problem is worth studying. Define the purpose, problem, and scope of the study, and state the research hypothesis or research questions. Describe the research methodology, experimental design, data collection and analysis methods used in the study. Articulate the expected results of the research, its significance and contribution to existing theory or practice.

Chapter 2, Theoretical Foundations and Literature Review. Summarize the research results that have been achieved by previous researchers and their research methods, and analyze the limitations and shortcomings of these results.

Chapter 3, Research Design. This paper intends to reveal the mechanism of the influence of technological innovation investment and technology alliance on the business performance of enterprises through in-depth analysis of the panel data of listed companies from 2010 to 2022, and construct the corresponding theoretical model on this basis, so as to provide theoretical basis for the construction of a scientific and reasonable evaluation system of the operational performance of enterprises.

Chapter 4, descriptive statistics and tests. First, the influencing factors and samples were defined, and using STATA17 software, descriptive statistics of the collected index variables and the industries involved were performed, and correlation and multiple covariance tests were conducted;

Chapter 5, Regression analysis and robustness tests. The model was subjected to identification tests, regression analysis of influencing and controlling factors, and endogeneity and robustness tests.

Chapter 6, Mechanism analysis. According to the research hypothesis and the constructed model, the mechanism analysis of the interrelationship between technological innovation investment, technological alliance and business performance of enterprises has been carried out, and the transmission path of its mediating effect has been explored.

Chapter 7, Summary and Prospects. The conclusions of this paper are briefly summarized, and the shortcomings of this paper are pointed out to provide reference for the subsequent theoretical research.

1.3.2 Research purpose

The research in this thesis focuses on the relationship between technological innovation investment, technology alliances and business performance.

First, it examines how technological innovation investment affects a company's operational performance. Therefore, the study of technological innovation investment has become an important aspect in the study of firm performance, and it is necessary to explore the impact of technological innovation investment on firm performance from multiple perspectives.

Second, how technology alliances affect technological innovation investment and improve the operational efficiency of enterprises. As an important form of cooperation, technology alliances can enable enterprises to share resources and complement each other's strengths, achieve technological innovation investment and improve their operational performance. In addition, through the establishment of technology alliance, it can also realize the advantages of risk sharing and economies of scale, so as to improve the operational efficiency of enterprises and enhance their competitiveness in the market.

1.4 Research methodology

1.4.1 Literature Research Method

The literature research method, a cornerstone of this study, involves the systematic collection, organization, and analysis of relevant literature to glean insights and data regarding the subject under investigation. Extensive literature, encompassing books, journals, theses, reports, archives, and program documents, was meticulously reviewed. This comprehensive literature review amalgamates knowledge from diverse disciplines including economics, accounting, management, and statistics. By synthesizing this wealth of information, the study constructs a robust performance evaluation index system for listed companies. The chosen methodology integrates multidisciplinary perspectives and culminates in the selection of the Data Envelopment Analysis (DEA) model, a quantitative tool essential for the subsequent analysis.

1.4.2 Quantitative Analysis Method

The quantitative analysis method is the basis of this research work. This study uses a panel data analysis method, utilizing a huge dataset of up to 20 years consisting of panel data from listed companies, with 21,355 samples carefully extracted. Through rigorous quantitative analysis, this study explores the complex mechanisms by which technological innovation and technological alliances affect business performance. This quantitative exploration provides a solid foundation for understanding the quantitative relationships between variables and lays the groundwork for drawing meaningful conclusions.

Chapter 2. Theory and Literature Review

2.1 Theoretical Foundations

2.1.1 Resource-based theory

Resource-based theory, originating from Penrose's seminal work in 1959[32], has evolved into a cornerstone of management research. Penrose proposed in her "Theory of Firm Growth" that a firm should be perceived as a collection of resources shaping its growth. Building upon this foundation, Wernerfelt (1984)[33] introduced the "Resource-Based View of the Firm," emphasizing the pivotal role of organizational capabilities, resources, and accumulated knowledge in explaining a firm's ability to achieve excess returns and maintain competitive advantage. Grant[34] further defined this theory in 1991, delineating resources as valuable, scarce, inimitable, and non-substitutable, laying the groundwork for contemporary resource-based theory (RBT).

According to RBT, firms striving for a competitive edge must focus on accumulating, developing, and acquiring resources. External complementary resources become indispensable for establishing competitive advantage. Das and Teng (2000)[35]highlighted firms' motivation for joining strategic alliances: sharing, exchanging, and acquiring resources unattainable through ordinary means or mergers and acquisitions. When innovating, a firm's internal knowledge and resources often prove insufficient, necessitating resource acquisition from external sources, especially knowledge beyond its core competencies. Strategic alliances facilitate rapid acquisition of essential resources and unique capabilities, extending a firm's resource scope beyond its boundaries.

RBT aptly explains cooperative innovation in strategic alliances, enabling firms to leverage external knowledge—a vital component in building competitive advantage. In addressing alliance issues, RBT emphasizes both value creation and minimization of transaction costs, offering a more comprehensive explanation than transaction cost theory. However, criticisms have emerged, with scholars highlighting potential tautological shortcomings and challenges in explaining the origins of a firm's valuable resources (Priem and Butler, 2001)[36].

2.1.2 Organizational learning theory

Fayol[37] and Taylor sorted out the content of workers' work, explored what methods could be used to improve efficiency, and then used the summarized workflow as a standard and promoted it. This systematic approach enhances the efficiency of high-tech firms and organizations in accomplishing their tasks (Lavie and Miller, 2008)[38]. The exploration carried out by Taylor and Fayol is known as scientific management and the beginning of modern management. Later, March elaborated on the idea of organizational learning, and only then did in-depth research on organizational learning begin.Argyris analyzed organizational learning on this basis, and concluded that organizational learning refers to the whole process of an organization identifying a problem, on the basis of which it rebuilds and summarizes the structure, so as to correct the problem (Baum et al., 2000)[39]. Later on, academic research on organizational learning has become more and more in-depth, which is also regarded as an important way for high-tech enterprises to summarize existing knowledge and then form new knowledge.

Some time after scholars proposed the learning organization (Rowley et al., 2000)[40], organizational learning has become even more widely explored (Parise and Casher, 2003)[41]. There is also a wealth of research in this area, with the more mainstream being adaptive theory, as well as dichotomous and 4I theories.

According to the viewpoint of adaptability theory, organizational learning refers to the fact that when the external environment changes, the organization adjusts itself so as to better adapt to the changing environment. For the organization, it must constantly adjust and optimize itself when making decisions, and change its behavior and cognition in this way, so as to ensure the match between itself and the external environment, and to achieve the long-term development and smooth operation of the organization. The core of adaptability theory lies in the ability of the organization and its members to continuously modify and optimize their own behaviors based on past experiences, and apply them to subsequent decisions. With the deepening of related research, some researchers began to put forward the dichotomy theory, which mainly divides organizational learning into two parts, namely, exploratory and exploitative learning.Crossan et al. based on the dichotomy theory to carry out a more in-depth analysis of the exploitative learning, the exploitative learning is considered to be the use of the organization's already accumulated knowledge and deepening, while exploratory learning is understood as the action taken in order to acquire new knowledge (Reuters). and action taken to acquire new knowledge (Reuer et al., 2002)[42]. Based on the analysis of existing studies, the researchers constructed a 4I model that reflects the various actions taken at different levels in learning; the first I is Intuiting, or individual knowing, the second I is Interpreting, or knowledge interpretation, the third I refers to Integrating, or knowledge integration, and the fourth I refers to Institutionalizing, which is institutionalization. Individual Perception and Knowledge Interpretation as well as Knowledge Integration and Institutionalization are able to connect organizational learning and individuals, and the fact that knowledge can be applied and created in the process actually corresponds to the two types of learning mentioned above. Therefore, the 4I model can be considered as an extension of Crossan et al. based on the dichotomy theory (Reuer et al., 2002).

According to the above research theories on organizational learning, it can be found that organizational learning refers to the whole process of the organization adjusting itself, acquiring and utilizing knowledge when the internal and external environment changes, which can reflect the changes in the organization's processing of information and knowledge. For high-tech enterprises, organizational learning is conducive to the enhancement of the enterprise's innovation ability, which is mainly manifested in the optimization of the way of information processing and the way of information acquisition, so that the organization can be improved based on past experience, and can correct the mistakes or prevent the possible risks in time.

2.1.3 Theories of technological innovation

The Technical Innovation Theory (TIT) was first systematically formulated by Joseph ASchumpeter in his Theory of Economic Development. Innovation is the establishment of a new production function, i.e., the realization of a new combination of production factors and production conditions that have never existed before, and its introduction into the production system. Innovation generally consists of five aspects (1) the manufacture of new products (2) the adoption of new methods of production (3) the opening up of new markets (4) the acquisition of new suppliers (5) the formation of new forms of organization to create or break the original monopoly of the new form of organization.

In traditional theories of technological innovation, technological innovation is usually viewed as a linear process, from basic research to applied research and development, and ultimately transformed into products or services. This view emphasizes the roles of scientists and engineers, and technological innovation is seen as an internal, closed activity. However, in practice, the limitations of this linear model gradually emerge, as technological innovation is often an open and dynamic process, influenced by a variety of factors. In order to better explain the real process of technological innovation, scholars have proposed the open innovation theory. The theory holds that enterprises no longer rely on internal research and development, but actively cooperate with external partners, suppliers, customers, and even competitors. The open innovation theory views the innovation process as an open system, where the acquisition of external knowledge and resources is closely related to internal innovation. This open innovation model prompts enterprises to respond more flexibly to market demand, better utilize external wisdom, and promote the rapid development of technological innovation. Currently, the theory of technological innovation gradually focuses on sustainable innovation and social innovation. The theory of sustainable innovation emphasizes that technological innovation should be consistent with social, environmental and economic sustainability. Social innovation theory, on the other hand, emphasizes the solution of social problems and the creation of social value by technological innovation. Overall, the development of technological innovation theories has experienced an evolution from linear models to systemic models to open innovation and innovation ecosystems. These theories have continuously enriched and expanded our understanding of the nature of technological innovation and its influencing factors, and provided theoretical guidance for innovation activities.

2.2 Overview of research related to technological innovation investment

2.2.1 Connotation of technological innovation investment

According to the definition of the World Economic Cooperation Organization (OECD), technological innovation activities are creative work carried out on a systematic basis for the purpose of increasing the stock of knowledge, which, specifically, encompasses human, social and cultural knowledge in many fields and the use of this stock of knowledge to design new applications (OECD, 2010).

In terms of practice, according to the "Guidelines for the Administration of the Recognition of High-tech Enterprises" issued jointly by the Ministry of Science and Technology, the Ministry of Finance and the State Administration of Taxation of the People's Republic of China in 2008, the Guidelines explicitly limit the accounts to which technological innovation expenditures can be accounted for, which include, among others, the salaries and benefits of personnel related to technological development, the costs of raw materials, depreciation of fixed assets, the amortization of intangibles, the costs of patent applications, and other expenses.

The strength of enterprise investment in technological innovation is crucial for promoting growth and competitiveness. This investment can be viewed from two perspectives: capital investment and technological innovation human resource investment. Capital investment includes initial financial support for exploring new technologies, optimization of capital during technology maturation, long-term strategies for ongoing research and development, and investments in external cooperation and technology introduction. technological innovation human resource investment focuses on talent acquisition, team cooperation, incentive mechanisms, and knowledge management.

2.2.2 Research on the relationship between technological innovation investment and business performance

① Positive correlation

Technological innovation investment has a non-negligible role in the development of the company, and at present, there are numerous studies in the academic world that can prove the relationship between technological innovation and business performance.There is a strong relationship between research expenses and the company's operating performance, and the higher the intensity of investment in research, the greater the company's operating performance will be improved.

Vithessonthi et al. (2016)[43]Liu, Ruizhi and Zhang, Ruxiu (2018)[44] concluded that there is a significant positive correlation between R&D investment and a company's market capitalization and operating performance, and a company's reputation plays a positive moderating role on these two relationships through the analysis of the Chinese stock market.

Liang Haishan et al. (2018)[45] took Haier as the research object, and the study showed that Haier's innovation ability can be divided into three stages, namely imitation learning, independent R&D and combined iteration, while combined iteration is in the form of knowledge integration, which directly contributes to the improvement of the company's performance, and thus verifies the positive impact of independent R&D on the company's performance.

Zhu Yongming.et al.(2022)project empirically analyzed the relationship between social responsibility, technological innovation and business performance of Chinese SMEs by using data from Chinese SMEs and GEM listed companies from 2015-2019. The results show that technological innovation has a positive contribution to firms' operating performance and plays a moderating role between firms' social responsibility and firms' operating performance. When the intensity of the company's technological innovation is different, the company's social responsibility produces a critical value on the company's business performance, and when the company's technological innovation intensity reaches the critical value, the company's social responsibility produces a greater impact on the company's business performance [46].

Yang Linbo et al. (2022) established a two-channel mediation model with a moderating effect of supply chain integration on NPD performance based on the theory of resource dependence, and concluded that regardless of whether the moderating effect of technological instability is considered or not, the mediating effect of exploratory innovation is significant in the relationship between supply chain integration and NPD performance, while the mediating effect of exploitative innovation is insignificant[47].

The project of Angel Wang (2022) used a combination of literature research and field research to develop a set of scales on network relationships among 355 technology-based enterprises in China. After statistically processing the questionnaire data, it was found that: the network relationship among enterprises has a significant positive impact on the technological innovation capability of enterprises and the technological innovation capability of enterprises; and all aspects of technological innovation have a moderating effect on all aspects of network relationship [48].

Guo H et al. (2022) examined the performance mechanism of two types of open innovation (technology purchase and collaborative R&D) based on the "knowledge" perspective. The results show that both technology purchasing and collaborative R&D have "inverted U" shaped effects on the performance of digital entrepreneurial firms; the higher the technological capability, the smoother the inverted U-shaped relationship between technology purchasing and firm performance, and the steeper the relationship becomes when the technological environment is more open[49].

Zhou Yi et al. (2022) empirically examined the correlation between technological innovation and firm performance using panel data of 1,286 firms in China's A-share market from 2000 to 2020, and explored the role of internationalization level and firm size in these two correlations. The results show that technological innovation can significantly improve firm performance; the internationalization level of MNCs and firm size have significant positive moderating effects on technological innovation and firm performance. As the internationalization level of the firm increases and the size of the firm expands, the enhancement effect of technological innovation on firm performance becomes more obvious[50].

Jia Changjin et al. (2022), based on the network embedding theory and the basic theory of resources, established an innovation collaboration network based on China's electronic information data from 2008 to 2017 from the perspectives of "relationship" and "structure" dynamics. On the basis of the 2008-2017 Chinese electronic information data, an innovation collaboration network was established from the dynamic perspectives of "relationship" and "structure", and the evolution of 283 innovation network communities was visualized, and its impact on innovation performance was analyzed[51].

Nie Jun (2023) investigates the impact of enterprises' social responsibility fulfillment on their value creation in the process of digital transformation from the perspective of technological innovation. Based on the data of Chinese listed companies from 2011 to 2020, through empirical research, we find that CSR can effectively improve the value creation of enterprises in the process of digital transformation, and CSR can significantly improve the relationship between "digital transformation-technology innovation performance", and the performance of CSR can significantly improve the performance of enterprises in the process of digital transformation. CSR can significantly improve the relationship between digital transformation and technological innovation performance, and CSR performance can significantly improve the technological innovation performance of enterprises in the process of digital transformation. The positive impact of CSR on STI activities is not only manifested in the quantity of STI activities, but also in the quality of STI activities; the positive moderating effect of CSR on enterprise performance is more significant in high R&D industries. The positive moderating effect exists in both state-owned and non-state-owned enterprises, and in both eastern and central-western regions. This project will help to better understand the intrinsic connection between the digital economy and CSR, and provide empirical evidence for the academic debate on whether CSR can play a positive role[52].

Wu Haoqiang et al. (2023) empirically examined the interplay of digital transformation, technological innovation and high-quality development based on the data of listed companies in China's manufacturing industry from 2008 to 2020. The results show that both digital transformation and technological innovation have a significant impact on the high-quality development of enterprises, and that technological innovation plays an important mediating role; digital transformation will enhance the effect of breakthrough technological innovation to promote high-quality development, and transform the substitution effect into incremental technological innovation, thus weakening its role in promoting high-quality development[53].

Gong Zhiwen et al. (2012) take the panel data of listed companies in China's biopharmaceutical and electronic information technology industries in 2007~-2009 as the research sample, and their results show that there is indeed a significant positive relationship between the R&D investment of enterprises and their profitability of the current year's main business, but it is important to point out that the study did not test whether the R&D investment has a lagging effect on the performance of enterprises[54].

Qiu Yunjie et al. (2016) empirically re-examined the impact of R&D investment on firm performance by using propensity score matching (PSM) method based on the database of Chinese industrial firms from 1998 to 2009. The study shows that the R&D behavior of enterprises can effectively improve their own performance, and the total factor productivity and profitability levels of enterprises with R&D investment are about 3 percentage points higher than those without R&D[55].

② negative correlation

Currently, in theory, in addition to technological innovation investment is favorable to company performance, some scholars have come to some research conclusions that technological innovation is unfavorable to company performance. Theoretically, the technological innovation investment of an enterprise is a non-continuous, time-spanning, decision-making-to-success process, which is affected by the external environment in addition to the enterprise itself, indicating that the process of technological innovation investment is very complex and its results have great uncertainty. When firms undertake technological research and development, managers may make pauses or adjustments due to changes in their own and external environments, thus exposing technological innovation to greater risks and negatively affecting firm performance.

For example, Cui and Mak (2002)[56] results show that technology R& D intensity has a negative impact on the firm's operating performance and a positive impact on the firm's value.

Hsu and Boggs (2003)[57] conclude that autonomous innovation of listed companies has a negative effect on the performance of listed companies through empirical analysis and empirical analysis.

In the same year, Majocchi and Zucchella (2003)[58] similarly found that there is a significant negative relationship between autonomous R& D and the company's business performance.

Guo Bin (2006)[59] empirically analyzed Chinese softwares firms and concluded that the R&D intensity of Chinese softwares firms has a significant negative effect on the profit and output of softwares firms.In addition to the above test results obtained by taking different types of firms as research samples, some authors have also categorized firms based on the number of R&D activities and explored their performance.

For example, Wei Jiang et al. (2013) [60] found that during the transition period, firms with more R& D investment have a higher degree of diversification in technological innovation, but the degree of technological diversification also adversely affects the firm's operational performance.

Based on the above literature, this paper argues that the cycle of technological innovation is longer, the cost is higher, the upfront investment is larger, and the risk of technological innovation is also higher, leading to a negative correlation between technological innovation and firms' operating performance. In particular, in the process of technological innovation, it will be affected by many factors, which is not only the enterprise's own reasons, many technological innovations will also change with the change of the external environment, for example, the change of external demand, the change of competitors and so on. Therefore, enterprises must make decisions on innovation and research and development according to the actual situation of the enterprise.

③ Irrelevant

Some scholars have argued that there is a nonlinear or nonexistent relationship between a firm's technological innovation investment and the firm's managerial performance.

Fred (2000)[61] The results of the study show that the extent of the impact of technological innovation on the firm's performance is related to the size of the firm, and that the extent of the impact of technological innovation on the firm's performance is insignificant for small firms.

Bae et al. (2008)[62] The results show that there is a nonlinear relationship between the level of technological innovation and operational performance in there is a nonlinear relationship between the level of technological innovation and operational performance in multinational corporations.

Goya et al. (2016)[63] The results of the study show that there is no significant correlation between a firm's independent R& D innovation capability and its managerial performance.

Zhou Yizhong et al. (2009) [64] categorized pharmaceutical intellectual property rights into patents, technical secrets, trademarks, and copyrights related to pharmaceuticals, etc., and found that there is no significant correlation between patented technology, patented technology and the business performance of pharmaceutical companies in China.

Li Dongqin et al. (2013) [65] selected the manufacturing industry as the research object, and the results show that there exists an "inverted U"-shaped relationship between industrial R&D inputs and enterprise output performance, and the impact of different industrial R&D inputs on the enterprise output performance is also significantly different.

Chen Yuke (2018) [66] showed that the effect of technological innovation behavior of enterprises on environmental protection behavior is not significant.

Lili Fan and Yuanyuan Chu (2019)[67] proposed a new research method on the relationship between low-carbon technological innovation behavior and its performance in the Chinese iron and steel industry. In addition,

Chen Shouyu (2014) [68] showed that the higher the risk level of innovation, the more difficult it is to realize the innovation, and therefore, the less likely the enterprise is to improve its business performance, that is to say, whether technological innovation can improve business performance is related to the degree of the enterprise's control of innovation risk.

Technological innovation shows a non-linear relationship or no relationship with business performance, which may be theoretically due to the following reasons: first, the company's technological research and development cycle is long, often for several years, therefore, the initial technological research and development requires a large amount of manpower and material resources and other resources, but successful technological research and development brings the company not only economic gains, but also reputation enhancement and diffusion,. Thus, it enhances the company's market competitiveness, and therefore, the later technological research results are likely to show a positive correlation with the company's performance. From the above two aspects, the non-linear correlation between technological innovation and performance has a strong existence, and this non-linear correlation reflects the uncertainty characteristic of technological innovation. Secondly, the risk of company R& D is high, when the company determines the R& D plan, in the execution, it will be due to the change of the internal and external environment of the company, which will lead to the success or failure of the company's R& D plan, or even the effect of the R& D plan does not match, which will lead to the relationship between the R& D plan and the company's operational performance becomes more complicated, so the relationship between the R& D plan and the company's operational performance are not related is a reasonable assumption.

2.3 Overview of research related to technology alliances

① Definition and classification of technology alliances

Technology alliance was initially proposed jointly by Nigel and Hopland, the president of DEC at that time in the United States, and so far, there have been a lot of scholars who have carried out in-depth research on it, among which Teece (1992) [69] and Stuart (1999) [70] are the representatives.According to Teece, the enterprise technology alliance is a kind of long-term and close cooperative relationship, which is a form of cooperation sought by several enterprises based on their own specific strategic objectives. Teece argues that an enterprise technology alliance is a long-term, close cooperative relationship, which is a form of cooperation sought by a number of enterprises based on their specific strategic goals, and in terms of its substance, it is the product of various resources integrated by the enterprises, and at the same time, it is also characterized by a certain kind of contract and trust. Similarly, Stuart points out that in a technology alliance, different firms will collaborate at a deeper level in terms of information and resources, bringing more benefits to both sides.

Sampson (2007) [71], in his study, explicitly classified enterprise technology alliances into different types and pointed out that technology alliances are driven by different motives and objectives, and from the perspective of organizational forms, technology alliances can be manifested as horizontal and vertical alliances.

Luiz (2018) [72] found that the benefits brought by vertical alliances and horizontal alliances exist in terms of focus with some differences, with the former being conducive to promoting firms' productivity improvements and the latter being conducive to promoting firms' technological innovations.

Simonin (1997)[73]According to the mode of cooperation between the allied firms, technology alliances are categorized into equity and contractual, and contractual alliances are also known as non-technology alliances.

Harrigan (1988)[74]found that, compared with equity-type alliances, contractual alliances are more flexible, fewer exit barriers, fewer legal constraints, less investment and dedication to resources, and less instability of the firm.

Belgraver Herman et al. (2018)[75] argued that alliances formed by equity have strong complementarities, strong sustainability, and are a strategic behavior conducive to the development of the firm.

Zhang Xiaomei (2018)[76] and others, based on incentive theory, summarize the meaning of technology alliance into four aspects: first, the purpose of enterprises to set up technology alliance is to achieve the strategic objectives of the enterprise; second, while cooperating, information and resources should be shared among the alliance members; third, each enterprise maintains a loose and collaborative relationship, and does not interfere with each other's enterprise's production operation; fourth, cooperation brings about greater common benefits than the sum of the benefits brought about by their respective individual operations.

Studies from the perspective of economics include Li Jie (2020) [77], who believes that the establishment of technology alliances is conducive to the formation of economies of scale, which is conducive to the expansion of the scope of operation of the alliance member enterprises and the improvement of the efficiency of the use of existing resources.

Xie Xuemei et al. (2020)[78]From the perspective of cooperation mechanism, technology alliance refers to a kind of cooperative organization formed on the basis of common interests and future development needs, clear objectives, legally binding contracts, and suitable operation methods.

Huadong et al. (2021)[79] analyzed the concept of cooperative innovation among enterprises on the basis of resource sharing and risk sharing from the perspective of game theory.

Li Chunli et al. (2016)[80] Horizontal alliance is considered to be a kind of technology alliance automatically formed on the same chain in order to achieve economies of scale, reduce costs, and improve one's competitive advantage. On this basis, through full and effective communication and integration of resources, the alliance enterprises can achieve a win-win situation, thus enhancing their core competitiveness.

Hu Huiyuan (2017)[81]When enterprises want to carry out vertical integration, but it is difficult to complete it by relying on their own strength alone, they can adopt the way of technology alliance to establish a cooperative relationship with upstream and downstream enterprises, which can also play a similar role to vertical integration, for example, it can reduce the transaction costs of enterprises.

Li Xin et al. (2020)[82] argued that both types of alliances can improve a firm's innovation performance, but contractual alliances have a greater positive effect on a firm's innovation performance.

② Selection of technology alliance partners

Most of the existing research focuses on the competitive ability of enterprises, while there is a lack of systematic research on interactions between enterprises and the effects they produce. However, most of the existing research focuses on resource sharing and benefit distribution among firms, and lacks a more systematic theoretical model and analytical method, i.e., the mechanism of inter-firm heterogeneity on inter-firm interactions is not clear.

Geringer (1988) divided the factors affecting alliance partner selection into relationship and task dimensions, explored the main factors considered in partner selection from both relationship and task dimensions, and analyzed the path of association between the relationship dimension and alliance innovation performance

[83].

Chung (2000) concluded on the basis of a study of alliances formed between banks: The possibility of investment bank alliance formation shows a positive correlation with the complementarity of their capabilities and the similarity of their status, and the factors influencing alliance performance are studied from the perspective of correlation [84].

Scholars such as Mike Beverland (2001), on the other hand, believe that technology alliances are formed because firms demand more market opportunities and gain greater competitive advantages [85].

Hitt et al. (2004) analyzed the impact of the choice of partners between China and Russia under different institutional backgrounds, and concluded that China considers the intangible assets, technology, and management of partners first; in the case of a less stable system, Russia first considers the partner's capital and its ability to complement its own; at the same time, from the perspective of the overall assets, the study of partner types on firms' innovation performance [86].

Paul (2007) found that strategic alignment, trust and strategic expediency at the individual level and the firm level have an impact on firms' partner selection behavior. In addition, the impact of partner choice on alliance innovation performance was explored from a strategic perspective.[87].

Yan Cimon (2008) and other scholars in the heterodyne severity of the impact on the relationship between firms' resources and firms' relationships found that firms are more likely to form technology alliances due to the asymmetry of resources[88].

Rodrigo Malheiros (2009) the choice of firms' technology alliances has a positive and positive significance for firms' technological innovations and corporate development[89].

Julia Connell (2007) argues that in technology alliances, the technological strength and material strength of enterprises occupy the same important position, and the complementarity between the two technological elements brings more indestructible relationship for enterprise alliances[90].Wassmer (2012) argues that in this context, selecting alliance partners based on the resource perspective can improve the innovation performance of enterprises[91].

Based on the data of more than 3,000 enterprises in the Netherlands, Hagedoorn (2016) constructed an evaluation index that includes the diversity of partner types and the relevance of partner types, and found that both indexes show an "inverted U" relationship with the relevance of partner types. However, due to the high degree of heterogeneity and high degree of correlation of inter-firm partnerships, the innovation performance of firms is not high. Due to the differences in the external knowledge environment and the differences in the modularization level of the industry, the impact of such heterogeneity and correlation on firms' innovation performance can be moderated[92].

At the level of alliance portfolio, Schilke and Goerzen (2010) viewed core firms' satisfaction with an alliance portfolio as an alliance portfolio performance and concluded that alliance portfolio management capabilities can significantly improve alliance portfolio performance[93].

Based on the two men's research, Castro and Roldá n (2015) built on this foundation and proposed a new theory of strategic management of firms, namely the theory of strategic management of firms[94].

A questionnaire survey with 144 companies in Spain showed that cooperative leadership is able to enhance portfolio performance through the moderating effects of relational governance and portfolio coordination, while relational governance is able to utilize the moderating effects of portfolio coordination to enhance portfolio performance. In addition, Duysters et al. (2012) used the probability of success of a single inter-firm cooperation as a measure of inter-firm cooperation performance. Through an empirical study of 161 firms across multiple industries, we find that alliance portfolio management capabilities help core firms dominate more diverse alliance portfolios and can significantly enhance the performance-enhancing effect of alliance portfolio diversity[95].

At the firm level, Sarkar et al. (2009) argued that, by increasing alliance portfolio capital, alliance portfolio management capability can improve the market performance of core firms[96], due to the synergistic generation and consumption of alliance portfolio capital, which makes it simultaneously rare, time-dependent, and sticky, and enables the core firms to gain and maintain a competitive advantage that is difficult to be imitated.

The indicators proposed by Yuan Lei (2001) for selecting alliance partners can be categorized into two main groups, namely, related individuals and related partnerships[97].

Lan Tian (2003) used resource theory to systematically analyze and summarize the problem of technology alliance preference under resource heterogeneit[98].

Wang Qiufang (2006) constructed an overall system for comprehensive evaluation of partner selection, on the basis of which a multi-level comprehensive evaluation index system was proposed and applied fuzzy theory and AHP method to optimize it[99].

Liu Erliang (2010) used factor analysis and other methods to conduct a systematic study of knowledge sharing among members in knowledge-based alliances[100].

By analyzing the two, we found that the most important reason why technology alliance can be created is to obtain the resource complementarity and sharing of the alliance. The advantage of the alliance lies in the resource advantages it possesses, while the choice of alliance partners and the required resources are the basis for enterprises to make cooperative choices. On this basis, some scholars have proposed a strategy based on inter-firm competition. You Daming (2016) used three quantitative methods and integrated them with the influencing factors of alliance partner selection in the process of researching technology alliance enterprises, on the basis of which, the existing partner selection assessment system was further improved to provide a basis for finally reaching the cooperation goal[101].

Wu Songqiang (2017) believes that corporate reputation, resource technology and enterprise technology alliance selection complement each other[102].

Hu Qiangguang, Xiang Aloe (2013) compared how the benefits of technological innovation are distributed between contractual technology alliances and entity-based technology alliances, and explored the method of distributing the performance and results of enterprises in technology alliances[103].

It is argued that the distribution of profits in an enterprise-type technology alliance is more suitable for a more insured equity-based approach. Li Xinyun, Ren Dong, and Yuan Shunmei (2013) based on the game analysis of the interests of industrial innovation and technology alliance, the following conclusions can be drawn: in the distribution of interests of technology alliance, the government's support and guidance are very important, and at the same time, it is also a very important link[104].

Therefore, how to get win-win in technology alliance and keep the stability of technology alliance has become an urgent problem. However, most of the existing researches focus on resource sharing and benefit distribution among enterprises, lacking a more systematic theoretical model and analysis method. Chen Hairong, Li Congdong, and Tong Rui (2013) argued that competition and cooperation in technology alliances are equally important, the core of which is collaboration and coordination among enterprises. Taking the industrial technology path as a link, the synergistic cooperation between enterprises is realized, and the win-win situation between enterprises is realized[105].

Meng Qi (2007) systematically discussed the competitive advantage of technology alliance and its generating mechanism[106] from four aspects of knowledge, technology, interest and relationship by establishing evaluation index system, building a comprehensive evaluation model of technology alliance and adopting case study and other methods.

By combing through the relevant literature, it can be found that many scholars have begun to incorporate resource heterogeneity among enterprises into the study of technology alliances. In order to obtain greater market opportunities and competitive advantages, enterprises must continuously explore the asymmetry and asymmetry that exists between organizations and discover the positive factors conducive to enterprise development. Heterogeneous relationships between enterprises rely on both the differences in tangible resources between enterprises and focus on the impact of intangible resources between enterprises on each other.

③ Evaluation of the performance of technology alliances

In terms of assessment perspectives, there are two existing assessment methods, one of which is from the perspective of wholeness, i.e., viewing the technology alliance as a whole. On this basis, a technology alliance based on the stability of technology alliance and strategic management of sustainable development is proposed.

Scholars Hill RC& Hellriegel (1994)[107], who support this viewpoint, point out that if all participating units are satisfied with the results of this study, the study is a success. Secondly, it is assessed from the perspective of the individual alliance and is used to measure the benefits of cooperation that alliance members receive from the alliance. The advantage of this assessment method is that it highlights the fact that the core of the alliance is each of the participating firms, and the research in this perspective focuses on the financial indicators of the firms themselves, and whether the expected goals of the individual firms have been achieved, etc.

Geringer & Hebert (1991)[108] viewed inter-firm cooperative relationships as a separate whole, and put forward the inter-firm cooperative relationships point of view.

According to Tomoko Tsai Na (2015)[109],business technology alliance performance includes both behavioral and outcome dimensions, but behavioral performance needs to be reflected through outcome performance. Moreover, in addition to bringing benefits, ensuring the efficient operation of alliance actions is also the result of alliance partners reaching strategic goals. Therefore, it is more scientific to assess alliance performance based on the desired goals of each participating enterprise.

With regard to evaluation indicators, there are three main types of indicators for evaluating the performance of technical alliances: one subjective, one objective, and one subjective-objective. Regarding the subjective evaluation indicators of alliance performance: the satisfaction index was first mentioned by Todd Saxton (1997)[110]; Keith (1998)[111] selected a subjective evaluation indicator, alliance members' performance satisfaction, as the subjective indicator of evaluation; Jeppe Christoffersen (2014)[112] was evaluated by inviting the alliance managers or administrators of the partners, such as: satisfaction, degree of goal attainment, customer service, reputation, etc.

Lehene Cosmin Florin (2021)[113] showed that the most widely used basis for evaluating the performance of alliances is the financial indicators of the firms, while the financial indicators that can be directly reflect the performance level of the enterprise are: the enterprise's revenue growth, input-output ratio, capital turnover, etc.

The enterprise performance evaluation system constructed by Xiong Li (2017)[114] has several dimensions, and all of them adopt quantitative methods, such as: for the item of financial performance, the return on net assets is selected to measure the enterprise performance.

Yi Zhang (2019)[115] selected subjective indicators such as customer satisfaction, customer maintenance rate, and customer acquisition rate, as well as return on net assets, sales revenue growth rate, and gross profit margin when evaluating the technology alliance of e-commerce companies.

Sun Jianbin et al. (2020)[116] mainly used the methods of event study, accounting indicator method, and non-financial indicator analysis method. Among them, the accounting indicator method based on factor analysis is the assessment of alliance performance, while the non-financial indicator analysis method includes four subjective indicators: brand awareness, customer satisfaction, R&D investment and personnel training.

Zhao Yanling et al. (2022)[117] analyzed 20 qualitative and quantitative indicators with customer satisfaction, partner trust, profitability, and market share. Then, a performance evaluation system of business alliance was established and empirically analyzed with the actual situation of enterprises.

Luo Jianhong (2018)[118] proposed a new strategic management strategy on this basis. Liu Jingdong et al. (2020)[119],from the perspective of normative diversity, argued that contract-based collaborative relationships do not significantly affect the effectiveness of alliances. However, technology alliances based on cooperative intentions tend to have higher performance, so when evaluating the performance of alliance firms, emphasis should be placed on selecting indicators that can reflect inter-firm relationships.

The results of Zhu Fei (2020)[120] show that the goal consistency of enterprises, the resource complementarity of enterprises and the cultural compatibility of enterprises are important factors affecting the performance of enterprise technology alliances.

Yin Hang et al. (2021)[121] suggested that technology alliance partner is the first step for enterprises to build alliances, and this step is the root of influencing alliance innovation performance and has a positive effect on alliance performance.

In terms of evaluation methods, currently, the more commonly used evaluation methods are: data envelopment analysis, factor analysis, hierarchical analysis, fuzzy comprehensive evaluation, fuzzy comprehensive evaluation, etc.

Nhu-Ty Nguyen (2020) established a model of alliance performance analysis based on the envelopment analysis method and applied it in the practice of technical alliance performance analysis of Vietnamese construction enterprises [122].

Zhou Yong et al. (2005)[123] applied BSC to the performance evaluation of technology alliance for the first time and constructed an evaluation system from financial, market, internal control, and growth levels based on BSC.

Wu Songqiang et al. (2014)[124] improved AHP, and then used the method to quantify the qualitative indicators and calculate the weights of each indicator, meanwhile, the horizontal joint innovation performance of SMEs in the Software Valley was effectively evaluated.

Tian Juan et al. (2021)[125] constructed the performance evaluation system of Taizhou industrial enterprise technology alliance through the comprehensive evaluation of multi-dimensional indicators.

Tan et al. (2017)[126], from the subject utility theory, established the performance evaluation index of high-tech enterprise technology alliance by using the factor analysis method.

Yi Zhang (2019)[127] proposed an equity technology alliance performance evaluation method based on BSC.

Guanzhong Li (2018)[128], in the process of establishing the alliance performance assessment model, used the hierarchical analysis method to determine the weights of each index, and then used the fuzzy comprehensive judgment method to assess the alliance performance.

④ Impact of technology alliances on business performance

Su Zhongfeng et al. (2007) conducted a questionnaire survey about technology alliances for more than 850 manufacturing firms, and at the same time, analyzed the results of the survey to verify how the motives and control styles of business alliances affect the performance of technology alliances[129].

Gao Gao and Xu Fei (2010) introduced opportunistic behavior into Hart's corporate boundary model, thus obtaining an alliance boundary model to analyze the cooperative relationship between two different interest groups[130]. Xu Erming and Xu Kai (2012) In this project, through a questionnaire survey of 650 firms, structural equation modeling was used to empirically test the effects of resource complementarity and opportunistic behavior between two subjects in an alliance on the alliance's financial performance and the alliance's innovation output[131].

Guo Chaoyang et al. (2014) used event analysis to classify technology alliances into four categories and comparatively analyzed the stock price effects brought by different types of technology alliances[132].

Zhang Han et al. (2015) used the Johnson-Niemann model to quantitatively analyze the relationship between the two variables in a questionnaire survey of a technology entrepreneurship alliance consisting of 204 startups. It was found that the size of the alliance network between firms would have a significant positive impact on the business performance of the firms when the degree of fairness of the firms is high[133].

Cai Jirong (2015) established a theoretical model of two types of cooperative relationships under property rights and contractual types[134].

Zhao Chao and Wang Tienan (2019) analyzed and researched the difference between the age of alliance partners and the age of the company by using the factual analysis method, which takes the cumulative abnormal return on shares before the announcement of a technology alliance as an indicator of the value of the alliance[135].

Li Wei et al. (2022) conducted an empirical study using a sample of 211 start-up firms and showed that both technology alliances and marketing alliances significantly contribute to the entrepreneurial performance of start-up firms; both policy uncertainty and competitive intensity positively moderated the positive relationship between technology alliances and entrepreneurial performance, while competitive intensity negatively moderated the positive relationship between marketing alliances and entrepreneurial performance[136].

Through a questionnaire survey of 200 alliance-based enterprises, Ma Yong (2022) found that the endogenous and exogenous resource orientation of alliance-focused enterprises can improve the green management level of alliance; the balance and combination of binary resource orientation have a significant relationship with the green management of enterprises; the "inverted U" shape effect of alliance green management on the innovation performance of alliance is also found effect on alliance innovation performance[137]

2.4 Summarize

Based on the above summarization and sorting out, this section will briefly review the existing research literature.

Since Griliches[138] made his pioneering research results in the 1960s, scholars at home and abroad have carried out a great deal of research work on the issue of the correlation between R&D investment and firm performance, and they have drawn many useful conclusions based on different perspectives, adopting different research samples, and utilizing different research methods. Against the background that enterprise innovation and development has increasingly demonstrated its important contribution in various economies in recent years, academic research on this issue has always been highly enthusiastic, which has greatly enriched the academic research results and provided theoretical guidance for the formulation of enterprise innovation investment strategies, which has also become an important research basis for this paper.

However, overall domestic and foreign research still has some shortcomings:

First ,existing studies usually only use technological innovation inputs to test the correlation with a single dimension of enterprise performance, such as financial performance, innovation performance and so on. The research angle is relatively single. R&D activities are complex and changeable, from the R&D investment until the response in the enterprise performance needs to go through a long process, with many influencing factors and high uncertainty, so it is not accurate and comprehensive enough to evaluate the role of technological innovation investment in enterprise performance only from a single perspective.

Secondly, most of the researches have affirmed the role of technology alliance in the business performance of enterprises, but they lack in-depth and systematic analysis of the mechanism of the role, and have not carried out quantitative research, which makes the conclusions of the researches lack of objectivity, and do not have a wide range of reference value.

Based on this, this paper is innovative in the selection of variables. For the evaluation of enterprise performance, this paper uses factor analysis to evaluate, constructing multiple indicators based on solvency, profitability, turnover, growth and market value. Through the five steps of factor extraction, factor rotation, factor score calculation, factor interpretation, and factor score calculation. The final result is a comprehensive evaluation of the performance of the enterprise. This method not only synthesizes multiple aspects of enterprise performance, but also carries out data dimensionality reduction and extracts key influencing factors.

In the selection of variables for technology alliance, this paper innovatively refers to the quantitative research on the degree of digital transformation, by crawling the annual reports of listed companies, and measuring the strength of enterprises in technology alliance through the frequency of corresponding keywords for technology alliance in the annual reports of listed enterprises. By analyzing the word frequency method, we can indirectly reflect the enterprise's active degree of technology alliance by calculating the frequency of occurrence of technology alliance-related words in the texts of company reports, press releases, and cooperation announcements. For example, the frequency of words such as "cooperation", "alliance", "joint research and development", etc. can to some extent reveal the tendency of enterprises in technical cooperation. This approach is a breakthrough from the previous literature, which was only at the stage of theoretical analysis and the degree of basic elaboration. It provides ideas for quantitative research on technology alliances.

Chapter 3. Research design

3.1 Data sources

This study focuses on Chinese listed enterprises in Beijing, Shenzhen, and Shanghai. The data selection process involved several criteria. Financial industry data were excluded, along with enterprises classified as ST or PT. The study period spans 2010-2022, considering the impact of the 2008-2009 US financial crisis. Enterprises with significant missing data were eliminated, resulting in 21,355 cleaned samples from 4,096 individual firms. The data format is unbalanced panel data. To ensure uniformity, logarithmic transformation was applied to data with wide value ranges, and continuous variables were processed with bilateral truncation at the 1% level. Data analysis was conducted using Stata 17, utilizing information from the CSMAR and CNRDS databases.

3.2 Variable selection

3.2.1 Explained variable: business performance

In evaluating business performance, single-factor and multi-factor methods are employed. The single-factor method, or single-indicator method, assesses performance based on a solitary indicator, often a major financial or non-financial metric like net profit or market share. In contrast, the multi-factor method integrates multiple indicators across various dimensions such as financial health, market performance, and innovation ability, providing a comprehensive evaluation of a company's multifaceted performance. While the single-factor approach offers a quick overview, it may miss crucial factors. The multi-factor method, employing techniques like principal component analysis and entropy weighting, provides a holistic perspective, capturing diverse aspects of a company's performance.

The literature on evaluating the business performance of listed companies encompasses various approaches and perspectives. Zhao Shuming et al. (2011)[139]delves into the connection between strategic international human resource management and corporate performance, underscoring the influence of human resource management and internationalization levels on overall performance. Gu Haifeng and Li Dan (2013)[140]employ factor analysis to establish a multi-factor evaluation index system, offering a comprehensive view of Chinese commercial banks' business performance from multiple angles. Liu Shao-Fei and Wan Dayan (2013)[141]explore executive compensation and firm performance, conducting empirical analyses to discern the impact of diverse ownership structures on performance while accounting for various factors. Si Xiaobin and Yuan (2018)[142] focus on the business performance of agricultural listed companies, utilizing factor analysis to amalgamate multiple performance indicators. In a more recent study, Jianhua Wang and Xiaoqing Ding (2021)[143] investigate the evaluation of business performance for listed companies in Northwest China, integrating the effects of various indicators through factor analysis and cluster analysis. Collectively, these researchers contribute a comprehensive and insightful assessment of the operational performance of listed companies over different periods, employing either the single-factor or multi-factor method to consider diverse perspectives or industry characteristics. This body of research provides robust academic support for corporate decision-making processes.

This paper adopts the multi-factor approach, leveraging principal component analysis and entropy weighting. Principal component analysis condenses complex business indicators into fewer comprehensive metrics, revealing internal dynamics and serving as a valuable reference for decision-makers. Meanwhile, the entropy weighting method, an objective approach, overcomes subjectivity issues by calculating information entropy between indicator values, accurately reflecting their relative importance. These methods collectively enhance the evaluation of listed enterprises' operational performance, ensuring a comprehensive and credible assessment.

Based on the above literature and analysis,This paper uses factor analysis to evaluate the performance of enterprises, and factor analysis can construct several indicators based on profitability， solvency, turnover, growth, and market value when evaluating the business performance of enterprises.In profitability, the use of return on assets, net profit on total assets, return on net assets, return on invested capital to measure a total of four indicators, in solvency, the use of current ratio, quick ratio, gearing ratio, tangible assets gearing ratio to measure a total of four indicators, in the Turnover capacity, this paper uses current asset turnover, total asset turnover, shareholders' equity turnover ratio three indicators to measure, growth capacity using operating income growth rate, fixed asset growth rate, owners' equity growth rate to measure, enterprise value is considered to use the Tobin's Q value, book-to-market ratio, the profitability of common stock to measure a total of three indicators. The list of indicators is organized as follows:

<Table 3 -1> Business Performance Evaluation Indicators

dimension (math.)	variable	notation	formula
solvency	current ratio	A1	Current ratio = Current assets / Current liabilities
	quick ratio	A2	Quick ratio = (current assets - inventories) / current liabilities
	gearing	A3	Gearing ratio = Total liabilities / Total assets
	Tangible assets gearing ratio	A4	Tangible gearing ratio = Total liabilities / (Total assets - Intangible assets)
Turnaround capacity	Current asset turnover ratio	B1	Current Asset Turnover = Operating Income / Average Current Assets
	Total asset turnover	B2	Total Asset Turnover = Operating Income / Average Total Assets
	Shareholders' equity turnover ratio	B3	Shareholders' equity turnover = Operating income / Average shareholders' equity
profitability	return on assets	C1	Return on Assets = Net Profit / Average Total Assets
	Net profit margin on total assets	C2	Net Profit Margin on Total Assets = Net Profit / Total Assets
	return on net assets	C3	Return on net assets = Net profit / Average net assets
	Return on invested capital	C4	Return on invested capital = Net profit / Invested capital

growth capacity	Revenue growth rate	D1	Operating income growth rate = (Current operating income - Previous operating income) / Previous operating income
	Fixed asset growth rate	D2	Growth rate of fixed assets = (Current net fixed assets - Prior period net fixed assets) / Prior period net fixed assets
	Owner's equity growth rate	D3	Owner's equity growth rate = (current owner's equity - previous owner's equity) / previous owner's equity
enterprise value	Tobin's Q	E1	Tobin's Q = Market Capitalization / Total Assets
	Book-to-market ratio	E2	Book-to-market ratio = Net worth / Total market capitalization
	Rate of interest earned on ordinary shares	E3	Earned Rate on Ordinary Shares = Dividend on Ordinary Shares / Market Price of Ordinary Shares

In this study, I have employed a set of key metrics to assess corporate performance. Solvency is measured through indicators such as the current ratio, quick ratio, gearing ratio, and tangible gearing ratio. Turnover capacity is evaluated using indicators like current asset turnover, total asset turnover, and shareholders' equity turnover. Profitability is analyzed through metrics including return on assets, net profit margin on total assets, return on net assets, and return on invested capital. Growth capacity is assessed through the operating income growth rate, fixed asset growth rate, and owners' equity growth rate. Additionally, enterprise value is examined using indicators like Tobin's Q, book-to-market ratio, and the profitability of common stock.

To conduct this evaluation, factor analysis is employed, enabling the construction of multiple indicators based on solvency, profitability, turnover, growth, and market value. The evaluation proceeds through several steps. First, factor extraction identifies potential main factors through eigenvalue decomposition of the covariance matrix or other factor extraction methods, representing common variability among different indicators. Second, factor rotation is performed to enhance the interpretability of factors. Orthogonal and oblique rotations are commonly used methods, allowing factors to be independent or correlated, respectively. Third, factor scores are calculated for each firm, reflecting its performance on the corresponding factor. These scores are determined as weighted averages of the raw metrics, with weights derived from factor loadings. Fourth, factors are interpreted based on the factor loadings matrix, revealing the aspects of business performance represented by each factor. Finally, composite scores are calculated by multiplying each firm's scores on each factor by the factor weights. These scores are combined to produce a final evaluation score, with factor weights adjusted to reflect the importance of each aspect.

The outcomes of the KMO test and Bartlett's test of sphericity are presented below.

<Table 3-2> KMO and sphericity test values

inspect	(be) worth
KMO	0.724
Bartlett's test of sphericity chi-square	5.30e+05
Bartlett's test of sphericity p-value	0.000***

Note: Values in the table were compiled by the authors.
*p<0.1 ** p<0.05 *** p<0.01

The KMO (Kaiser-Meyer-Olkin) test value, which measures the correlation between the original variables, is 0.724. The KMO value ranges between 0 and 1, where higher values indicate that the raw data is suitable for factor analysis due to high correlations among variables, facilitating the extraction of potential factors.

Bartlett's test of sphericity yields a chi-square value of 5.30e+05 and a p-value of 0.000. Bartlett's test assesses the suitability of correlation between variables for factor analysis. A low p-value indicates that the data does not meet the assumption of sphericity, implying that the correlation between variables is not exactly equal. This result suggests that factor analysis is appropriate.

Considering the high KMO value and the low p-value from Bartlett's test of sphericity, these findings support the application of factor analysis for a comprehensive evaluation. Therefore, the steps of factor extraction, rotation, and score calculation can be pursued to conduct a detailed assessment of firms' business performance in terms of solvency, profitability, turnover, growth, and market value.

In the factor analysis process, the number of potential factors and their explanatory power over the variance of the original variables were determined by extracting eigenvalues and the explained variance rate. Principal component analysis was used for extraction, with eigenvalues greater than or equal to 1 indicating the extraction of factors. The factor extraction results are presented in <Table 3-3> below:

<Table 3-3> Factor extraction results

(math.) factor	eigenvalue (math.)	Difference in eigenroot values	variance explained rate	Cumulative variance explained
Factor 1	3.9111	0.9414	0.2301	0.2301
FactoR2	2.9697	0.5509	0.1747	0.4048
Factor3	2.4188	0.5076	0.1423	0.5470
Factor4	1.9112	0.7716	0.1124	0.6595

Factor5	1.1395	.	0.0670	0.7265

Note: Values in the table were compiled by the authors.

Eigenvalue differences signify each factor's contribution relative to the previous one. The variance explained ratio indicates the proportion of the original variable's variance explained by the factor, while the cumulative variance explained ratio represents the cumulative proportion of variance explained by the factor up to the current factor. The variance explained ratio being greater than 50% suggests effective factor extraction, and the relatively balanced eigenvalues indicate comparable information carried by each factor.

Subsequently, the factor component coefficient matrix was utilized to calculate factor scores, presented in <Table 3-4>:

<Table 3-4> Factor Component Coefficient Matrix

Variable	Factor 1	FactoR2	Factor3	Factor4	Factor5
A1	-0.0579	0.3642	0.0744	0.1129	0.0635
A2	-0.0577	0.3633	0.0743	0.1138	0.0713
A3	-0.0138	-0.2191	0.0306	0.0943	0.1830
A4	-0.0109	-0.2270	0.0153	0.0747	0.1866
B1	0.0003	0.0324	0.3449	-0.0147	-0.0899
B2	-0.0073	0.0734	0.4146	-0.0515	-0.0319
B3	-0.0404	0.0385	0.3766	-0.0104	0.0668
C1	0.2507	-0.0326	-0.0039	-0.0019	0.0119
C2	0.2473	-0.0126	-0.0135	-0.0067	0.0021
C3	0.2423	-0.0580	-0.0298	0.0341	0.0333
C4	0.2562	-0.0650	-0.0190	0.0182	0.0002
D1	0.0056	-0.0438	-0.0286	0.0005	0.4213
D2	0.0040	-0.0323	-0.0314	-0.0252	0.5276
D3	0.0402	0.0766	0.0192	0.0404	0.5275
E1	0.0036	-0.0998	0.0150	-0.4654	-0.0617

E2	-0.0017	0.0024	-0.0360	0.4405	-0.0256
E3	0.1281	0.0783	-0.0258	0.3497	-0.2300

Note: Values in the table were compiled by the authors.

For each sample, we can use the following formula to calculate its score on each factor: for Factor1, the sample's score on Factor1 is: A1 × Factor1's factor loadings + A2 × Factor1's factor loadings + A3 × Factor1's factor loadings + ... + E3 × Factor1's factor loadings. For FactoR2, the score of the sample on FactoR2 is: A1 × FactoR2 factor loadings + A2 × FactoR2 factor loadings + A3 × FactoR2 factor loadings + ... + E3 × FactoR2 factor loadings. + E3 × factor loadings of FactoR2. Similarly, we can calculate the sample's scores on the respective factors for Factor3, Factor4, and Factor5. In these formulas, the variables A1, A2, A3, ... , E3 represent the different metrics respectively, while the values under Factor1, FactoR2, Factor3, Factor4, Factor5 are the corresponding factor loadings obtained from the factor analysis. Finally, after obtaining all the factor scores, this paper calculates the composite score to measure the business performance of the enterprise, and the calculation formula is organized as follows:

PERF= (Factor1*0.2301+ FactoR2*0.1747+ Factor3*0.1423+ Factor4*0.1124 +Factor5*0.0670)/0.7265

3.2.2 Explanatory variables: Investment in technological innovation

Enterprise investment in technological innovation plays a pivotal role in fostering growth and competitiveness. Examining capital investment and R&D human resource investment provides a comprehensive understanding of how enterprises approach technological innovation. Capital investment involves substantial financial support during the startup phase for exploring new technologies, mid-term optimization for scaling up production, long-term strategies for continuous research and development, and external cooperation. In R&D human resource investment, talent is crucial for accelerating technological innovation through collaboration. Introducing and cultivating talents, fostering team cooperation, and implementing incentive mechanisms are key factors in promoting active employee participation and efficient innovation activities.

The synergy between capital and human resource investments is indispensable, requiring flexible adjustments based on technological innovation strategy and market demand. Balancing these investments enables enterprises to realize the best effects of technological innovation, promoting sustainable growth and competitiveness. The rationality of R&D investment, considering human capital and R&D capital, is a key theme in enterprise innovation research.

In terms of human capital investment, Yan Zhu and Mengchang Zhang (2013)[144] empirically analyzed the relationship between the human capital of the management team and R&D investment, emphasizing the role of human resources in promoting enterprise innovation. Kunpeng Sun, Ting Luo, and Xing Xiao (2021)[145] further explored the impact of talent policy and R&D staff recruitment on enterprise innovation, underscoring the importance of reasonable human capital investment.

Regarding R&D capital investment, Xie Weimin and Fang Hongxing (2011)[146] and Li Bo and Zhu Taihui (2020)[147] analyzed the impact of financing constraints on firms' R&D investment, emphasizing the importance of capital flow. Li Changqing, Li Yukun, and Li Maoliang (2018)[148] and Luo Hong and Qin Jidong (2019)[149] focused on the effects of equity pledges and state-owned equity participation on firms' innovation investment, revealing the impact of capital structure on R&D investment.

Collectively, these studies underscore the centrality of human capital and R&D capital investments in corporate innovation. Balancing these investments allows enterprises to better realize technological innovation, improve efficiency, and accurately assess the benefits of R&D investment. This conclusion is supported by Nai-Ping Zhu, Li Zhu, Yusheng Kong, and Yang Shen (2014)[150], Mei-Qun Yin, Lei Sheng, and Wen-Bo Li (2018)[151], and Yi-Hua Yu, Qi-Feng Zhao, and Xiaosheng Ju (2018)[152], providing different perspectives on technological innovation investment, social responsibility, executive incentives, and inventor-executives, strengthening the theoretical and practical understanding of measuring the rationality of enterprise R&D investment in terms of human capital and R&D capital.

Combining these results and measurement methods, this paper uses the ratio of R&D funds to total assets to measure R&D investment strength. This ratio comprehensively reflects the proportion of financial support for R&D activities relative to overall assets, ensuring relativity and comparability. Using the number of R&D personnel to total employees ratio measures R&D manpower investment, reflecting the proportion of human resource investment in innovation activities. This indicator not only reveals a firm's value of knowledge and skills investment but also showcases strategic choices in human resource allocation.The calculation formulas are as follows:

$$HC = \frac{\text{Total number of R\&D staff}}{\text{Total number of staff}}$$

$$RD = \frac{\text{Amount of R\&D investment}}{\text{Total enterprise assets}}$$

3.2.3 Moderating variable: technology alliances

Previous research primarily focused on the mere existence of technology alliances, neglecting the depth and type of these alliances. Quantifying the degree of technology alliances has been a challenge, often hindered by the complexity, confidentiality, and multi-dimensional nature of these partnerships.

The use of word frequency method to measure digital transformation of enterprises has been widely applied and recognized in many academic studies. The study by Xuesong Li et al. (2022)[153] focuses on the relationship between digital transformation, global innovation network convergence and innovation performance. This study provides insights into the impact of digital transformation on innovation performance by analyzing aspects of digital transformation through the word frequency method and revealing the position and role of firms in global innovation networks. The article by Nie Xingkai et al. (2022)[154], on the other hand, focuses on whether digital transformation of firms affects the comparability of accounting information. By using the word frequency method, they are able to quantitatively measure the stages of a firm's digital transformation process and then analyze its possible impact on the comparability of accounting information. This approach provides an intuitive and effective way to analyze the complex transformation process. Yuan Chun et al. (2021)[155] explored the relationship between digital transformation and the division of labor in firms, including specialization and vertical integration considerations. Through the word frequency method, they were able to clearly track the various aspects of enterprises in the process of digital transformation, and further explored how to balance the needs of specialization and integration. Chenyu Zhao et al. (2021)[156] investigated how digital transformation affects firms' total factor productivity.By using the word frequency method, the method is able to accurately quantify previously poorly quantified variables, which are then analyzed in correlation with the explanatory variables to reveal their complex interactions.

This paper innovatively employs a word frequency analysis of annual reports from listed companies to gauge the strength of technology alliances. Due to the intricate and confidential nature of these alliances, measuring them directly is daunting. Utilizing words such as "cooperation," "alliance," and "joint research and development" in company reports, this method indirectly reflects the extent of technology alliance activities. Word frequency analysis, being intuitive and easily implementable, proves advantageous in large-scale data analysis.

This study constructs specific keywords related to technology alliances, ensuring alignment with corporate annual report vocabulary. Utilizing the Jieba participle method, the annual report text is disassembled, and high-frequency words from these reports are selected for analysis. The chosen keywords for measuring technology alliances are detailed in <Table3- 5>.

<Table 3-5> Technology Alliance Measurement Keywords

byword	byword	byword	byword	byword
strategic	organize	unite	conform	(reach an) agreement
program	organization	complementarity	profitable both sides	irrigation ditch
be tactful	union	reciprocal	collaborative	synergistic
tactics	contractual	mutually beneficial	merger and acquisition (M and	multilateral

			A)	
program	set (mathematics)	interchangeable	joint venture	commission
planner	become a member of an alliance or union	switch (telecom)	authorizations	subcontracting
plan and prepare	companion	interoperable	contractor	joint

After obtaining the word frequency of all keywords, this paper eliminates the keywords with lower word frequency by conducting a one-sample t-test on the keyword word frequency, and further eliminates the keywords with lower correlation with other keywords through clustering analysis, and the final list of remaining keywords is organized as follows:

<Table 3-6> Revised list of keywords for technical alliances

byword	byword	byword
strategic	companion	joint venture
program	unite	irrigation ditch
planner	switch (telecom)	synergistic
organization	conform	commission
contractual	collaborative	joint
become a member of an alliance or union	merger and acquisition (M and A)	

Next, factor analysis was used to extract scores for measuring the degree of technical alliance. The results of the collapsed KMO test and sphericity test are as follows:

<Table 3-7> Results of KMO Test and Sphericity Test for Technology Alliances

inspect	(be) worth
KMO	0.757
Bartlett's test of sphericity chi-square value	31539.894

Bartlett's test of sphericity p-value	0.000***

Note: Values in the table were compiled by the authors.
*p<0.1 ** p<0.05 *** p<0.01

Analyzing the results of the <Table 3-7>, the KMO value is 0.757, which means that the data is suitable for factor analysis to some extent, and the p-value is 0.000<0.1, which means that this result is statistically significant,i.e., it passes the test of sphericity, and it can be analyzed for factor analysis. Next the results of factor extraction were organized:

<Table 3- 8> Factor extraction results for technology alliances

(math.) factor	eigenvalue (math.)	eigenroot difference (math.)	variance explained rate	Cumulative variance explained
Factor 1	2.04461	0.5517	0.1203	0.1203
FactoR2	1.49291	0.01068	0.0878	0.2081
Factor3	1.48223	0.16769	0.0872	0.2953
Factor4	1.31455	0.11224	0.0773	0.3726
Factor5	1.20231	0.08243	0.0707	0.4433
Factor6	1.11988	.	0.0659	0.5092

Note: Values in the table were compiled by the authors.

From the analysis of the above table, a total of five factors were extracted, and the cumulative variance explained is more than 50%, indicating that the extraction is valid. Next, the factor component coefficient matrix was analyzed and the collation matrix is as follows:

<Table 3-9> Factor Component Coefficient Matrix

Variable	Factor 1	FactoR 2	Factor 3	Factor 4	Factor 5	Factor 6
strategic	0.2567	-0.0540	0.1038	-0.0307	0.1782	-0.0473
program	0.1711	0.1248	-0.0328	0.0442	0.1991	-0.1777

planner	-0.0468	0.0182	0.0374	0.0457	-0.1654	0.6744
organization	-0.0351	-0.0295	-0.0809	-0.0875	0.2324	0.5881
contractual	-0.1111	-0.2149	0.1981	-0.0497	0.5265	-0.0247
become a member of an alliance or union	-0.1250	-0.0388	0.0492	0.6430	0.0336	-0.0811
companion	0.4849	-0.0716	-0.2041	-0.0567	-0.1689	-0.0438
unite	0.0828	-0.1175	0.0331	-0.1201	0.2522	0.1446
switch (telecom)	-0.0832	0.5299	-0.1143	-0.0351	0.0195	0.0237
conform	-0.0285	0.0993	0.4126	0.0776	-0.0892	0.0936
collaborative	0.3427	0.0065	-0.0952	0.0060	-0.0958	0.1211
merger and acquisition (M and A)	-0.1499	-0.0883	0.6320	-0.0170	-0.0357	-0.0469
joint venture	-0.0983	0.3473	0.1172	-0.0179	0.1039	-0.0849
irrigation ditch	0.0339	-0.0220	-0.0496	0.5619	-0.0173	0.0698
synergistic	0.2753	-0.0986	0.1069	-0.0478	0.0431	-0.1085
commission	-0.0242	0.1860	-0.2484	0.1121	0.5275	-0.0057
joint	0.0181	0.4199	0.0774	-0.0524	-0.1960	0.0348

Note: Values in the table were compiled by the authors.

After the factor scores were calculated, the composite scores were calculated using the weighted mean method, and the formulas were organized as follows:

TA= (Factor1*0.1203 + FactoR2*0.0878+ Factor3*0.0872+ Factor4*0.0773 +Factor5*0.0707 +Factor6*0.0659)/0.5092

3.2.4 Control variables

(1) Enterprise Size: Measured as the natural logarithm of the firm's total assets. From a theoretical standpoint, asset size is fundamental to a firm, influencing its operational methods and strategic positioning. Thus, firms of different sizes may diverge in their innovation strategies and capabilities, potentially affecting how technological innovations impact business performance. Larger firms typically possess more assets and a wider business portfolio, potentially enabling them to better endure the risks associated with innovation project failures, thereby influencing the impact of innovation on business performance. Introducing asset size as a control variable aids in accurately estimating the independent effect of technological innovation on business performance, eliminating potential confounding factors.

(2) Cash Flow Level: Measured as net cash flow from operating activities divided by total assets. Sufficient cash flow not only supports a company's investments in R&D, technology adoption, and innovation projects but also enhances its flexibility and resilience in market competition. Therefore, cash flow levels are closely related to a company's innovation strategy and its innovation effects. Adequate cash flow ensures timely payment of various expenses, maintaining normal operations, potentially improving business performance. Insufficient cash flow can lead to operational disruptions and lower business performance. Given the inherent risks associated with technological innovations, the adequacy of cash flow directly influences a firm's ability to withstand these risks, significantly shaping the effect of

firm innovation on operational performance.

(3) Corporate Governance Structure: Includes board size, board independence, and whether the director and CEO hold concurrent positions. Specifically, board size is measured by the natural logarithm of the number of board members, board independence is the ratio of independent directors to total directors, and the director-CEO concurrency is represented as a dummy variable, with a value of 1 indicating concurrent roles and 0 otherwise. Board size profoundly impacts a firm's strategic direction and decision-making processes. Larger boards offer a broader range of expertise and perspectives, contributing to a comprehensive and balanced innovation strategy. However, excessively large boards may lead to inefficient decision-making and blurred responsibilities. Board size is also linked to a firm's size, complexity, and market positioning, interacting with the relationship between technological innovation and business performance. Board independence signifies the proportion of non-executive directors on the board. More independent boards are typically more effective in monitoring and guiding management, ensuring alignment between innovation strategies and overall firm strategies, and shareholder interests. Independent directors often bring extensive experience and diverse contacts, facilitating the firm's access to innovation resources and market opportunities. Concurrent positions of directors and CEOs reflect the power structure and decision-making processes within a firm. Concurrent roles may enhance the CEO's autonomy in strategic decision-making and execution, potentially increasing the firm's responsiveness and flexibility to innovation opportunities. However, this may also introduce strategic biases and risks. Furthermore, director-CEO concurrency is

intertwined with a firm's culture, leadership style, and external regulatory environment, further impacting innovation strategy and effectiveness.

(4) Equity Structure: Encompasses equity concentration and equity checks and balances. Equity concentration is measured by the proportion of shares held by the largest shareholder, and equity checks and balances are represented as the proportion of shares held by the second-largest shareholder divided by the proportion held by the largest shareholder. When analyzing the impact of corporate technological innovation on business performance, introducing equity structure factors as control variables is a reasonable and useful approach. Equity structure significantly shapes firms' decision-making dynamics and strategic direction, especially in the high-risk, high-return domain of innovation activities. Higher equity concentration enhances shareholders' control and monitoring of management, potentially increasing firms' commitment to long-term and riskier innovation investments. However, it may reduce the influence and protection of other stakeholders, especially minority shareholders, potentially affecting firms' incentives to innovate and access resources. High equity concentration may also be related to firm size, industry characteristics, and development stage, leading to complex interactive effects with innovation strategy and effectiveness. Equity checks and balances pertain to the balance of power and mutual constraints among multiple shareholders. Reasonable equity checks and balances facilitate diverse perspectives and interests, contributing to a comprehensive and sustainable innovation strategy. By balancing the interests and influence of different shareholders, equity checks and balances may also mitigate governance risks and costs. However, excessive equity checks and balances may lead to

decision-making deadlocks and efficiency losses, potentially reducing firms' commitment and responsiveness to cutting-edge and disruptive innovations. Additionally, equity structure interacts with factors such as a firm's organizational culture, leadership style, market competition, and external regulation.

(5) Firm Age: Calculated using the formula ln(current year - year of company's establishment+1). Firm age reflects various aspects of maturity, experience accumulation, resource endowment, market positioning, organizational structure, and cultural idiosyncrasies. These factors interact in complex ways with the relationship between technological innovation and business performance. Newly established firms tend to be more flexible, agile, and innovative. However, they may lack the necessary resources, credibility, and partnerships, exposing them to higher innovation risks and uncertainties. In contrast, established firms typically possess more experience, stable resources, and broader market access, factors that facilitate continued investment and success in technological innovation. However, mature firms may also be relatively conservative and rigid due to established business models, organizational structures, and market positioning. This rigidity may reduce their openness and responsiveness to cutting-edge and disruptive innovations.

(6) Administrative Expense Ratio: Calculated as management expenses divided by operating income, reflecting the enterprise's management efficiency and cost structure. Technological innovation often requires substantial resource investments, including human, material, and financial resources. These inputs can increase management expenses, subsequently affecting the administrative expense ratio. A firm's technological innovation capability and strategic direction may also be related

to its management efficiency and cost control ability. Therefore, the administrative expense ratio captures the characteristics of operational efficiency and cost structure within a firm. By controlling for the administrative expense ratio, potential confounders related to firm size, industry characteristics, and competitive market conditions can be mitigated, improving the accuracy and robustness of the relationship between technological innovation and business performance. Introducing the administrative expense ratio provides a strategic and tactical understanding of the complex relationship between technological innovation and business performance, revealing insights into a firm's management processes and cost control.

(7) Industry Controls: In panel regression analysis of listed firms, controlling for industry is crucial, enhancing the accuracy and interpretability of the model. Industries exhibit significant differences in market structure, competition levels, profitability, growth potential, regulatory environments, and risk exposures. Failing to control for industry effects may confound the relationships between key variables, leading to misleading conclusions. Introducing industry controls mitigates or eliminates the interference of industry-specific factors, revealing the intrinsic links between analyzed objectives (e.g., investment, financing, innovation, performance, etc.) and key explanatory variables (e.g., corporate strategy, structure, culture, resources, etc.). Industry controls also enhance the generalizability and comparability of results, allowing interpretations and applications across diverse industries and market contexts. Yearly fluctuations in economic and business environments, stemming from macroeconomic cycles, government policies, technological advancements, sociocultural trends, and globalization dynamics, can confound

causality or correlation.

In summary, the list of organizing variables is as follows:

<Table 3-10> List of variables

variable	variable name	variable symbol
explained variable	business performance	PERF
explanatory variable	R&D capital investment	rd
	R&D human capital investment	hc
Mediating variables	Technology alliance	TAS
Control variables	asset size	lnSize
	Cash flow levels	Cashflow
	Board size	Board
	Board independence	Indep
	Director and CEO	Dual
	shareholding concentration	Top1
	Shareholding checks and balances	Balance1
	Age of business	lnFirmAge
	management cost ratio	Mfee
	Industry control	Industry

3.3 Modeling

The data in this paper is panel data, necessitating analysis through a panel regression model. Panel regression, a widely employed statistical method in econometrics, is designed to analyze data across individuals and time. This method combines cross-sectional data (multiple entities at a specific point in time) and time-series data (one or more entities at consecutive points in time), allowing for the capture of complex individual and time effects. With such a structure, researchers can account for potential unobservable heterogeneity, utilizing fixed-effects models for entity-specific effects that remain constant over time, while random-effects models assume these effects are random. Additionally, panel regressions can control for possible time effects, such as macroeconomic cycles or seasonal fluctuations. These controls enhance efficiency, accuracy, and understanding of underlying causality, especially when considering lagged explanatory variables, capturing the impact of past events on current outcomes. However, panel regression poses challenges, such as dealing with possible cross-sectional and serial correlations, which can lead to standard error bias affecting statistical inference. Nonetheless, with the right model setting and estimation techniques, such as generalized least squares, maximum likelihood estimation, or instrumental variables estimation, panel regression remains a powerful tool to analyze complex economic and social phenomena, especially in contexts that need to account for individual heterogeneity and time dynamics.

Traditional panel regression models include mixed-effects, fixed-effects, and random-effects models, each representing different assumptions and approaches to dealing with cross-sectional and time-series data. Mixed-effects models are a general form of both fixed-effects and random-effects models, allowing individual-specific effects to be partly fixed and partly random. These models capture effects specific to each entity and random fluctuations within the time series. Because mixed-effects models are more flexible, the appropriate estimation method can be chosen based on the characteristics of the data and the needs of the research question. Fixed-effects models are more specific, assuming each cross-sectional entity has constant unique effects over the observation period. By introducing dummy variables for each entity or differencing, fixed-effects models eliminate unobservable individual-specific effects, reducing bias and focusing the analysis on changes over time. Fixed-effects models are suitable when individual-specific effects are correlated with other explanatory variables. On the other hand, random-effects models assume that individual-specific effects are randomly distributed and uncorrelated with other explanatory variables. This allows individual-specific effects to be treated as random variables and estimated by generalized least squares or maximum likelihood methods. Random-effects models are usually superior in efficiency as they use both time series and cross-sectional variation. However, they may be subject to bias if individual effects are correlated with explanatory variables.

Significant differences exist in the principles and assumptions underlying the treatment of panel data between the mixed effects model, the fixed effects model, and the random effects model. The mixed effects model combines characteristics of fixed and random effects to capture both individual fixed characteristics and random fluctuations. This model is suitable when individual effects are partially fixed and partially random, balancing the advantages of both fixed and random effects models but requiring more sophisticated estimation methods. Fixed-effects models assume that each entity has its own unique effects that remain constant over the observation period but may differ between individuals. The core of the fixed-effects model is to eliminate unobservable individual-specific effects, reducing bias. If individual-specific effects are correlated with explanatory variables, the fixed effects model is the appropriate choice. However, this model can only estimate the effects of time-varying variables and not for time-invariant explanatory variables. The random effects model assumes that individual-specific effects are randomly distributed and independent of other explanatory variables. This makes the random effects model generally superior to the fixed effects model in terms of efficiency as it uses not only time-series variation but also cross-sectional variation. However, random effects models may be subject to bias if individual-specific effects are correlated with explanatory variables. The random effects model makes stronger assumptions about the data than the fixed effects model and may be more vulnerable to limitations in practical applications. Overall, the difference between the three models lies mainly in how individual-specific effects are handled. Fixed-effects models reduce bias by controlling for the inherent characteristics of each entity, while random-effects models allow these effects to be distributed randomly, thereby increasing efficiency. Mixed-effects models aim to combine the best of both worlds. The choice of model depends on the nature of the individual-specific effects and their relationship to the explanatory variables. In practical analysis, formal statistical tests are often needed to determine which model is more appropriate for the given data and research question.

To find the optimal model among the three—mixed effects, fixed effects, and random effects—the F-test, the BP-test, and the Hausman test are commonly used. The F-test assesses the difference between a fixed effects model and ordinary least squares regression, examining whether the fixed effects for all individuals are simultaneously equal to zero. If the test rejects the null hypothesis, indicating at least one individual's fixed effect is not equal to zero, the fixed effects model is more appropriate. The BP-test compares the random effects model to ordinary least squares regression, testing the null hypothesis that the variance is zero, indicating no random effects. If the null hypothesis is rejected, suggesting the presence of random effects, the random effects model is more appropriate. Finally, the Hausman test compares a fixed effects model to a random effects model, focusing on the difference between the estimates of the two models. The fixed effects model is consistent when individual-specific effects are related to the explanatory variables, while the random effects model is valid when individual-specific effects are not related to the explanatory variables. The null hypothesis of the Hausman test is that the random effects model is appropriate. If rejected, indicating that the fixed effects model is more suitable, it helps in model selection. In summary, these three tests work together to assist the researcher in choosing the most appropriate panel data model. The F-test determines the presence of fixed effects, the BP-test determines the presence of random effects, and the Hausman test chooses between fixed effects and random effects. The combined use of these tests provides a structured approach to selecting the most appropriate panel data model based on the characteristics of the data and the needs of the research question.

3.3.1 Main effects regression model

This paper is based on multiple regression theory, regardless of the model finally accepted as any model, are based on the basic model to start the analysis. Discuss the impact of technological innovation on business performance.The regression model is established as follows:

$$\begin{aligned}\mathrm{PERF}_{it} = {} & \alpha_0 + \alpha_1\mathrm{RD}_{it} + \alpha_2\mathrm{lnSize}_{it} + \alpha_3\mathrm{Cashflow}_{it} + \alpha_4\mathrm{Board}_{it} + \alpha_5\mathrm{Indep}_{it} \\ & + \alpha_6\mathrm{Dual}_{it} + \alpha_7\mathrm{Top1}_{it} + \alpha_8\mathrm{Balance1}_{it} + \alpha_9\mathrm{lnFirmAge}_{it} \\ & + \alpha_{10}\mathrm{Mfee}_{it} + \sum \mathrm{Industry} + \varepsilon_{it}\end{aligned}$$

$$\mathrm{PERF_{it}} = \alpha_0 + \alpha_1\mathrm{HC_{it}} + \alpha_2\mathrm{lnSize_{it}} + \alpha_3\mathrm{Cashflow_{it}} + \alpha_4\mathrm{Board_{it}} + \alpha_5\mathrm{Indep_{it}} + \alpha_6\mathrm{Dual_{it}} + \alpha_7\mathrm{Top1_{it}} + \alpha_8\mathrm{Balance1_{it}} + \alpha_9\mathrm{lnFirmAge_{it}} + \alpha_{10}\mathrm{Mfee_{it}} + \sum \mathrm{Industry} + \varepsilon_{it}$$

In the above equation, the α_0 is a constant, and α_1 are the regression coefficients of all core explanatory variables, the α_2 - α_{10} is the regression coefficient of each control variable, $\sum \mathrm{Industry}$ is the industry control,. ε_{it} is the model residuals.

3.3.2 Moderating effects regression model

Moderated effects models are employed to explore how independent variables influence the direction or strength of the dependent variable relationship, moderated by specific variables (interaction terms). Introducing an interaction term, the product of the independent variable (X) and the moderator (Z), is crucial. In a linear regression model (Y as the dependent variable, X as the independent variable, and Z as the moderator), both X and Z, along with their interaction term (X-Z), are incorporated into the model. Estimating this model provides the coefficient of the interaction term, indicating how the moderating variable affects the relationship between the independent and dependent variables.

The direction of the moderating effect is determined by the sign and significance of the interaction term's coefficient. If the estimate is significantly greater than zero, it signifies a synergistic effect where increasing the moderator enhances the positive impact of the independent variable or mitigates the negative impact. Conversely, a significantly negative estimate indicates an antagonistic effect, where increasing the moderator weakens the positive impact of the independent variable or amplifies the negative impact. Non-significance suggests the absence of a moderating effect.

In this paper, technology alliance is introduced as a moderating variable, which is included in the model by generating corresponding interaction terms with the core explanatory variables and organizing the model equation as follows:

$$\begin{aligned}PERF_{it} = {} & \beta_0 + \beta_1 RD_{it} + \beta_2 TA_{it} + \beta_3 RD * TA_{it} + \beta_4 lnSize_{it} + \beta_5 Cashflow_{it} \\ & + \beta_6 Board_{it} + \beta_7 Indep_{it} + \beta_8 Dual_{it} + \beta_9 Top1_{it} + \beta_{10} Balance1_{it} \\ & + \beta_{11} lnFirmAge_{it} + \beta_{12} Mfee_{it} + \sum Industry + \varepsilon_{it}\end{aligned}$$

$$\begin{aligned}PERF_{it} = {} & \beta_0 + \beta_1 HC_{it} + \beta_2 TA_{it} + \beta_3 HC * TA_{it} + \beta_4 lnSize_{it} + \beta_5 Cashflow_{it} \\ & + \beta_6 Board_{it} + \beta_7 Indep_{it} + \beta_8 Dual_{it} + \beta_9 Top1_{it} + \beta_{10} Balance1_{it} \\ & + \beta_{11} lnFirmAge_{it} + \beta_{12} Mfee_{it} + \sum Industry + \varepsilon_{it}\end{aligned}$$

In the above equation, the β_0 is a constant, and β_3 is the regression coefficient for all core interaction terms, the β_4 -α_{12} is the regression coefficient for each control variable, $\sum$ Industry is the industry control. ε_{it} is the model residuals, i represents firms, and t represents year.

Chapter 4. Descriptive Statistics and Basic Tests

4.1 Full sample descriptive statistical analysis

4.1.1 Full sample descriptive statistics

Descriptive statistical analysis was performed on the sample and the results were collated as follows:

<Table 4-1> Full Sample Descriptive Statistics Results

Variable	N	Min	Max.	Mean	SD	CV
PERF	21355	0	0.727	0.3545	0.0298	0.0841
rd	21355	0.609	0.9022	0.8181	0.0485	0.0593
hc	21355	0.0039	0.7192	0.1735	0.139	0.8011
lnSize	21355	20.0128	26.2734	22.1583	1.2522	0.0565
Cashflow	21355	-0.1323	0.2341	0.0519	0.0643	1.2397
Board	21355	1.6094	2.6391	2.0961	0.1931	0.0921
Indep	21355	0.3333	0.5714	0.3785	0.0529	0.1397
Dual	21355	0	1	0.3523	0.4777	1.3559
Top1	21355	0.0848	0.7367	0.3311	0.1439	0.4346
Balance1	21355	0.0136	0.9997	0.3922	0.2823	0.7197
lnFirmAge	21355	1.7918	3.5264	2.9346	0.3034	0.1034
Mfee	21355	0.0091	0.3449	0.0808	0.0575	0.7116

Note: Values in the table were compiled by the authors.

In the analysis of R&D and innovation indicators, significant disparities are observed. R&D capital investment shows stability among companies, while human resources investment varies widely, indicating challenges in talent acquisition.

For corporate performance and financial indicators, stability is noted in firm performance and asset size, indicating operational efficiency and balanced resource allocation. However, cash flow levels vary significantly, reflecting diverse strategies and capabilities in liquidity management. Firm life cycle and industry-specific needs contribute to cash flow disparities. Overhead ratios vary widely, indicating differences in cost control, management level, and industry context. Automation and digitization adoption may impact overhead costs, particularly in technology-oriented sectors.

Regarding governance structure, board size stability implies consistent governance structures, possibly indicating maturity but lack of flexibility. Board independence disparities hint at varied implementation, linked to ownership structure and cultural background. Director-CEO divergence signals differences in strategic direction and organizational cultures. Equity structure complexity, influenced by firm size, industry, and history, underscores the intricate nature of equity concentration and checks and balances.

This comprehensive analysis highlights the multifaceted nature of Chinese firms' R&D, innovation, financial management, and governance structures, emphasizing the need for nuanced approaches in understanding their dynamics.

4.1.2 Group comparisons

The nature of enterprises in China is characterized by a very typical clear demarcation between SOEs and non-SOEs. The difference in the nature of property rights between SOEs and non-SOEs in China mainly stems from factors such as the country's history, economic system, policy orientation and stage of development, and the necessity of discussing the differences between SOEs and non-SOEs is high. This paper organizes the results of grouped descriptive statistics as follows:

<Table 4-2> Results of descriptive statistics based on grouping by nature of ownership

Nature of property rights	non-state enterprise	nationalized business
PERF	0.3545	0.3542
rd	0.8233	0.8008
hc	0.1847	0.1357
lnSize	21.8769	23.1093
Cashflow	0.0517	0.0524

Board	2.0687	2.1885
Indep	0.3800	0.3734
Dual	0.4271	0.0997
Top1	0.3151	0.3854
Balance1	0.4187	0.3026
lnFirmAge	2.9023	3.0436
Mfee	0.0843	0.0692

Note: Values in the table were compiled by the authors.

Comparative Analysis of State-Owned Enterprises (SOEs) and Non-State-Owned Enterprises:

- R&D Labor Input:

Non-SOEs invest significantly more in R&D labor, reflecting their proactive approach towards innovation in the competitive market. SOEs, focusing on stability, allocate comparatively less to R&D human capital.

- Asset Size:

SOEs have slightly larger assets, indicating their dominance in key sectors and large projects, while non-SOEs are generally smaller and more agile in their operations.

- Director-CEO Concurrency:

Non-SOEs exhibit higher rates of director-CEO concurrency, showcasing their flexible management structure. SOEs, on the other hand, adhere to stricter governance mechanisms.

- Equity Concentration:

SOEs have a more centralized equity structure due to government support, whereas non-SOEs opt for a decentralized approach to attract external investors.

- Management Expense Ratio:

  SOEs maintain lower management expense ratios, emphasizing stringent budget control. Non-SOEs invest more in management for flexible and efficient operations.

- Market Competition Perspective:

  Non-SOEs, facing fierce competition, continually innovate to stay ahead. Human capital investment is pivotal for innovation, leading non-SOEs to invest significantly in R&D human resources.

- Innovation-Driven Perspective:

  Non-SOEs rely on product and service innovation for market growth, making substantial investments in human resources, a core element of innovation.

- Organizational Culture Perspective:

  Non-SOEs foster a culture of flexibility and openness, attracting and retaining R&D talents, thereby promoting investment in R&D human resources.

- Government Objectives:

  SOEs align investments with government objectives, leading to cautious resource allocation to meet social and economic goals, impacting R&D human capital investments.

- Decision-Making Challenges:

  Lengthy decision-making processes and complex structures limit SOEs' ability to invest and innovate in R&D, hindering quick responses to market changes.

- Regulation and Government Intervention:

  Stricter regulation and government intervention restrict SOEs' freedom to innovate, affecting investments in R&D human capital.

- Competitive Landscape:

  SOEs' dominance in key sectors shapes their unique R&D strategies, differing significantly from those of non-SOEs.

This comparative analysis highlights the diverse approaches of SOEs and non-SOEs in investment strategies, reflecting their distinct organizational cultures, market challenges, and government roles.

4.2 Correlation analysis and multiple covariance test

4.2.1 Correlation test

In this study, Pearson correlation analysis was employed to examine the relationships between variables.In the results R&D capital investment is insignificantly related to firm performance and firm human capital investment is negatively related to firm performance. The reasons for this may be:

First, the non-significant relationship may mean that the linear relationship between R&D capital investment and firm performance is not strong in the sample data. There may be other variables that are not considered or the relationship may be non-linear.

Second, R&D capital investment does not necessarily translate directly into improved firm performance. The investment may go to inefficient projects, or it may take some time to translate into products and profitability. This relates to the complexity of innovation management, and the R&D process may involve high risk and uncertainty, so the relationship between financial investment and final performance may be relatively complex and non-direct.

Third, the negative correlation between firms' human capital investment and firm performance may indicate that more human capital investment is associated with lower firm performance in the sample. This may suggest efficiency issues or a misunderstanding of the relationship between human capital inputs and outputs.

Fourth, human capital theory emphasizes the productivity gains from human investment. However, more investment in human capital may not lead to higher performance if human resources are not managed properly, e.g., wastage of human resources, mismatch between talents and jobs. Similarly, over-investment in human resources may crowd out funds for other important resources, which may somehow harm overall performance.

In addition, the data in this paper are panel data, and the results of correlation analysis do not faithfully reflect causally inferred relationships; correlation analysis usually considers linear relationships between variables without considering unobserved individual and time effects, and fixed effects analysis analyzes changes between observations by eliminating the non-time-varying characteristics of each individual, which allows for unobserved heterogeneity to be captured; If there are unobserved individual or time effects in the data, correlation analysis alone may miss these important factors, leading to inconsistent results. If important explanatory variables are omitted from the model, these may be correlated with both the explanatory and the explained variables, which can lead to biased estimates. If the explanatory variables are correlated with the error term, this can also lead to biased estimates. Fixed-effects models can eliminate some of the endogeneity problems, but they cannot solve them completely, and in the face of these econometric problems, correlation and fixed-effects analyses are handled differently, and thus may lead to inconsistent results. For this reason, this paper does not use the results of correlation analysis to feedback the causal relationship between firm performance and firm R&D investment.

<Table 4-3> Results of pearson correlation analysis

Note: Values in the table were compiled by the authors.

	PERF	rd	hc	lnSize	Cashflow	Board	Indep	Dual	Top1	Balance1	lnFirmAge	Mfee
PERF	1											
rd	-0.002	1										
hc	-0.096***	0.489***	1									
lnSize	0.087***	-0.140***	-0.203***	1								
Cash flow	0.330***	0.026***	-0.116***	0.082***	1							
Board	0.020***	-0.077***	-0.110***	0.269***	0.035***	1						
Indep	-0.022***	0.018***	0.042***	-0.012*	0.006	-0.588***	1					
Dual	0.017**	0.094***	0.104***	-0.204***	-0.012*	-0.168***	0.105***	1				
Top1	0.178***	-0.135***	-0.193***	0.134***	0.125***	-0.01	0.053***	-0.014**	1			
Balance1	-0.018**	0.072***	0.100***	-0.078***	-0.018***	0.004	-0.007	0.021***	-0.612***	1		
lnFir	-0.0	-0.0	-0.1	0.18	0.02	0.08	-0.0	-0.1	-0.0	-0.0	1	

mAge	49***	63***	20***	4***	7***	5***	12*	21***	51***	29***		
Mfee	-0.338***	0.078***	0.277***	-0.308***	-0.138***	-0.061***	0.029***	0.054***	-0.130***	0.046***	-0.144***	1

*p<0.1 ** p<0.05 *** p<0.01

4.2.2 Multicollinearity test

When performing regression analysis, correlation analysis shows the associations between explanatory variables. If these associations are strong, the problem of multicollinearity exists. Multicollinearity can lead to instability in parameter estimates, making it less capable of explaining the effect of individual explanatory variables on the dependent variable and reducing the statistical significance of certain variables. More importantly, it can directly undermine the predictive accuracy of the model. Therefore, after observing correlations between explanatory variables, a multicollinearity test is necessary to ensure the accuracy and reliability of the regression model and to ensure that the conclusions and insights drawn from the model are rigorous and in the right direction. If multicollinearity is found in the test, appropriate measures will need to be taken to correct it to ensure the validity of the analysis.This paper adopts two solutions: first, the explanatory variables are separated and regressed independently. Second, the multicollinearity between the explanatory variables and the control variables is tested using the VIF value, and if the VIF value exceeds 5, the model has a serious multicollinearity problem. The results of the collation multicollinearity test are as follows:

<Table 4-4> Results of multicollinearity test

Variable	VIF	Variable	VIF	Variable	VIF	Variable	VIF	Variable	VIF	Variable	VIF	Variable	VIF
Board	1.73	Board	1.73	Board	1.73	Board	1.73	Board	1.73	Board	1.73	Board	1.73
Top1	1.72	Top1	1.71	Top1	1.69	Top1	1.69	Top1	1.70	Top1	1.70	Top1	1.70
Balance1	1.62	Balance1	1.62	Balance1	1.62	Balance1	1.62	Balance1	1.63	Balance1	1.62	Balance1	1.63

lnSize	1.31	lnSize	1.31	lnSize	1.31	lnSize	1.33	lnSize	1.31	lnSize	1.30	lnSize	1.30
Mfee	1.20	Mfee	1.15	Mfee	1.15	Mfee	1.15	Mfee	1.15	Mfee	1.15	Mfee	1.15
hc	1.15	Dual	1.07	lnFirmAge	1.08	lnFirmAge	1.08	lnFirmAge	1.08	lnFirmAge	1.08	lnFirmAge	1.08
lnFirmAge	1.08	lnFirmAge	1.07	Dual	1.07	Dual	1.07	Dual	1.07	Dual	1.07	Dual	1.07
Dual	1.07	rd	1.05	Cashflow	1.04	Cashflow	1.04	Cashflow	1.04	Cashflow	1.04	Cashflow	1.04
Mean VIF	1.35	Mean VIF	1.34	Mean VIF	1.33	Mean VIF	1.34	Mean VIF	1.33	Mean VIF	1.33	Mean VIF	1.33

Note: Values in the table were compiled by the authors.

The results of the multicollinearity test show that the variance inflation factor (VIF) for all variables is below 1.73 and the mean VIF varies between 1.35 and 1.33. This result indicates that the correlation between the explanatory variables in the model is not high and therefore the problem of multicollinearity is unlikely to arise. A low VIF value is usually a good indication that the correlation between each explanatory variable and the other explanatory variables is low and therefore the correlation between the variables does not create a significant problem when estimating the regression coefficients. In conclusion, these results show no signs of multicollinearity problems.

Chapter 5. Regression Analysis and Robustness Tests

5.1 Optimal model identification test

The selection of mixed effects, fixed effects and random effects models was determined by the F-test, Breusch-Pagan (BP) test and Hausman test.The F-test is used to test the overall significance of all explanatory variables, the original hypothesis is that the coefficients of all explanatory variables are equal to zero, the original hypothesis is rejected to choose the fixed effects model, and if not rejected, the mixed effects model is chosen.The BP test is used to check whether the intercept term varies with individuals. is used to check whether the intercept term varies with individuals, the original hypothesis is that the intercept term does not vary with individuals, the original hypothesis is rejected to choose the random effects model, and not rejected to choose the mixed effects model. the Hausman test compares the difference between the fixed and random effects estimates, the original hypothesis is that the random effects model is sufficient, the original hypothesis is rejected to choose the fixed effects model, and not rejected to choose the random effects model. Combining these three tests, the F-test is performed, followed by the BP-test, and if the mixed effects model is rejected, the Hausman test is performed to determine which model is best suited for the given data. This paper organizes the results of all the tests as follows:

<Table 5-1> Optimal model identification test results

mould	F-test	BP test	Hausman test	optimal model
rd-perf	4.47***	5287.32***	892.92***	fixed effects model
hc-perf	4.46***	5315.32***	948.87***	fixed effects model

Note: Values in the table were compiled by the authors.
*p<0.1 ** p<0.05 *** p<0.01

Based on the given test results, the analysis shows that in each model, the results of the F-test are significant, which means that we rejected the original hypothesis that the coefficients of all explanatory variables are equal to zero, and therefore the mixed effects model is excluded and the fixed effects model is adopted. Next, the results of the BP test were also significant, meaning that we rejected the original hypothesis that the intercept term does not vary by individual. Since the purpose of the BP test is to determine the presence of random effects, a significant result means that we choose the random effects model over the mixed effects model. Finally, we come to the Hausman test. In all models, the results of the Hausman test are significant, which means that we reject the original hypothesis that the random effects model is sufficient. Therefore, we choose the fixed effects model instead of the random effects model. In summary, the results of the F-test, BP-test and Hausman test for each model consistently point to the fixed effects model as the optimal model choice. This reflects the fact that there is a systematic association between the explanatory variables and the unobserved individual effects in the data, making the choice of a fixed effects model appropriate.

5.2 Analysis of the impact of technological innovation investment on business performance

The results were analyzed using the fixed effects model, first discussing the relationship between the impact of technological innovation inputs on firm performance, and organizing the fixed effects results as follows:

<Table 5-2> Regression results of the total effect of technological innovation investment on business performance

	(1) PERF	(2) PERF
rd	0.0186***	
	(4.0089)	
hc		0.0102***
		(6.4554)
lnSize	-0.0001	-0.0001
	(-0.8664)	(-0.4033)
Cashflow	0.1266***	0.1280***
	(43.7197)	(44.3962)
Board	-0.0024*	-0.0021*
	(-1.9506)	(-1.7673)
Indep	-0.0176***	-0.0177***
	(-4.1639)	(-4.1979)
Dual	0.0013***	0.0012***
	(3.3946)	(3.2482)
Top1	0.0351***	0.0357***
	(21.5867)	(21.9086)
Balance1	0.0107***	0.0107***
	(13.3911)	(13.4247)
lnFirmAge	-0.0070***	-0.0068***
	(-11.1811)	(-10.8245)
Mfee	-0.1623***	-0.1656***
	(-45.5342)	(-45.8697)
_cons	0.3650***	0.3757***
	(60.2739)	(77.8238)
IND	YES	YES
N	21355	21355

R^2	0.2544	0.2552
Adj R^2	0.2531	0.2540
F	592.6029***	595.8723***

Note: Values in the table were compiled by the authors.
Values in parentheses are t-statistics; *p<0.1 ** p<0.05 *** p<0.01

In the model tests, the adjusted R-squares for the two models were 0.2531 and 0.2540, respectively, indicating their ability to explain the variation in the dependent variable. The F-statistics for both models were 592.6029 and 595.8723, respectively, significant at the 1% level, suggesting that at least one explanatory variable in these models significantly affects the dependent variable.

Analyzing the regression results, in Model (1), the explanatory variable is R&D capital investment, and the dependent variable is firm performance. The coefficient estimate for R&D capital investment is 0.0186, signifying statistical significance at the 1% level. This implies rejecting the original hypothesis that R&D capital investment is unrelated to firm performance. Specifically, firm performance is expected to increase by 0.0186 units when R&D capital investment increases by 1 unit. The t-statistic, with a value of 4.0089, further confirms the significance of this result. In Model (2), the explanatory variable is R&D human input, and the dependent variable is firm performance. The coefficient estimate for R&D manpower input is 0.0102, again statistically significant at the 1% level. Rejecting the hypothesis that there is no association between R&D human input and firm performance, the result suggests that firm performance is expected to increase by 0.0102 units when R&D manpower investment increases by 1 unit. The t-statistic, with a value of 6.4554, further supports the significance of this result. Overall, both models indicate a positive relationship between R&D investment (either financial or human) and firm performance.

Regarding the control variables, asset size showed a non-significant effect on firm performance in both models, with a coefficient of -0.0001. Cash flow level had a significant positive effect on firm performance in both models, with coefficients of 0.1266 and 0.1280, respectively, both significant at the 1% level. Board size was significantly negatively related to firm performance in both models, with coefficients of -0.0024 and -0.0021, both significant at the 10% level. Board independence was significantly negatively related to firm performance in both models, with coefficients of -0.0176 and -0.0177, both significant at the 1% level. Director-CEO concurrency was significantly positively related to firm performance in both models, with coefficients of 0.0013 and 0.0012, both significant at the 1% level. Equity concentration was significantly and positively related to firm performance in both models, with coefficients of 0.0351 and 0.0357, both significant at the 1% level. Equity checks and balances were significantly positively correlated with firm performance in both models, with coefficients of 0.0107, both significant at the 1% level. Firm age was significantly negatively related to firm performance in both models, with coefficients of -0.0070 and -0.0068, both significant at the 1% level. Management expense ratio was significantly negatively related to firm performance in both models, with coefficients of -0.1623 and -0.1656, both significant at the 1% level. In summary, asset size had no significant effect on firm performance, cash flow level had a significant positive effect on firm performance in both models, board size was significantly negatively correlated with firm performance, board independence was significantly negatively correlated with firm performance, concurrent directors and CEOs, equity concentration, and equity checks and balances were significantly positively correlated with firm performance, while firm age and management expense ratio were significantly negatively correlated with firm performance.

The significant positive impact of R&D capital investment on enterprise performance, in line with relevant theoretical analysis, can be explained through the resource-based theory. According to this theory, the unique resources and capabilities of an enterprise are key factors for its advantage in the competitive market. R&D capital investment enables enterprises to transform financial resources into knowledge assets and technological capabilities, accumulating unique technological resources and enhancing R&D capabilities. This facilitates breakthroughs in product innovation and technological improvement. The resource-based theory emphasizes the alignment between enterprise resources and the market environment, and R&D investment enables enterprises to respond flexibly to market changes, meet market demands through continuous innovation, and enhance enterprise performance. Additionally, R&D investment is not merely a response to current market competition; it is also part of the enterprise's long-term strategic plan. Overall, from the perspective of innovation-driven theory, the positive impact of R&D capital investment on enterprise performance is demonstrated through the accumulation of enterprise knowledge and skills, development of new market opportunities, establishment of a continuous innovation mechanism, and enhancement of market adaptability. These factors contribute to enterprise growth and success, making R&D investment a core element in enhancing enterprise performance.

The significant positive effect of investment in R&D human capital on firm performance underscores the role of human resources. Through a well-designed recruitment and selection process, firms can attract and select R&D personnel with the required skills and potential. This provides a strong foundation for firms to innovate and improve effectively in a competitive market environment. Moreover, by providing targeted training and development for R&D personnel, firms can align their human capital with organizational goals and strategies. These initiatives motivate employees to work diligently to achieve organizational goals, promoting higher levels of performance and efficiency. Finally, through ongoing career development and career planning support, firms can help R&D personnel achieve personal and professional growth, thereby retaining key talent and reducing brain drain. In summary, investment in firms' R&D human capital realizes a significant positive impact on firm performance through various aspects of HRM theory.

Combined with previous research results, Li Changhong et al. (2013) studied the relationship between innovation input, innovation output and enterprise performance of small and medium-sized companies listed on the SME board through the CDM model, and the results showed that innovation input has a positive driving effect on enterprise performance. Zhang Aihui (2017) conducted an analysis of differentiation strategy and technological innovation input on corporate performance of GEM listed companies and found that technological innovation input is positively related to corporate performance. Yin Meigun et al. (2018) divided the sample into three types of industries: technology-intensive, capital-intensive and labor-intensive from an endogenous perspective, and found that the endogenous relationship between innovation investment and firm performance interacting with each other is complex, especially there is a cyclical effect of innovation investment in technology-intensive industries, and compensation incentives of executive incentives have a positive moderating effect on corporate innovation investment and firm performance. Li Lin and Tian Siyu (2021) explore the relationship between innovation investment, internal control and firm performance with a sample of A-share listed companies, and the results show that innovation investment is significantly and positively correlated with firms' financial performance. To summarize, all of the above literatures reveal the positive association between innovation investment and corporate performance from different perspectives and levels.

5.3 Endogeneity test based on omitted variables and bidirectional causation

(1) Theoretical foundations of endogeneity of omitted variables

This study employs an endogeneity test centered on omitted variables, focusing on the influence of prior period business performance on the current and subsequent periods, addressing potential biases caused by omitted variable endogeneity. Omitted variable endogeneity arises due to unobserved variables related to both independent and dependent variables in statistical analysis, leading to biased estimation results. This study considers the impact of past business performance, rooted in resource-based and path-dependence theories, emphasizing the persistence and self-reinforcing mechanisms of firm performance. Successful prior performance may lead to resource accumulation and positive circular effects, affecting current and future performance. Ignoring this persistence effect results in omitted variable endogeneity, introducing lag 1 period of explanatory variables in subsequent models to mitigate this issue.

Examining endogeneity in explanatory variables omission, this study explores the impact of industry-level technological innovation input, output, and efficiency on individual firm-level counterparts. Resource-based theory underscores internal resources and capabilities as vital for competitive advantage, with sub-industry technological innovation levels reflecting available technological resources and industry-wide accumulation. Diffusion of innovation theory highlights industry-wide technology adoption, influencing individual firms' innovation inputs, outputs, and efficiency. Industry competition levels affect firms' innovation behavior, prompting increased investment in technological innovation in highly competitive industries. This study introduces instrumental variables, using mean values of technological innovation indicators by industry as instruments. These mean values, reflecting industry-level innovation, exhibit correlation with individual firms' technological innovation, meeting good correlation and exogeneity requirements.

In summary, this study employs instrumental variables derived from industry-level technological innovation mean values, addressing endogeneity concerns. These instruments, capturing industry-wide innovation dynamics, effectively mitigate potential biases arising from omitted variable endogeneity.

(2) Theoretical foundations of bi-directional causal endogeneity

There is a significant bi-directional causal endogeneity issue between enterprise technological innovation and enterprise business performance. First, resource-based theory emphasizes the impact of the combination and utilization of enterprise resources and capabilities on enterprise performance. Under this theoretical framework, technological innovation, as the core resources and capabilities of an enterprise, can significantly improve its business performance by improving production efficiency, promoting new product development and enhancing market responsiveness. At the same time, an enterprise's business performance in turn affects its technological innovation capability, as better business performance usually leads to more investment, higher quality talent and stronger market position, thus providing more favorable conditions for technological innovation. Furthermore, the dynamic capabilities theory further explains the relationship between technological innovation and business performance. The theory emphasizes how firms adapt to changing environments by continuously integrating, reorganizing and updating their resources and capabilities. In this context, technological innovation is viewed not only as a means to improve business performance, but also as a key dynamic capability for firms to adapt to market changes and maintain competitive advantage. At the same time, an enterprise's business performance also provides the necessary resource support for technological innovation, such as capital, talent and information, thus realizing the mutual promotion and enhancement between an enterprise's technological innovation and business performance. In addition, the theory of diffusion of innovation provides insight into understanding this bi-directional relationship. The theory highlights the process of diffusion of innovations within and between organizations, explaining how technological innovations impact on firm performance through different diffusion channels and mechanisms. In this process, firm business performance, as a result of innovation diffusion, in turn promotes more technological innovation because better business performance enhances the firm's market influence, attracts more partners, and promotes broader innovation diffusion. In summary, there is a significant bidirectional causal endogeneity problem between enterprise technological innovation and enterprise business performance, and this paper incorporates the explanatory variables lagged by one period into the model to eliminate the bidirectional causal endogeneity problem of the model.

(3) Description of model selection and testing

Analysis using a two-stage regression model The use of a two-stage regression model (Two-Stage Least Squares (2SLS)) is able to eliminate the endogeneity of the model under certain conditions due to the fact that the 2SLS method utilizes exogenous instrumental variables to solve the endogeneity problem. The endogeneity problem usually arises when the causality is caused by reverse influence or omitted variables, which makes the estimation results biased.The basic idea of 2SLS is to transform the endogeneity problem into a two-stage process by introducing instrumental variables, thus replacing the endogenous variables with exogenous instrumental variables, thus realizing an accurate estimation of the causality. In the first stage, the relationship between the instrumental variables and the endogenous variables is modeled and the predicted values (estimates) of the endogenous variables are estimated through regression. Instrumental variables are only used at this stage to predict the endogenous variables and are not directly related to the explanatory variables. In the second stage, the predicted values of the endogenous variables estimated in the first stage are used to estimate causality by replacing the actual endogenous variables. The advantage of this is that more accurate estimates are obtained because the predicted values of the endogenous variables are not affected by endogeneity.

In a two-stage regression model, this paper will use the LM test statistic for underidentification (Anderson or Kleibergen-Paap) for instrumental variable non-identification test as well as the F statistic for weak identification (Cragg-Donald or Kleibergen-Paap) instrumental variable weak identification test, where the problem of non-identifiability implies that the instrumental variables are not sufficient to accurately estimate the endogenous variables. In order to test whether the instrumental variables are not identifiable, the LM test, also known as the Anderson test or Kleibergen-Paap test, can be used.The original hypothesis (H0): the instrumental variables are identifiable and there is no non-identifiability problem. Alternative hypothesis (H1): the instrumental variable has an illegibility problem. First, a two-stage regression is conducted using the instrumental variables to obtain the predicted (estimated) values of the endogenous variables. Then, the predicted values of the endogenous variables are added to the original regression model as additional explanatory variables and regressed again. The LM test statistic for the regression coefficients of the additional explanatory variables is calculated. For large samples, this statistic approximately follows a chi-square distribution with degrees of freedom as the number of instrumental variables minus the number of endogenous variables. If the value of the statistic is large and exceeds some critical value, the hypothesis of non-identifiability can be rejected, indicating that the instrumental variables may be identifiable. The problem of weak identifiability implies that the instrumental variables are relatively weak and are not effective in removing the endogeneity problem. Weak identifiability may lead to inaccuracy and invalidity in the estimation results. The original hypothesis (H0): the instrumental variables are strong enough that there is no weak identifiability problem. Alternative hypothesis (H1): instrumental variables have weak identifiability problem. In two-stage regression, the predicted values of the instrumental variables are obtained and the F-test statistic of the regression coefficients of the added explanatory variables is calculated. This F-test statistic measures the degree of weak identifiability of the instrumental variables, the numerator of which is the square of the coefficients of the instrumental variables, and the denominator is the square of the standard error of the estimation, and the distribution of the statistic is affected by a number of factors, including the sample size, the number of instrumental variables, and the strength of the influence of the endogenous variables, and so on. If the value of the F-test statistic is small, close to 1, it may indicate that a weak identification problem exists and the estimates may be unreliable. In two-stage regression, if the number of instrumental variables is equal to the number of endogenous variables, the instrumental variable overidentification test is usually not needed. This is because when the number of instrumental variables is equal to the number of endogenous variables, there are no redundant instrumental variables and no additional endogeneity problems are introduced, thus avoiding the overidentification problem. The instrumental variable over-identification test aims to test whether too many instrumental variables are used, which may lead to unstable or even invalid results of the estimation. Under normal circumstances, the number of instrumental variables should be less than the number of endogenous variables to ensure that the instrumental variables are valid instruments that can solve the endogeneity problem. However, when the number of instrumental variables is equal to the number of endogenous variables, there is a corresponding instrumental variable for each endogenous variable, and in this case there is no redundancy of instrumental variables, and therefore the problem of over-identification does not occur.

(4) Analysis of regression results

This paper uses two-stage regression to analyze, lagging the explanatory variables by 1 period to deal with, introducing the lag 1 period of the explanatory variables, and organizing the regression results as follows:

<Table 5-3> Results of two-stage regression of technological innovation investment on firm performance

	(1) PERF	(2) PERF
L. PERF	0.5039*** (64.2123)	0.5105*** (57.9262)
L.rd	0.0548*** (3.0620)	
L.hc		0.0819*** (3.8622)
L.lnSize	0.0007*** (3.7107)	-0.0002 (-0.7451)
L. Cashflow	0.0608*** (12.2927)	0.0461*** (13.3521)
L. Board	0.0014 (1.1136)	-0.0011 (-0.7058)
L. Indep	0.0059 (1.3682)	0.0078* (1.6685)
L. Dual	-0.0013*** (-2.9935)	-0.0006 (-1.2162)
L. Top1	0.0093***	0.0024

	(5.0455)	(0.8105)
L. Balance1	0.0006	0.0003
	(0.6810)	(0.3303)
L. lnFirmAge	0.0011	-0.0009
	(1.4404)	(-0.8504)
L. Mfee	-0.0442***	-0.0034
	(-9.0533)	(-0.2525)
_cons	0.1159***	0.0962***
	(10.2991)	(6.7710)
IND	YES	YES
N	17003	17003
idstat	104.6609***	60.2168***
widstat	105.0862	60.3028

Note: Values in the table were compiled by the authors.
Values in parentheses are t-statistics; *p<0.1 ** p<0.05 *** p<0.01

Analyzing the results in the table above, the instrumental variable non-identification test LM statistic (idstat) showed significance, indicating the rejection of the original hypothesis, that is, there is no problem of non-identification of instrumental variables. The analysis of the results of the instrumental variable weak identification test, Cragg-Donald or Kleibergen-Paap statistic is equal to 105.0862, 60.3028 respectively, which are significantly greater than the 10% critical value of 16.38, indicating the rejection of the original hypothesis, that is, the instrumental variable does not have a weak identification problem. Analysis of the results shows that in the two regression models, the explanatory variables include one period lag of firm performance (L. Firm Performance), one period lag of R&D capital investment (L. R&D Capital Investment) and one period lag of R&D manpower investment (L. R&D Manpower Input), first of all, the coefficients of L. Firm Performance in both models are 0.5039 and 0.5105 respectively, and all of them are significant at 1% of the level of significance. This result shows that there is a positive and significant association between the lagged period of firm performance and the current period's firm performance, i.e., the previous period's firm performance has a strong effect on the current period's firm performance. Secondly, in the first regression model, the coefficient of L. R&D capital investment is 0.0548, which is significant at 1% level of significance. This finding confirms the existence of a positive and significant relationship between the lagged period of R&D capital investment and firm performance. Specifically, increasing capital investment in R&D significantly improves firm performance.

Again, in the second regression model, the coefficient of L. R&D manpower input is 0.0819, which is significant at 1% level of significance. This indicates the same positive and significant relationship between lagged period of R&D manpower investment and firm performance. This result implies that increasing R&D manpower investment will significantly contribute to the growth of firm performance. Overall, these two regression models together reveal a positive and significant relationship between firm performance and its lagged period of R&D capital investment, R&D manpower investment and itself.

5.4 Robustness Tests

5.4.1 Robustness test based on high level of tailoring

The robustness test based on a high level of tailoring aims to enhance the reliability of the analysis by addressing the impact of outliers in the dataset. Outliers, caused by various factors such as data errors or extreme observations, can significantly distort estimation results and lead to misleading interpretations.

High-level tailoring involves limiting the influence of extreme values on the analysis, thus ensuring a more accurate analysis outcome. In this study, a 5% level of bilateral shrinkage was applied to the dataset, in contrast to the previous 1% level, to examine the robustness of the regression results. The adjusted regression results following this higher level of shrinkage are presented below:

<Table 5-4> Regression Results of Technological Innovation Inputs on Firm Performance after High Shrinkage

	(1) PERF	(2) PERF
rd	0.0186***	
	(3.3765)	
hc		0.0109***
		(5.8482)
lnSize	-0.0005***	-0.0004**
	(-2.5951)	(-2.0884)
Cashflow	0.1415***	0.1433***
	(42.6042)	(43.3610)
Board	-0.0018	-0.0016
	(-1.1647)	(-1.0451)
Indep	-0.0165***	-0.0166***
	(-3.0753)	(-3.0940)
Dual	0.0014***	0.0013***
	(3.5709)	(3.4424)
Top1	0.0369***	0.0375***
	(21.1771)	(21.4637)
Balance1	0.0108***	0.0109***
	(13.2217)	(13.2691)
lnFirmAge	-0.0067***	-0.0064***
	(-9.5243)	(-9.1965)
Mfee	-0.2139***	-0.2178***
	(-47.4392)	(-47.6953)
_cons	0.3718***	0.3822***

	(50.9135)	(64.9895)
N	21355	21355
IND	YES	YES
R2	0.2549	0.2557
Adj R2	0.2537	0.2545
F	594.7094***	597.6240***

Note: Values in the table were compiled by the authors.
Values in parentheses are t-statistics; *p<0.1 ** p<0.05 *** p<0.01

The regression results show a significant positive effect of R&D capital investment and R&D labor investment on firm performance. Specifically, the relationship between R&D capital investment and firm performance is statistically significant with a coefficient of 0.0186 and a very strong significance (t-value of 3.3765). Similarly, the effect of R&D manpower investment on firm performance is also significant with a coefficient of 0.0109 and a t-value of 5.8482, indicating that an increase in R&D manpower investment leads to an increase in firm performance. This result reflects the key role of R&D investment in improving firm performance. The effect of R&D capital investment is slightly larger than the effect of R&D labor investment, implying that capital may play a more central role in some aspects. Overall, these findings support the view that firms increase their R&D investment to enhance performance, highlight the importance of both capital and manpower in the R&D process, and provide useful insights for firms' strategic decisions. As a high level of tailoring has been applied, this result also further ensures the robustness and confidence of the estimates by excluding potential outliers and anomalous observations from interfering with the analysis.

5.4.2 Robustness test based on panel quantile regression

Panel quantile regression is a powerful statistical method used to analyze the conditional distributional properties of different quantiles in panel data. Unlike traditional least squares regression, it captures the entire distribution of the data, providing insights into various quantiles beyond the mean. This method extends traditional regression approaches by characterizing the conditional distribution at different quantiles of the relationship between dependent and independent variables. Panel quantile regression does not rely on assumptions like homoskedasticity or normal distribution of error terms, making it robust in the face of data violations of these assumptions. This technique is especially valuable when exploring complex relationships across time and individuals in panel data, allowing researchers to understand data heterogeneity more deeply.

Panel quantile regression is widely applicable in fields like economics, finance, and social sciences, where differences across quartiles can be significant. Analyzing various quartiles reveals hidden patterns, enriching research conclusions. Its flexibility, depth, and relaxed assumptions about error term distributions make it essential for understanding complex data structures.

In this study, business performance, our explanatory variable, is divided into quartiles (0.25, 0.50, and 0.75) to explore the impact of technological innovation on enterprise performance at different quantiles. First, we examine the panel quantile regression of technological innovation inputs on business performance, presenting the results as follows:

<Table 5-5> Panel quantile regression results of technological innovation investment on firm performance

	(1)	(2)	(3)	(4)	(5)	(6)
	0.25	0.50	0.75	0.25	0.50	0.75

	PERF	PERF	PERF	PERF	PERF	PERF
hc\rd	0.0065***	0.0099***	0.0136***	0.0356***	0.0203***	0.0032
	(3.1363)	(5.5272)	(5.7456)	(6.3851)	(4.1984)	(0.5034)
lnSize	0.0002	-0.0000	-0.0003	0.0001	-0.0001	-0.0004*
	(1.0413)	(-0.2702)	(-1.4266)	(0.5793)	(-0.7525)	(-1.7627)
Cashflow	0.1198***	0.1273***	0.1355***	0.1175***	0.1258***	0.1349***
	(35.5402)	(43.7030)	(35.1305)	(35.0460)	(43.3252)	(35.1201)
Board	0.0008	-0.0019	-0.0048***	0.0006	-0.0021*	-0.0051***
	(0.5555)	(-1.5234)	(-2.9454)	(0.4599)	(-1.6942)	(-3.1491)
Indep	-0.0147***	-0.0174***	-0.0204***	-0.0144***	-0.0173***	-0.0205***
	(-3.0678)	(-4.2066)	(-3.7195)	(-3.0269)	(-4.1917)	(-3.7505)
Dual	0.0011**	0.0012***	0.0014***	0.0011**	0.0013***	0.0015***
	(2.4542)	(3.1624)	(2.6545)	(2.3643)	(3.2942)	(2.9616)
Top1	0.0371***	0.0358***	0.0345***	0.0369***	0.0353***	0.0336***
	(20.1992)	(22.6075)	(16.4300)	(20.2466)	(22.3960)	(16.0861)
Balance1	0.0093***	0.0106***	0.0121***	0.0092***	0.0106***	0.0121***
	(9.8727)	(13.0771)	(11.2417)	(9.8805)	(13.0720)	(11.2686)
lnFirmAge	-0.0049***	-0.0066***	-0.0086***	-0.0048***	-0.0068***	-0.0091***
	(-6.4614)	(-10.2467)	(-10.0318)	(-6.3750)	(-10.5729)	(-10.6835)
Mfee	-0.1867***	-0.1675***	-0.1465***	-0.1860***	-0.1646***	-0.1407***
	(-37.7392)	(-39.1798)	(-25.8721)	(-37.9178)	(-38.7459)	(-25.0355)
N	21355	21355	21355	21355	21355	21355

Note: Values in the table were compiled by the authors.
Values in parentheses are t-statistics; *p<0.1 ** p<0.05 *** p<0.01

In the aforementioned models, Models 1 to 3 represent the quantile regression results of R&D human capital investment on enterprise performance, while Models 4 to 6 indicate the quantile regression results of R&D capital investment on enterprise performance. Analyzing the consolidated results reveals a statistically significant and positive relationship between R&D human capital investment and enterprise performance across the three quartiles: 0.25, 0.50, and 0.75.

At the 0.25 quantile level, the coefficient for the relationship between R&D

manpower investment and firm performance is 0.0065, signifying a significant improvement in firm performance with increased R&D manpower investment at lower performance levels. Moving to the 0.50 quantile level, which represents the median performance, the coefficient rises to 0.0099, indicating a more substantial effect of increasing R&D human investment on firm performance. At the 0.75 quantile, corresponding to higher performance levels, the coefficient further increases to 0.0136, suggesting even greater benefits of R&D manpower investment at high levels of firm performance. Across all three quartiles, the consistent positive relationship between R&D manpower investment and firm performance reinforces the robustness of the model, aligning with previous research findings.

Regarding R&D capital investment's impact on enterprise performance, significant differences emerge across the quartiles. At the 0.25 quantile level, the coefficient for the relationship between R&D capital investment and firm performance is 0.0356, indicating a substantial improvement in firm performance with increased R&D capital investment at lower performance levels. However, at the 0.50 quantile level, the coefficient decreases to 0.0203, signifying a weakened effect of R&D capital investment on firm performance at median performance levels. By the time performance reaches the 0.75 quantile, the coefficient further decreases to 0.0032 and loses statistical significance. These results underscore the variation in the impact of R&D capital investment on firm performance at different performance levels. Firms with lower performance levels can significantly enhance performance with increased R&D capital investment. As performance improves, the marginal benefits of R&D capital investment diminish, and at high performance levels, further increases in R&D capital investment do not yield significant performance improvements.

In summary, the core explanatory variables consistently exhibit positive effects, and the findings remain in line with previous research, reinforcing the robustness of the model.

Chapter 6. Institutional analysis

6.1 Analysis of the moderating effects of technology alliances

Based on the theoretical analysis of the previous paper, this paper explores the moderating effect of technology alliance in the process of the impact of technological innovation on enterprise performance, based on the model setting of the previous paper, this paper introduces the interaction term of explanatory variables and moderating variables for analysis. Firstly, we analyze the moderating effect of technology alliance in the influence of technological innovation input on enterprise performance, and organize the regression results of moderating effect as follows:

<Table 6-1> Regression results of the moderating effect of technology alliances in the impact of technological innovation inputs on firm performance

	(1) PERF	(2) PERF
rd	0.0447***	
	(7.0292)	
hc		0.0238***
		(10.5561)
TAS	0.2519***	0.0060
	(5.4731)	(1.3420)

TAS*rd	-0.3390***	
	(-5.8966)	
TAS*hc		-0.1795***
		(-8.3662)
lnSize	0.0001	0.0002
	(0.4916)	(1.0003)
Cashflow	0.1267***	0.1281***
	(43.7887)	(44.5319)
Board	-0.0025**	-0.0023*
	(-2.0608)	(-1.9441)
Indep	-0.0173***	-0.0178***
	(-4.0993)	(-4.2346)
Dual	0.0013***	0.0013***
	(3.4990)	(3.4184)
Top1	0.0350***	0.0352***
	(21.5469)	(21.6107)
Balance1	0.0107***	0.0106***
	(13.4315)	(13.2802)
lnFirmAge	-0.0070***	-0.0067***
	(-11.1958)	(-10.5991)
Mfee	-0.1603***	-0.1649***
	(-44.9389)	(-45.6625)
_cons	0.3402***	0.3699***
	(48.0597)	(76.1362)
IND	YES	YES
N	21355	21355
R2	0.2567	0.2588
Adj R2	0.2553	0.2575
F	500.8467***	507.3712***

Note: Values in the table were compiled by the authors.

Values in parentheses are t-statistics; *p<0.1 ** p<0.05 *** p<0.01

The regression results highlight the impact of the interaction between technology alliances and R&D capital investment, as well as R&D human investment, on firm performance. Model (1) reveals a significant negative relationship between the interaction of technology alliances and R&D capital investment and firm performance, indicated by a coefficient of -0.3390 and a highly significant t-value of -5.8966. Similarly, in model (2), the interaction between technology alliances and R&D manpower investment exhibits a significant negative effect on firm performance, with a coefficient of -0.1795 and a highly significant t-value of -8.3662. These findings suggest that increased investment in R&D capital and manpower during participation in technology alliances might not lead to the anticipated performance improvement. Instead, it appears to negatively impact firm performance, challenging the positive aspects observed in prior studies on technology alliances.

Three possible reasons for this negative moderating effect are as follows:

Over-Reliance on Technology Alliances:In-depth analysis from the perspective of resource dependence theory underscores the drawbacks of firms over-relying on technology alliances. While these alliances provide crucial resources like technology, knowledge, and market information to enhance innovation capability and competitiveness, excessive reliance may lead to several adverse consequences. Firms, in their over-dependence on technology alliances, might focus excessively on cooperative relationships, neglecting the cultivation of independent innovation capabilities. This over-dependence can render the firm vulnerable in terms of key technologies and core competencies, diminishing its competitive position in the market. It can also create a resource allocation dilemma, potentially leading to an imbalance in resource distribution and impacting overall firm performance. Over-reliance may hinder firms from developing their own resources, resulting in inefficiency and resource wastage. Additionally, a crisis of trust and conflict of interest among partners may arise, potentially leading to the dissolution of the cooperative relationship and negatively affecting overall enterprise performance. Thus, while technology alliances offer vital resources, careful consideration of the associated risks and balanced resource allocation is essential for sustainable innovation and performance improvement.

Technology Theft in Technology Alliances:An examination from the technology theft perspective reveals that technology alliances, despite promoting collaborative innovation, introduce the risk of unauthorized technological acquisition. Information sharing among partners exposes core technical details, providing opportunities for technology theft. Partners might exploit the alliance relationship to gain access to key technologies and trade secrets, potentially harming the innovating firm's competitive advantage and market position. This theft can erode trust and cooperation within the alliance, leading to reduced effectiveness and innovation capabilities. Furthermore, exposed technology theft may damage the firm's reputation, impacting market attractiveness. This issue can influence a firm's long-term innovation strategy, prompting protective measures that limit external collaboration, hindering resource access, and reducing market competitiveness. In essence, technology theft within technology alliances emerges as a key factor negatively impacting the positive effect of technological innovation inputs on firm performance.

Negative Willingness to Pay and Mutual Wait-and-See in Technology Alliances:A perspective centered on negative willingness to pay, mutual wait-and-see, and excessive focus on contribution measurement within technology alliances elucidates potential drawbacks in the collaborative process. The collaborative nature of technology alliances requires resource sharing, but firms may hesitate due to concerns about imbalanced returns. This reluctance hampers the depth of cooperation, diminishing the overall impact of technology alliances. Additionally, a mutual wait-and-see stalemate can impede progress and even halt cooperation entirely. Lack of clear cooperation norms and mutual trust may foster conservatism and self-protective behavior, hindering active engagement in cooperation. Furthermore, an exaggerated focus on contribution measurement may result in tensions and conflicts, with dissatisfaction and disappointment leading to potential breakdowns in the cooperative relationship. Conflicts and disagreements arising from disparate objectives and interests may exacerbate mistrust and alienation. In summary, negative willingness to pay, mutual wait-and-see, and excessive emphasis on contribution measurement contribute to technology alliances negatively regulating the positive impact of technological innovation inputs on firm performance. Careful attention to cooperation norms, trust-building, and balanced contribution is crucial for successful and effective technology alliances.

6.2 Discussion of Heterogeneity in the Nature of Property Rights

Examining the diversity in property rights is crucial in understanding the relationship between corporate innovation and firm performance. Property rights theory underscores how different structures influence firms' behavior and investment in innovation. Variations in property rights lead to diverse incentives and constraints, impacting innovation efficiency. Business organization theory highlights the influence of organizational purpose and culture on innovation activities. Firms with distinct property rights exhibit varied goals, shaping their innovation direction. Furthermore, the innovation ecosystem theory stresses the broader context of innovation, involving social, economic, and technological factors. Heterogeneous property rights provide diverse resources and networks, shaping unique innovation paths and strategies. Interactions with partners, markets, and technological systems result in diverse innovation patterns and performance outcomes. This complexity underscores the need to consider property rights nature heterogeneity when studying the impact of firm innovation on performance, emphasizing the role of factors such as property rights structure, organizational purpose, and innovation ecology.

In this study, enterprises are categorized as state-owned and non-state-owned, with separate group regression analyses conducted. The results are as follows, focusing on the impact of technological innovation inputs on enterprise performance concerning the nature of property rights.

<Table 6-2> Regression results of grouping the nature of property rights on the impact of technological innovation investment on firm performance

	(1)	(2)	(3)	(4)
	nationalized business		non-state enterprise	
	PERF	PERF	PERF	PERF
rd	0.0237***		0.0145**	
	(3.5587)		(2.4252)	
hc		0.0015		0.0125***
		(0.5204)		(6.7828)
lnSize	0.0022***	0.0022***	-0.0007***	-0.0006***
	(7.9572)	(7.9808)	(-3.1704)	(-2.9162)
Cashflow	0.1226***	0.1235***	0.1278***	0.1290***

	(23.5280)	(23.6694)	(37.6168)	(38.1871)
Board	-0.0062***	-0.0061***	0.0002	0.0004
	(-3.2612)	(-3.2249)	(0.1034)	(0.2459)
Indep	-0.0183***	-0.0181***	-0.0173***	-0.0176***
	(-3.0259)	(-2.9918)	(-3.1980)	(-3.2610)
Dual	-0.0011	-0.0012	0.0010**	0.0009**
	(-1.0880)	(-1.2231)	(2.3242)	(2.0810)
Top1	0.0217***	0.0216***	0.0389***	0.0397***
	(8.0630)	(7.9977)	(19.2683)	(19.6552)
Balance1	0.0041***	0.0039***	0.0118***	0.0118***
	(2.9591)	(2.8391)	(12.3251)	(12.3663)
lnFirmAge	0.0024**	0.0023*	-0.0090***	-0.0086***
	(2.0677)	(1.9230)	(-12.0758)	(-11.4959)
Mfee	-0.1352***	-0.1377***	-0.1673***	-0.1720***
	(-19.2660)	(-19.6729)	(-40.5850)	(-41.1228)
_cons	0.2915***	0.3100***	0.3801***	0.3870***
	(30.7032)	(38.9099)	(47.6891)	(59.0196)
IND	YES	YES	YES	YES
N	4876	4876	16479	16479
R2	0.3290	0.3273	0.2536	0.2554
Adj R2	0.3241	0.3224	0.2520	0.2538
F	159.7095***	158.0656***	459.2551***	464.3864***

Note: Values in the table were compiled by the authors.

Values in parentheses are t-statistics; *p<0.1 ** p<0.05 *** p<0.01

The analysis of regression results based on the distinction between state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs) yields valuable insights into the impact of property rights heterogeneity. In the sample of SOEs, R&D capital investment significantly enhances firm performance, indicating a robust positive relationship (model 1, coefficient = 0.0237, t-statistic = 3.5587, 1% significance). Conversely, R&D manpower investment in SOEs (model 2, coefficient = 0.0015, t-statistic = 0.5204) shows no significant correlation with firm performance.

In non-SOEs, R&D capital investment has a positive impact on firm performance, although it is significant at the 5% level (model 3, coefficient = 0.0145, t-statistic = 2.4252, 5% significance). Notably, R&D manpower investment in non-SOEs significantly boosts firm performance, demonstrating a strong positive relationship (model 4, coefficient = 0.0125, t-statistic = 6.7828, 1% significance).

Overall, R&D capital investment positively affects the performance of both SOEs and non-SOEs. However, its impact on SOEs is more pronounced, likely due to their stable capital chains and governmental support. SOEs prioritize technological innovation and R&D capabilities, contributing to the significant impact of R&D capital investment on their performance. In contrast, non-SOEs rely on the innovative abilities of their workforce, leading to a significant positive correlation between R&D manpower investment and firm performance. Non-SOEs, aiming for short-term gains, emphasize immediate human resource output over long-term technological investments. This nuanced understanding sheds light on the differing dynamics within the Chinese enterprise landscape.

6.3 Discussion of Heterogeneity in Firm Size

Analyzing the imp act of firm innovation on firm performance requires careful consideration of firm asset size heterogeneity. Firm asset size serves not only as an indicator of firm scale and market position but also correlates closely with firms' innovation strategies, resource allocation, and market competitiveness.

According to the resource-based theory, larger firms possess abundant resources such as capital, human resources, and technology, which drive innovation. These resources enable large firms to conduct extensive R&D activities, take higher innovation risks, and leverage economies of scale. Additionally, organizational learning theory suggests that larger firms typically have superior organizational structures and management experience. This advantage allows them to effectively integrate internal and external resources, promote innovation, accumulate knowledge, enhance skills, and consequently improve firm performance.

In contrast, smaller firms tend to be more adaptable and responsive to market changes. They adopt agile and targeted innovation strategies, enabling them to excel in specific areas or market segments. Competitively, a firm's asset size often determines its market negotiating power and brand influence. Larger firms with substantial assets wield significant market dominance. On the other hand, smaller firms may discover opportunities in niche markets through innovation, establishing a competitive edge.

Understanding these dynamics is essential in comprehensively evaluating how firm innovation strategies intersect with asset size, influencing both market position and overall performance.

Next, this paper analyzes the regression results of enterprise size grouping of the impact of technological innovation investment on enterprise performance, and organizes the regression results as follows:

<Table 6-3> Firm size group regression results of the impact of technological innovation investment on firm performance

	(1)	(2)	(3)	(4)
	High asset size group		Low asset size group	
	PERF	PERF	PERF	PERF
rd	0.0277***		0.0105	
	(4.6496)		(1.4379)	

hc		0.0023		0.0159***
		(0.9211)		(7.7185)
lnSize	0.0012***	0.0012***	-0.0022***	-0.0022***
	(4.0052)	(4.1936)	(-5.0283)	(-5.1565)
Cashflow	0.1287***	0.1307***	0.1255***	0.1271***
	(29.8191)	(30.4119)	(32.2957)	(32.8375)
Board	-0.0016	-0.0016	-0.0040**	-0.0037**
	(-0.9801)	(-0.9473)	(-2.2406)	(-2.0837)
Indep	-0.0116**	-0.0116**	-0.0273***	-0.0279***
	(-2.0254)	(-2.0225)	(-4.4036)	(-4.5168)
Dual	0.0001	0.0001	0.0018***	0.0017***
	(0.0927)	(0.2250)	(3.6827)	(3.4611)
Top1	0.0250***	0.0252***	0.0393***	0.0403***
	(10.9349)	(10.9880)	(16.6327)	(17.0731)
Balance1	0.0069***	0.0069***	0.0122***	0.0122***
	(5.8581)	(5.8756)	(10.9940)	(11.0158)
lnFirmAge	-0.0036***	-0.0038***	-0.0100***	-0.0094***
	(-3.9972)	(-4.2201)	(-11.4957)	(-10.7152)
Mfee	-0.1646***	-0.1647***	-0.1618***	-0.1680***
	(-27.1938)	(-26.9438)	(-35.8966)	(-36.7704)
_cons	0.3176***	0.3386***	0.4284***	0.4330***
	(35.6804)	(44.4180)	(35.6351)	(41.0251)
IND	YES	YES	YES	YES
N	9075	9075	12280	12280
R2	0.2629	0.2612	0.2556	0.2590
Adj R2	0.2599	0.2582	0.2534	0.2569
F	234.2051***	231.5961***	350.4423***	357.8380***

Note: Values in the table were compiled by the authors.
Values in parentheses are t-statistics; *p<0.1 ** p<0.05 *** p<0.01

The regression results reveal notable differences in the impact of R&D capital investment and R&D human input on firm performance, particularly when considering high and low enterprise asset sizes.

For firms with high asset sizes, the analysis indicates a significant positive relationship between R&D capital investment and firm performance. These firms often possess robust financial resources, allowing them to invest substantially in advanced equipment, cutting-edge technology, and potential projects. Consequently, increasing capital investment in R&D activities enhances their performance. Conversely, the effect of R&D human input appears relatively weak for high-asset firms. Although human resources are vital, they are not a bottleneck factor when compared to capital. Hence, these firms prioritize driving R&D activities through increased capital investment.

In contrast, for firms with low asset sizes, the impact of R&D capital investment on firm performance is relatively small and insignificant. These firms, facing financial constraints, focus on developing and utilizing human resources, especially upgrading the skills and knowledge of their R&D teams. Limited capital prompts these firms to enhance performance by improving the efficiency and output of human resource inputs. Moreover, low-asset firms may adopt a flexible and innovative R&D approach, optimizing human resources allocation to drive growth.

Market environments and industry characteristics play a role in this phenomenon. High-asset firms often operate in mature, competitive markets, where capital investment can lead to technological and market breakthroughs. Conversely, low-asset firms operate in fast-growing, emerging markets, where human resource flexibility and creativity are crucial for gaining a competitive edge.

Corporate culture and strategic positioning also influence this pattern. High-asset firms prioritize economies of scale, market share, and technological leadership, driving these objectives through financial investments. In contrast, low-asset firms emphasize innovation, flexibility, and market acumen, investing more in human resources to achieve their strategic goals.

Chapter 7. Conclusions and outlook

7.1 Conclusion

This paper based on the resource base theory, organizational learning theory, technological innovation theory selected China Beijing Shenzhen Shanghai 2010-2022 listed companies data as a sample, using Stata software for data analysis, empirically verified the impact of technological innovation inputs and technology alliances on enterprise performance, the main conclusions of the study are as follows:

(1) Both technological innovation capital investment and technological innovation human capital investment have a positive impact on enterprise performance. This result is in line with the conclusion of previous studies that investment in technological innovation plays a positive role in enterprise performance.

(2) The Negative Moderating Role of Technology Alliances in the Relationship between Technological Innovation Inputs and Firm Performance. This disproves the findings of previous studies on the role of technological innovation inputs in firm performance. This disproves previous conclusions about the positive impact of technology alliances in the Relationship between Technological Innovation Inputs and Firm Performance.

7.2 Contribution

7.2.1 Theoretical Contribution

（1）Expansion of enterprise performance evaluation methods:

The idea of changing the traditional single-dimension indicators and enriching and improving the evaluation methods of enterprise investment performance is proposed. By using the factor analysis method combined with profitability, solvency, turnover, growth and market capitalization indicators to measure the performance of enterprises, it reflects the overall performance of enterprises' technological innovation investment more objectively and comprehensively.

（2）An in-depth analysis is quantified on the mechanisms of technology alliances on firm performance:

In contrast to prior qualitative examinations solely focused on technology alliances, this research employs the word frequency method to quantify the extent of enterprise involvement in technology alliances. It delves into the mechanism's role in technology innovation input and enterprise performance, introducing an innovative perspective by identifying a negative correlation effect. This contribution enhances the understanding of the interplay between technology alliances and firm performance, offering novel insights for the evaluation criteria of technology alliances and serving as a valuable reference for future research on related mechanisms.

7.2.2 Practical Contribution

The findings highlight the potential negative effects of technology alliances. Over-reliance on such alliances may weaken the impact of technological innovation inputs, affecting overall firm performance. Strategic decision-making, therefore, requires careful consideration of technology partners and alliance structures.

Maintaining a moderate level of technology alliance participation is crucial to achieving optimal firm performance.

Firms can adopt various strategies to navigate potential issues in technology alliances and strengthen cooperation in technology innovation activities:

Clear Frameworks and Norms for Cooperation: Establish clear cooperation frameworks and norms at the initial stage of a technology alliance to clarify responsibilities and rights, reducing uncertainty and potential conflicts.

Effective IP Protection Strategy: Ensure adequate protection of intellectual property in technology alliances through clear confidentiality agreements and shared rights agreements to prevent theft and improper use of technology.

Mutual Trust Mechanisms: Strengthen trust between partners by fostering a favorable cooperative atmosphere and implementing mutual trust mechanisms. Regular communication and information sharing can reduce misunderstanding and suspicion.

Balanced Resource Contribution: Ensure a balance in the resource contribution of each party in the technology alliance to avoid over-dependence or under-contribution. Establish a transparent resource-sharing mechanism for fair returns.

Foster a Culture of Co-Innovation: Encourage partners to share innovative ideas and experiences, fostering a culture of co-innovation. Establish common values and goals for better integration and minimizing cultural differences.

Specialized Cooperation Management Team: Set up a specialized cooperation management team responsible for coordinating and solving problems that may arise in the cooperation. This team can develop collaboration plans, oversee the process, and handle conflicts.

Long-Term Strategic Partnership: Consider establishing long-term strategic partnerships rather than short-term collaborations. Long-term relationships build stable trust and promote deeper technological innovation.

Ongoing Performance Evaluation: Establish an ongoing performance evaluation mechanism to monitor partnership effectiveness. Timely identification of problems and corrective measures maintain a good state of cooperation.

Adopting these strategies enables firms to navigate challenges in technology alliances, establish stable and sustainable partnerships, and enhance innovation capacity and competitiveness.

7.3 Research Outlook

This study empirically employs panel data in order to construct a relational model that elucidates the impact of technological innovation on firm performance. The study examines the moderating role of technological alliances, aiming to reveal the mechanism by which technological innovation affects firm performance. The findings have theoretical and practical implications for research related to enterprise performance and provide valuable guidance for enterprises to improve their performance. However, the study also has some specific limitations that deserve to be further explored in future research, mainly in the following two aspects:

1. Lack of Longitudinal Studies and Dynamic Mechanism Evolution:

The study relies on cross-sectional data, allowing in-depth exploration of technological innovation, market position, digital transformation, and business performance at specific stages under diverse environmental and technological strategies. Nonetheless, conclusions drawn from cross-sectional data might lack generalizability concerning enterprises' evolutionary mechanisms of achieving business performance at various stages. To address this limitation, future studies could benefit from longitudinal data collection and empirical research. Analyzing the impact of technological innovation on business performance across different stages of development would enhance the persuasiveness of conclusions and broaden their applicability.

2. Exploring Matching Mechanisms for Other Resources and Capabilities:

Organizational practices are often considered foundational in strategic management research, acting as microfoundations of organizational and dynamic capabilities. However, ambiguity persists regarding the development and reassessment of these practices within firms. The profound uncertainty induced by rapid technological change underscores the pivotal role of managing organizational practices, particularly in manufacturing. Future research could delve into the mechanisms through which organizational practices contribute to the model studied in this paper. Moreover, factors such as corporate culture (as highlighted by Tilson and Lyytinen et al., 2010) and digital agility (as indicated by Chakravarty and Grewal et al., 2013) are suggested to significantly impact firms' business performance. However, existing research has not explored whether these factors affect the theoretical model constructed in this paper. Subsequent research endeavors could focus on investigating the impact of these factors on the proposed model, providing valuable insights for further analysis.

Addressing these areas of further study would bolster the depth and breadth of understanding regarding the intricate relationships between technological innovation, organizational practices, digital transformation, market position, and business performance, thereby enriching the scholarly discourse in this domain.

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Even if I can buy laurel wine and get afloat,could our youth renew?

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