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Unveiling the Masking Effect: The Role of R&D Human Capital in Collaborative Innovation and Sustainability

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Abstract

Purpose – This research aims to investigate the causal relationships among collaborative innovation, R&D human capital, and sustainable innovation. Emphasize the mediating role of R&D human capital in the link between collaborative innovation and sustainable innovation.

Design/methodology/approach – Our research utilizes data from Chinese A-share listed companies spanning 2009 to 2022. We first identify a solid causal relationship between collaborative innovation and sustainable innovation. Then, the existence of a masking effect role of R&D human capital between the two is revealed. Grouped and quantile regression analyses are further employed to explore the heterogeneities of the masking effect across different cooperation types, asset scales, and industries.

Findings – Our findings demonstrate that collaborative innovation significantly enhances sustainable innovation through R&D human capital, but the masking effect of R&D human capital slightly dampens this enhancement. The enhancement is evident in inter-firm collaborations but not in industry-university partnerships. It holds across enterprise sizes, but the effect is more pronounced for firms with lower R&D levels. We argue for the importance of prioritizing quality over quantity in collaborative and sustainability.

Practical implications – Firms can benefit from human resources (HR) sharing. Policymakers should back human resource integration to boost innovation quality and efficiency.

Originality/value – We are the first to study the mediating role of R&D human capital in connecting collaborative and sustainable innovation. While previous studies on the effects of collaboration have mainly focused on the quantity of innovation outcomes, we find that an excessive emphasis on quantity can negatively affect sustainability.

Keywords Open innovation; R&D human capital; sustainable innovation; mediation effect; industry-university-research

1. Introduction

Technological disruptions and environmental challenges have led to increasing uncertainties for businesses (Huang and Zhou, 2025). This makes innovation a key factor for achieving organizational successes and maintaining competitive advantages. However, companies often face the "dual high" problem in the innovation process—high adjustment costs and high financing costs of R&D investments. As a result, businesses find it difficult to achieve sufficient sustainable innovation by relying solely on their own resources and capabilities (Caloghirou *et al.*, 2004).

Innovation is fundamentally driven by R&D human capital, investment on which has a strong positive externality or spillover effect (Foreman-Peck and Zhou, 2023). Enterprises enhance their competitiveness through knowledge creation and transformation (Liu, 2008). Development of information technology and shift from traditional production factors to knowledge assets have amplified the spillover effect, promoting accumulation of sustainable technologies and practices (Chen *et al.*, 2023). Recent studies have shown that collaborative innovation, by optimizing the structure of human capital and integrating resources, not only improves R&D efficiency but also supports environmental sustainability (Wang *et al*., 2023).

The Chinese government places a great emphasis on collaborative innovation. The "14th Five-Year Plan for National Economic and Social Development and the Long-Range Objectives Through the Year 2035," issued in 2022, calls for fostering innovation cooperation across the supply chain. It also encourages collaboration among businesses of all sizes. The "14th Five-Year Plan for Promoting SME Development" outlines specific strategies. These strategies aim to accelerate industry-academia-research collaboration and encourage cooperation among enterprises. The overall aim is to boost supply chain stability and competitiveness, and build a modern economic system.

Based on the Knowledge-Based View (KBV) theory and its empirical insights, enterprises can enhance their innovation capabilities through collaborative cooperation, sharing knowledge, and integrating resources (Grant, 1996; Spender, 1996; Chesbrough, 2003a). According to the endogenous growth theory and human capital theory, inter-firm collaboration in innovation leads to accumulation through positive externalities and knowledge spillovers (Romer, 1990; Lucas, 1988), which enhances individual skills and optimizes human capital allocation (Becker, 1964; Jiang *et al*., 2012). This significantly boosts R&D efficiency and continuously promotes innovation capacity.

Existing studies focus on the links between "collaborative innovation - sustainable innovation" and "collaborative innovation - human capital." However, they are segmented dots to be connected in a unified framework. First, existing research primarily focuses on collaboration leading to sustainable innovation (Ghobakhloo and

Fathi, 2021; Ghobakhloo *et al*, 2021; Vimalnath *et a*l., 2022) and the unidirectional relationship between collaboration and human capital (Jiang *et al*., 2012; Eppinger *et al*., 2021; Timothy, 2022), lacking a comprehensive path analysis that links collaboration to human capital and then to sustainable innovation (Cillo *et al*., 2019). Moreover, in empirical studies, previous research often measures the effects of collaborative innovation through the total number of patent applications (Hagedoorn and Cloodt, 2003; Li, 2012; Dechezleprêtre *et al*., 2017). This approach overlooks the perspective of R&D investment efficiency and fails to adequately assess the quality impact of sustainable innovation (Lanjouw and Schankerman, 2004). Finally, although human resources are considered key to innovation, their specific role and quantitative contribution in collaborative innovation have not been systematically studied. These research gaps limit a deeper understanding of the mechanisms of collaborative innovation and its sustainability, highlighting the need for further exploration.

This study fills the research gap by focusing on R&D human capital as the core perspective, integrating KBV, endogenous growth theory, and human capital theory. It is the first to propose and validate the mechanism of "collaborative innovation – R&D human capital – sustainable innovation." By revealing the "masking effect," it deepens the understanding of how collaborative innovation optimizes human capital, shares information, and integrates resources to drive sustainable innovation. This effect is crucial, as it contrasts with the mainstream view that R&D investment consistently promotes innovation. Our paper aims to make three contributions to the literature. First, validate the mediating role of R&D human capital in collaboration and sustainable innovation, which fills the research gap of the missing mechanism between collaboration and sustainability. Second, examine the moderating effects of different collaboration types (inter-firm and industry-university-research cooperation) and investment intensities (R&D-intensive and non-R&D-intensive firms), providing rich heterogeneities of the mechanism. Finally, while previous studies on collaborative innovation have mainly focused on the number of patent applications, our study uses per capita patent applications by R&D personnel as a novel measure, emphasizing the view that innovation quality outweighs quantity. This highlights the critical role of R&D human capital efficiency in sustainable innovation. This

provides a clear quality-first strategic basis for enterprises to navigate complex innovation environments and optimize R&D resource allocation.

This study also enhances the practical value of intellectual capital research. It does so by examining the masking effect through the specific impacts of various collaboration types and R&D intensities, thus broadening its theoretical and empirical scope. It also aims to provide insights into how enterprises can balance R&D investment with sustainable innovation outcomes.

The structure of the paper is as follows: Section 2 reviews the relevant literature and develops research hypotheses. Section 3 describes the research design. In Section 4, the empirical analysis first demonstrates the causal relationship between collaborative innovation and sustainable innovation, and then analyzes the mediating role of R&D human capital. After performing robustness tests for the mediating effect, the paper conducts subgroup analysis based on collaboration types and industry classifications. Quantile regression analysis is applied to firms of different scales to reveal the differences across groups. Finally, conditional mediation analysis is used to further explore underlying mechanisms. Section 5 concludes with implications for future research.

2. Literature Review and Hypothesis Development

This section reviews the existing literature to support our empirical model. First, we establish a theoretical foundation for the role of R&D human capital within the causal mechanism. Based on this, we then conduct a literature review on the transmission mechanism of "collaborative innovation - R&D human capital - sustainable innovation." We begin by analyzing the relationship between collaborative innovation and sustainable innovation. Next, we investigate how collaborative innovation enhances the efficiency of R&D human capital by utilizing both internal and external labor markets. Third, we discuss the critical role of R&D human capital in driving innovation. Finally, we synthesize existing evidence to outline the interconnections among these three factors.

2.1 Theoretical Support for Mechanism Research

This study is theoretically grounded in the Knowledge-Based View (KBV), endogenous growth theory, and human capital theory. Meanwhile, the Resource-Based View (RBV) and Dynamic Capabilities View (DCV) further complement and refine the theoretical framework. These theories work together to form a more comprehensive foundation for sustainable innovation theory, providing a multidimensional perspective and rich contextual support for the research.

The Knowledge-Based View (KBV), proposed by Grant (1996), asserts that an organization's competitive advantage comes from its ability to acquire, integrate, and apply knowledge. Knowledge capital, by combining existing knowledge with new insights, creates value and drives the enhancement of dynamic capabilities, laying the foundation for sustainable innovation (Spender, 1996). In collaborative cooperation, organizations integrate external knowledge resources and R&D human capital, efficiently share knowledge, enhance innovation capabilities, and maintain long-term competitive advantage (Grant, 1996).

Endogenous growth theory explores how investments in human capital and R&D activities promote long-term economic growth through positive externalities and knowledge spillover effects. Technological progress is an endogenous process, with the knowledge capital accumulated from R&D investment playing a fundamental role in driving sustainable innovation (Romer, 1990). R&D-driven innovation, through the creation of new products, services, and technologies, becomes a key driver of economic growth (Aghion and Howitt, 1998). Human capital accumulation leads to increasing returns to scale, particularly in technology- and innovation-driven industries (Lucas, 1998). Human capital theory (Becker, 1964) also points out that the skills and knowledge of individuals within an organization directly contribute to the enhancement of innovation capabilities. By improving the human capital of R&D staff, companies can more effectively develop innovations.

Collaborative innovation (Chesbrough, 2003a) emphasizes the importance of cooperation between organizations, research institutions, and other stakeholders. It promotes the pooling of R&D human capital and resources between companies and

industries, reducing the risks of R&D investment, enabling breakthrough innovations, and expanding sustainable development potential.

Finally, the Resource-Based View (Barney, 1991) argues that a firm's sustained competitive advantage comes from its possession of rare, valuable, inimitable, and non-substitutable resources. Intangible assets, such as patents, brand reputation, and corporate culture, enhance internal capabilities like R&D human capital, supporting innovation activities. Their synergy with R&D human capital provides a theoretical foundation for sustainable innovation. The Dynamic Capabilities View (Teece *et al*., 1997) proposes that a firm's ability to integrate, build, and reconfigure resources drives innovation in dynamic environments. This occurs through knowledge codification, expertise documentation, and organizational routines that enable resource adaptation (Teece, 2007, 2018a). Under globalization and the guidance of SDG 17 (Global Partnerships), cross-industry and global collaborations offer diverse knowledge and technological resources, strengthening dynamic capabilities and enriching the theoretical basis for sustainable innovation.

Building on these theories, the next section will examine the relationships between collaborative cooperation, R&D human capital, and sustainable innovation.

2.2 Collaborative Innovation and Sustainable Innovation

Geroski *et al*. (2007) define sustainable innovation as a dynamic process of knowledge accumulation and technological progress, arguing that long-term innovation activities enhance sustainability. Chesbrough (2020) explored the practical effects of open innovation in his research, pointing out that collaborative mechanisms can effectively enhance firms' capabilities for sustainable innovation and better achieve environmental sustainability goals. Leveraging external resources for collaborative research can serve as a breakthrough point for mid- to low-level innovation within firms (Badawy, 2007). Laursen and Salter (2006) analyzed manufacturing firms in the UK and found that open collaboration between firms can facilitate knowledge flows and accumulation. This, in turn, can significantly enhance sustainable innovation capabilities, especially in technology-intensive industries. The research by Ghobakhloo and Fathi (2021) clarifies the relationship between

Industry 4.0 technologies and energy sustainability, emphasizing the role of collaboration in energy-saving technologies.

Collaborative innovation drives sustainable innovation within innovation ecosystems, with intangible assets enhancing this relationship. The Resource-Based View (RBV) sees these assets as vital for collaboration. Vimalnath et al. (2022) found patents enable tech-sharing among European manufacturing partners, supporting sustainable outcomes. Linnenluecke and Griffiths (2010) note that brand reputation and corporate culture boost trust and efficiency in collaborations. Dul and Ceylan (2014), based on 103 firms, show that a supportive organizational culture fosters an innovation climate, boosting collaborative performance, as supported by Ahmed (1998). Complementarily, the Dynamic Capabilities Theory posits that knowledge codification and organizational routines adapt resources for collaboration (Teece et al., 1997; Teece, 2007). Zollo and Winter (2002) highlight that knowledge codification transforms tacit knowledge into explicit knowledge, documents expertise, and embeds it into organizational routines to sustain innovation. Donate and de Pablo (2015) highlight organizational routines enabling knowledge-sharing practices among Spanish tech firms, reinforcing sustainable innovation.

Moreover, the effect of collaborative innovation on sustainable innovation exhibits heterogeneity across different contexts. Ghobakhloo *et al*. (2021) further found that global collaborative innovation significantly supports the development of sustainable technologies, such as energy-efficient solutions in smart manufacturing. Similarly, Cainelli *et al*. (2015) studied the Spanish manufacturing industry and found that cross-industry collaboration promotes knowledge spillovers by providing diverse technological knowledge, thereby supporting environmental innovation.

By integrating Sections 2.1 and 2.2, we draw on the Knowledge-Based View (KBV) perspective (Grant, 1996), which highlights knowledge integration as a critical driver of competitive advantage. Empirical research supports this view, demonstrating that collaborative efforts improve knowledge sharing and foster innovation (Chesbrough, 2003b, 2020). Within the open innovation model, the ability to ac-

quire, integrate, and apply knowledge resources is essential for achieving competitive advantage and sustaining innovation (Grant, 1996). Based on this reasoning, we propose our first hypothesis:

H1: Collaborative innovation positively impacts sustainable innovation.

2.3 Collaborative Innovation and the Internal and External Human Resource Market

The commercialization of enterprises can be pursued from either internal or external sources. Enterprises integrate both internal and external ideas into their systems; external channels for ideas and internal channels are equally important. Therefore, the characteristics of innovation activities determine that enterprises need to secure the sustainability of innovation investment activities through both internal and external financing (Jiang *et al*., 2012).

Collaborative innovation relies on the allocation of internal and external human resources. A key condition for gaining a competitive advantage is the internal flow of individual knowledge within an organization, which enhances innovation capacity and enables better value creation and utilization (Tsai, 1998; Barney, 1991). By investing in training, organizations can enhance human capital, making it a primary source of new perspectives and knowledge (Youndt *et al*., 1996). In a case study on Tanzanian SMEs, Timothy (2022) demonstrated that cross-departmental collaboration improved innovation efficiency.

The demand for external labor in collaborative innovation is reflected in the shortage of R&D human capital, which hinders knowledge-driven innovation efforts. Jiang *et al*. (2012) proposed that internal and external market synergies can jointly enhance employees' human capital. Zhou *et al*. (2018) used data from China between 2008 and 2018 to analyze the role of high-tech professional talent mobility in promoting regional sustainable development. Fifty percent of Procter & Gamble's innovations and ideas in 2003 originated from external sources. Companies like Lucent Technologies, IBM, and Dow Chemical generated over $100 million annually through technology licensing (Chesbrough, 2003b).

In collaborative innovation, human resource allocation is also influenced by a firm's intangible assets. For example, intellectual property can attract high-end external talent to collaboration network (Teece, 2018b). Meanwhile, an innovation-oriented organizational culture fosters an innovation climate, integrating internal human resources to indirectly enhance sustainable innovation (Hogan and Coote, 2014). Additionally, the impact of collaborative innovation on the labor market varies depending on the collaboration model. On a global scale, multinational corporations optimize the allocation of R&D human capital through talent mobility and knowledge transfer (Eppinger *et al*., 2021).

Through collaborative innovation, companies can optimize the allocation of R&D human capital, driving technological progress and enhancing innovation capabilities (Grant, 1996). Collaborative innovation integrates internal and external resources, compensates for R&D shortcomings, and accelerates the innovation process. This significantly enhances the efficiency of R&D human capital (Chesbrough, 2003b), thereby supporting sustained innovation and the acquisition of competitive advantages. Based on this, our second hypothesis is:
H2: Collaborative innovation, utilizing internal and external resources, has a positive impact on R&D human capital.

2.4 The Mediating Effect of R&D Human Capital

Human resources can effectively influence innovation efficiency. In his endogenous growth model, Romer (1990) proposed that human capital and technological knowledge are fundamental forces driving technological progress and economic development. Employee creativity plays a mediating role under the influence of transformational leadership, thereby promoting organizational innovation (Chaubey *et al*., 2019). Bai *et al*. (2016) found that transformational leadership, by affecting team atmosphere and employee relationships, stimulates employee creativity at the team level. Timothy (2022) found that top management's high human capital boosts innovation activities, which in turn improves SME productivity. Zhang and Lian (2023), through their research on A-share listed companies in China, concluded that optimizing human capital structure can improve employee job satisfaction and creativity, thereby promoting business performance. Nejjari and Aamoum (2022),

through meta-analysis, found that intellectual capital can impact a company's innovation capabilities through various avenues and is seen as a source of innovation in businesses.

It is important to note that, under high investment, the over-concentration of resources in R&D human capital may weaken innovation quality, reflecting a masking effect. Laursen and Salter (2006) found through their empirical analysis of UK manufacturing firms that collaborative innovation, if focused solely on quantity while neglecting quality, may undermine innovation performance. Similarly, Arora *et al*. (2016a) pointed out that innovators need to balance the quantity and quality of collaborative innovation and patent applications in practice to avoid a decline in quality due to over-concentration of resources.

R&D human capital connects collaborative innovation and sustainable innovation, supporting efficiency improvements and long-term development. Combined with the support of empirical literature on the mediating effect of human capital, we propose:
H3: R&D human capital significantly mediates the relationship between collaborative innovation and sustainable innovation.

3. Research Design

3.1 Data and Sample

The data used in this article come from two primary sources: the China Stock Market & Accounting Research (CSMAR) database and the China National Intellectual Property Administration (CNIPA) database. These databases provide comprehensive information on all Chinese A-share listed companies, including their basic information, operating conditions, and financial data. The CSMAR database supplies the basic information and financial data of the listed companies. Financial indicators are extracted from the "Financial Statement Database" section of CSMAR, which contains historical financial data from both the Shenzhen and Shanghai Stock Exchanges since their inception. Basic company information, such as contact details,

registered addresses, legal representatives, establishment dates, and industry classifications, is sourced from the "Listed Companies Basic Information Database." This section also includes data on the professional structure, age, and educational background of company personnel.

To focus on collaborative innovation, we excluded companies without research and development (R&D) activities, limiting our analysis to firms that applied for R&D in the respective year. We also restricted our sample to A-share companies, excluding those classified as ST or *ST due to financial distress. Additionally, financial industry companies were removed from the sample to avoid bias, as their unique characteristics, such as debt ratios and R&D indicators, differ significantly from other industries.

Patent information is sourced from the CNIPA database, the authoritative national platform for intellectual property in China. CNIPA archives all patents filed since September 1985, including invention patents, utility model patents, and design patents. Invention patents, which require higher levels of creativity and practicality, are chosen as an indicator of innovation because they better reflect a company's core technological capabilities (Hall *et al*., 2001; Pakes, 1985). This aligns with our study's focus on R&D quality (Arora *et al*., 2016b). Patent data were collected by searching the CNIPA website using the names of the listed companies. The data from CSMAR and CNIPA were matched using the companies' stock codes. After pairing financial and patent information, we retained complete data from 2009 to 2022. Initially, over 100,000 data samples were collected from both databases. Following data cleansing, we obtained a final sample of 7,602 observations from A-share listed companies spanning 15 years (2007–2021), forming an unbalanced panel dataset. Table I provides definitions and data sources for all variables used in our regression analysis.

Table I: Definition of Variables

Variables	*Variable Description*	*Source*
$Aqua$	Patent granted num/application num	CNIPA/CSMAR
$Apatnt$	Patent application num/ R&D personnel	CNIPA/CSMAR
$CoRD$	Co-innovation or not: yes = 1, no = 0	CNIPA
$Jinv$	Co-innovation patent application volume	CNIPA
Iur	Co-innovation with college or not: yes = 1, no = 0	CNIPA
$Capsize$	Total assets (million in CNY)	CSMAR
$Cash$	Operating cash flow ratio	CSMAR
$Rdcr$	R&D staff num/staff num	CSMAR
Lev	Asset/liability ratio	CSMAR
$Profit$	Main operation profit ratio	CSMAR
Fix	Fixed asset ratio	CSMAR
Soe	Enterprise type: state-owns = 1, private = 0	CSMAR
Cur	Current ratio = current assets/current liabilities	CSMAR
Sub	Government subsidy (million in CNY)	CSMAR
Rd	The proportion of R&D expenditure to total assets	CSMAR

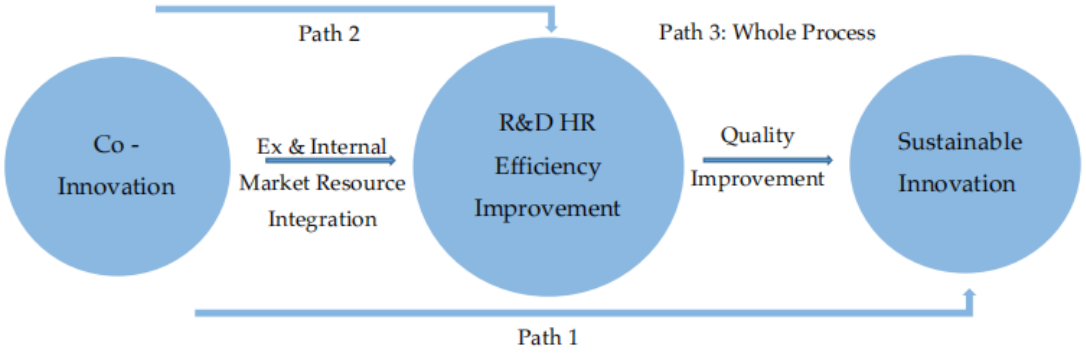
3.2 Study Design

Our primary objective is to study how collaborative innovation improves R&D efficiency by using both internal and external resources, leading to sustainable innovation. Specifically, we establish a causal mechanism among "collaborative innovation - R&D human capital - sustainable innovation" to explore their interrelationships.

As illustrated in Figure I, collaborative innovation drives sustainable innovation (Path 1) while improving R&D efficiency through enhanced human capital development (Paths 2 & 3). When these pathways are effective concurrently, we argue that collaborative innovation enhances sustainable innovation through the improvement of R&D human capital, positioning R&D human capital as a mediator between the two. External collaboration reduces costs related to searching, matching, hiring,

and competition. Internal collaboration strengthens R&D human capital through information sharing and continuous learning. Together, both forms of collaboration ultimately enhance the overall innovation efficiency of R&D personnel. This improvement in R&D human capital subsequently bolsters sustainable innovation by increasing intangible assets and improving the efficiency of patent applications, thus impacting both the potential and quality of sustainable innovation.

Figure I: Theoretical model



R&D human capital is typically represented by the overall quality and capabilities of R&D personnel, such as their number, education level, and average years of experience. However, when examining the link between collaboration and sustainable innovation, dynamic capabilities must also be considered. According to Teece (1997, 2007) and his theory of dynamic capabilities, a company's ability to integrate and transform resources is a critical driver of sustainable innovation. This transformation efficiency can be viewed as a reflection of R&D efficiency. Unlike traditional human capital, which focuses on static attributes like education and experience, the alignment of technological change with human capital efficiency plays a key role in driving innovation (Acemoglu, 1998). For this reason, in this study, "R&D Human Capital" is defined as "patent applications per R&D personnel." This metric serves as a proxy for the effectiveness of R&D personnel, highlighting how efficiently human capital is utilized in the innovation process. By focusing on this dynamic and efficiency-oriented measure, we emphasize the key drivers of sustainable innovation.

Patents are a key measure of innovation outcomes, and joint patents further indicate that these innovations were achieved through collaboration (Arora *et al*., 2016a; Belderbos *et al*., 2014). Joint patents directly reflect the co-development and sharing of intellectual property, making them a clear indicator of collaborative innovation (Boons, 2013). For this reason, "joint patent applications" is selected as the representative variable for collaborative innovation.

"Patent application success rate" is chosen as the indicator for sustainable innovation quality. Companies with a high patent grant rate are able to continuously innovate and adapt to the market, maintaining technological advantages and market competitiveness. This is because a high patent success rate demonstrates the company's ability to effectively convert R&D investment into market-valued innovative outcomes. This capability is crucial for sustainable innovation and long-term competitive advantage (Teece, 2007). It reflects both the quantity and quality of innovation. Additionally, it directly impacts the company's market competitiveness and the technological value protected by intellectual property rights (Pakes, 1985). Furthermore, a high patent success rate enhances the company's technological position and market influence, promoting technological progress and economic growth (Zhao *et al*., 2015).

During the data cleaning and key variable construction process, we included multiple control variables to reduce confounding biases. However, limitations in data access may have led to some factors being undermeasured. For example, the database may lack direct quantitative indicators for factors like corporate culture, manager characteristics, or industry effects, which could indirectly influence our results. To address this limitation, we employed robustness checks and diverse analytical approaches, such as grouping or conducting quantile regressions based on factors like company size (e.g., asset size and R&D scale), industry distribution, and the type of collaboration, to mitigate the indirect effects. Moreover, due to the limitations in the availability of corporate data, our study does not cover non-listed companies or foreign companies. Future research on uncovered enterprises will provide prospects and plans for further studies. It could help enhance the general applicability of mechanism research and form a more comprehensive research framework.

3.3 Empirical Specification

To prove the role of R&D human capital in both collaborative and sustainable innovation, we must first establish the validity of Path 1. That is, collaborative innovation directly impacts sustainable innovation. To examine this, we estimate the following baseline empirical model:

$$Aqua_{i,t} = \theta_0 + \theta_1 lnJinv_{i,t} + \beta_1 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \qquad (1)$$

The dependent variable, *Aqua*, measures sustainable innovation capability in terms of quality, defined as the "ratio of patents obtained in the subsequent period to the number of patent applications". Our main variable of interest is *lnJinv*, which represents the "number of joint patent applications", and its logarithm is taken to represent the growth in collaborative innovation intensity.

The regression includes a set of control variables that are shown to be associated with sustainable innovation by prior studies (Blundell *et al.*, 1999; Griliches *et al.*, 1987; Pakes, 1985; Chesbrough, 2010; Chesbrough, 2003b; Cohen and Levinthal, 2000; Dahlander and Gann, 2010; Belderbos *et al.*, 2004; Tether, 2002; Chesbrough, 2006; Li *et al.*, 2008; Lin and Liu, 2000). We control for the financial status of the enterprises, government subsidies, and the potential development characteristics of collaboration. Specifically, financial indicators of the enterprises include the logarithm of total assets, operating cash flow ratio, R&D staff ratio, asset/liability ratio, main operation profit ratio, fixed asset ratio, current ratio, and enterprise type. Government subsidies include operational and innovative grants; we represent this by the proportion of subsidy amounts to total assets. For detailed explanations of the control variables, please refer to Table I.

It is noteworthy that, according to the research findings of Liu *et al.* (2020), the "U" shaped impact of collaboration depth might occur. Therefore, we include the squared term of the collaboration variable as a control variable to account for this effect. We anticipate collaborative innovation will improve sustainable innovation. R&D staff ratio will be positively impacting sustainability, it can better absorb and

utilize external knowledge, thereby promoting sustainable innovation (Cassiman and Veugelers, 2006; Nieto and Santamaria, 2007). Large firms may experience diminishing returns on innovation due to their scale, which could weaken their ability to sustain innovation despite having substantial assets and revenue potential. (Cohen and Klepper, 1996; Hall and Ziedonis, 2001).

Secondly, we estimate the impact of collaborative innovation on R&D human capital by model (2). This is used to demonstrate that collaborative innovation can also impact R&D human capital:

$$lnApatnt_{i,t} = \alpha_0 + \alpha_1 lnJinv_{i,t} + \beta_2 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \qquad (2)$$

Where *Apatnt* represents the "number of patent application per R&D personnel", its logarithm is used as a measure of R&D human capital.

Based on the direct impact relationships in models (1) and (2), we demonstrate the mediating effect of R&D human capital between collaborative innovation and sustainability. We then regress collaborative innovation and R&D human capital on sustainable innovation to connect the three factors as model (3):

$$Aqua_{i,t} = \gamma_0 + \gamma_1 lnJinv_{i,t} + \varphi lnApatnt_{i,t} + \beta_3 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \qquad (3)$$

If α_1, θ_1, and φ are all significant, we can conclude that there is a mediating effect of *lnApatnt* in *lnJinv* and *Aqua*, indicating that collaborative innovation can influence sustainable innovation through HR R&D capital (MacKinnon *et al.*, 2004). Additionally, we pay attention to the positive or negative sign of the mediating effect coefficient $\alpha_1 * \varphi$.

3.4 Descriptive Statistics

Table II reports the descriptive statistics for the dependent and explanatory variables employed in the baseline regression. The mean value of the approved patent applications, representing the efficiency of sustainable innovation for the enterprises, is relatively low at only 7.3%. The mean value of patent application per R&D personnel, representing the efficiency of R&D human capital, is 0.709, also indicating

considerable variation among enterprises. There is a significant difference in asset scale, ranging from a minimum of 54.089 million to a maximum of 61,590 million. Approximately 43.1% of the enterprises engage in collaborative innovation, represented by CoRD. These enterprises have an average collaboration count of 7.712 and a standard deviation of 45.821, indicating significant fluctuations in the number of collaborations among enterprises. Among them, the proportion of enterprises engaging in industry–university–research cooperation is 12.53%.

Table II: Descriptive Statistics

Variables	*N*	*Mean*	*SD*	*Min*	*Max*
$Aqua$	7,602	0.073	0.161	0	1
$Apatnt$	7,600	0.709	6.726	1	487.75
$CoRD$	7,602	0.431	0.495	0	1
$Jinv$	7,602	7.712	45.821	0	1947
Iur	7,602	0.125	0.331	0	1
$Capsize$	7,602	8338	28,810	54.089	615,900
$Cash$	7,602	0.049	0.07	-0.454	0.874
$Rdcr$	7,582	18.487	14.168	0	93.67
Lev	7,602	0.372	0.182	0.014	1.412
$Profit$	7,602	0.051	1.523	-60.927	101.942
Fix	7,602	0.181	0.13	0	0.833
Soe	7,602	0.152	0.359	0	1
Cur	7,602	2.806	2.962	0.162	68.304
Sub	7,602	53.689	209.2	0	6324
Rd	7,561	0.027	0.022	0	0.3

4. Empirical Evidence

4.1 Baseline Results

Table III presents the baseline results testing the relationship between collaborative innovation and sustainable innovation. Using an Ordinary Least Squares (OLS)

model, with sustainable innovation as the dependent variable and collaborative innovation as the variable of interest, the results show that collaborative innovation significantly enhances sustainable innovation. The coefficient of 0.025 is statistically significant at the 1% level. This confirms a direct positive relationship between collaborative innovation and sustainable innovation, supporting our Hypothesis 1.

The explanatory power of the control variables is consistent with prior literature (Belderbos *et al.*, 2004; Tsai, 2001; Bogers *et al.,* 2020). Specifically, the negative effects of capital size (*Capsize*) and profit (*Profit)* among the control variables indicate that the A-share listed companies in our study are relatively large. As these companies have already reached a significant scale, the additional benefits of collaboration gradually diminish, potentially leading to a decline in resource utilization efficiency. Larger companies have a lower demand for collaborative R&D compared to smaller companies, whose marginal value is higher (Cohen and Klepper, 1996; Hall and Ziedonis, 2001). Additionally, there is a resource conflict between short-term profits and long-term innovation investment. *Jinv2* supports the "U-shaped" effect of collaborative cooperation on sustainable innovation, emphasizing the principle of moderation in collaborative cooperation (Liu *et al*., 2020). On the positive side, it indicates that R&D intensity plays a significant role in driving corporate innovation.

In contrast, some control variables show insignificant coefficients, which may stem from sample characteristics or their limited indirect influence on innovation. Our sample consists of A-share listed companies, which typically have strong financing capabilities. As a result, cash flow (*Cash*) and leverage ratio (*Lev)* have a relatively minor impact on innovation, since abundant funding reduces the importance of these factors. Additionally, differences in company size, industry, and strategy may weaken the effects of certain variables (Schumpeter, 1942; Cohen and Klepper, 1996). This suggests that some control variables influence innovation indirectly through other factors rather than having a direct effect (Wooldridge, 2010). To address this, a more robust analytical approach is needed, including an expanded analysis of company size in the mechanism analysis section.

Table III: Baseline Results

VARIABLES	*Aqua*	*Aqua*
Jinv	0.043***	0.025***
	(12.79)	(3.21)
Jinv2		0.006**
		(1.99)
Capsize		-0.013**
		(-2.32)
Cash		-0.035
		(-1.05)
Rdcr		0.001*
		(1.73)
Lev		-0.004
		(-0.19)
Profit		-0.001***
		(-2.73)
Fix		-0.032
		(-0.94)
Soe		0.003
		(0.26)
Cur		-0.001
		(-1.11)
Sub		-0.017
		(-1.37)
Rd		0.098
		(0.60)
Constant	0.037***	0.405***
	(13.35)	(2.81)
Observations	7,602	7,550
R-squared	0.075	0.084
Firm FE	YES	YES
Year FE	YES	YES

Table III reports the results of the OLS regression for the relation between collaborative innovation and sustainable innovation. The dependent variable is the measurement of sustainable innovation, *Aqua***.** The variable of interest is *lnJinv*, the collaborative innovations. We control for the firm and year fixed effects. Robust t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

4.2 Identification Tests

We have demonstrated that collaboration directly promotes sustainable innovation. Next, we need to verify whether this result is stable and reliable. To check the robustness of our results, we conduct identification tests to address potential concerns over self-selection bias, systematic differences between firms with and without collaborative innovations, and reverse causality. The results confirm that the effects of

collaborative innovation on sustainable innovation are robust to: 1) Propensity Score Matching (PSM); 2) Lag terms; and 3) Alternative measurements of collaborative innovation. Table IV presents the results of the three Identification Tests.

Table IV: Identification Tests

VARIABLES	*PSM* *(1)* *Aqua*	*Lag Terms* *(2)* *Aqua*	*Alternative Measurement* *(3)* *Invention*
Jinv	0.017*		0.226***
	(1.82)		(6.02)
Jinv2	0.008***		0.018*
	(3.02)		(1.76)
l.Jinv		0.041***	
		(11.60)	
l.Jinv2		0.002***	
		(2.68)	
Constant	0.319	0.064	3.077***
	(1.30)	(0.77)	(2.63)
Observations	3,767	7,549	7,273
R-squared	0.090	0.083	0.090
Control Variables	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table IV reports the results of the Identification Tests of the relation between collaborative innovation and sustainable innovation, for the propensity score matched sample. Column (1) is the regression results of Propensity Score Matching (PSM), the dependent variable is the measurement of sustainable innovation, *Aqua*. The variable of interest is *lnJinv*, the collaborative innovations. Column (2) reports the results of the OLS regression for the relation between lagged collaborative innovation and sustainable innovation. The dependent variable is the measurement of sustainable innovation. The variable of interest is *l.lnJinv*, the collaborative innovations in previous period. Column (3) reports the results of the OLS regression for the relation between collaborative innovation and alternative measurement of sustainable innovation, i.e. number of inventions. The dependent variable is the alternative measurement of sustainable innovation, *Invention*. The variable of interest is *lnJinv*, the collaborative innovations. For all regressions, we control for the firm and year fixed effects. Robust t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

4.2.1 Propensity Score Matching (PSM)

The impact of collaborative innovation may stem from differences between companies, such as whether they engage in such innovations. We use PSM to reduce the interference of unrelated factors. Specifically, PSM first calculates the likelihood of each company participating in collaborative innovation, then pairs companies with

similar conditions for comparison. This helps eliminate the effects of differences like size or industry, making the results more reliable.

$$lnJinv_{i,t} = \alpha_0 + \alpha_1 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \qquad (4)$$

First, we estimate the probability of a firm engaging in collaborative innovation. This probability is derived from the logistic model in equation (2), which is specifically employed to predict this probability. The predictors include company characteristics such as profitability, size, R&D intensity, state ownership, industry, net operating cash flow, government subsidy amount, and intangible assets, aligning with prior literature (Laursen and Salter, 2006; Balsmeier *et al*., 2017; Greco *et al*., 2017; Zhang *et al*., 2018; Mei *et al*., 2019; Moretti and Biancardi, 2020).

Next, we match companies with collaborative innovations to those without. We call the first group "participants" (the treatment group) and the second "non-participants" (the control group). To do this, we pair each participant with a non-participant that has a very similar chance of joining collaborative innovation. This chance comes from our earlier calculations. We also make sure the pairs are close enough by setting a small limit, like a tiny gap of 0.01. This keeps the two groups as similar as possible. Column (1) in Table IV presents the multivariate regression results using the PSM procedure. Consistent with our baseline results, the PSM findings indicate that collaborative innovation significantly enhances sustainable innovations.

4.2.2 Lag Terms

Regarding the second concern about identification issue. To make sure effects come after causes, we use data from the previous year for all explanatory variables. This means we look at last year's collaborative innovation to predict this year's sustainable innovation. Column (2) in Table IV presents the results of the lagged terms, demonstrating that our findings remain robust after mitigating endogeneity issues.

4.2.3 Alternative Measurements

Finally, we use an alternative measure to test the identification issue. Innovation performance is linked to the results or success level of an innovation (Audretsch and Acs 1993; Arundel and Kemp 2009; Calik and Bardudeen 2016). Therefore, sustainable innovation performance refers to the outcomes of sustainable innovations, indicating how successful these innovations are in achieving the anticipated

economic, social, and environmental results. Therefore, we use number of inventions as an alternative measurement for the sustainable innovation in our analysis. Column (3) in Table IV shows that collaborative innovation significantly enhances the sustainable innovation, which is consistent with our baseline results.

4.3 Transmission Mechanism - The Role of R&D Human Capital

We have confirmed the positive impact of collaboration on sustainable innovation. From this section onward, we introduce R&D human capital as a mediating factor linking the two and conduct a mediation analysis using models (1) - (3).

Table V reports the results of the main research focus of this paper, which is the mediating effect of R&D human capital in collaborative innovation and sustainable innovation. To ensure robustness, we conducted extreme value exclusion analysis using the middle 80% of the data on patent application quantity. Additionally, Sobel and Bootstrap tests were performed to validate the findings.

Column (1) reports the baseline result as shown in Table III. While controlling for enterprise asset size, cash flow, liability ratio, fixed assets, and enterprise characteristics, the coefficient of *lnJinv* in column (2) is 0.292 at 1% significant level. It indicates a positive relationship between the collaborative innovation and R&D human capital. This result support Hypothesis 2. When *lnJinv* and *lnApatnt* are included in model (3), their coefficients remain significant at the 1% level. It can be observed that the coefficient of *lnJinv* in column (3) is 0.035, which shows the direct effect of collaborative innovation on sustainable innovation. It is larger than in column (1), indicating a stronger positive effect. Combining the coefficients of *lnJinv* in column (2) and *lnApatnt* in column (3) reveals a negative mediating effect for R&D human capital, which is -0.003 ($\alpha_1 * \varphi = 0.029 \times (-0.032)$).

The direct effect is positive, while the mediating effect is negative. This indicates a suppression effect of R&D human capital between collaborative innovation and sustainable innovation (Preacher and Hayes, 2008; Hayes, 2017). In this study, we use the term "masking effect" to describe the unexpected negative mediating role

of R&D human capital in the mediation analysis, emphasizing its concealing characteristic within the context of collaborative innovation. These findings support Hypothesis 3.

The results above indicate that in the impact pathway of "collaborative innovation – R&D human capital – sustainable innovation," collaborative innovation has a greater positive effect on sustainable innovation, while the masking effect of R&D human capital slightly dampens this enhancement. If the reallocation of resources does not support high-quality R&D outcomes, it may increase the number of patent applications per R&D personnel without significantly improving actual innovation. This could lead to a negative masking effect (Rosenbusch *et al*., 2011).

This indicates that more applications do not necessarily equate to better outcomes. Pursuing quantity over quality may lead to a slight negative impact. This result aligns with the findings of Laursen and Salter (2006), who, in their empirical analysis of 2,707 UK manufacturing firms, emphasized that collaborative innovation should prioritize quality over quantity. Similarly, Arora *et al*. (2016a) highlight the importance of balancing collaborative innovation and patent applications in practice. Innovators should adopt strategies that ensure both the quantity and quality of innovation. Our results further demonstrate that the masking effect still exists in the causal pathway.

Due to significant differences in enterprise size, research outcomes vary across companies of different scales. The extreme values in larger and smaller companies may bias the results of the mechanism analysis. Therefore, to mitigate this bias, we truncate the top and bottom 10% of the data based on the total number of patent applications. We then use only the middle 80% of the data for the analysis of the mediating effect. The results of (4) - (6) show that the mediating effect of *lnApatnt* is consistent with the baseline model, confirming the transmission mechanism of R&D human capital.

Table V: Transmission Mechanism – The Role of R&D Human Capital

VARIABLES	*Transmission Mechanism*	*Trim (10–90%)*

	(1) Aqua	(2) lnApatnt	(3) Aqua	(4) Aqua	(5) lnApatnt	(6) Aqua
lnApatnt			-0.032 ***			-0.034 ***
			(−11.00)			(-10.71)
lnJinv	0.025 ***	0.292 ***	0.035 ***	0.012 *	0.111 ***	0.016 **
	(3.21)	(7.67)	(4.39)	(1.80)	(3.34)	(2.47)
lnJinv2	0.006 **	0.022 **	0.006 **	0.015 ***	0.045 ***	0.016 ***
	(1.99)	(2.17)	(2.28)	(5.41)	(4.05)	(6.18)
lncapsize	-0.013 **	-0.638 ***	-0.033 ***	-0.009	-0.629 ***	-0.030 ***
	(−2.32)	(-11.07)	(-5.68)	(-1.62)	(-11.24)	(-5.21)
cash	-0.035	-0.428 *	-0.048	-0.071 *	-0.172	-0.076 **
	(-1.05)	(-1.96)	(-1.44)	(-1.90)	(-1.02)	(-2.04)
rdrc	0.001 *	-0.033 ***	0.000	0.001 **	-0.035 ***	0.000
	(1.73)	(-7.70)	(-1.26)	(2.03)	(-9.25)	(-1.33)
lev	-0.004	-0.111	-0.007	-0.007	-0.015	-0.006
	(-0.19)	(-0.59)	(-0.31)	(-0.30)	(-0.10)	(-0.28)
profit	-0.001 ***	-0.004	-0.001 ***	0.000	0.002	0.000
	(−2.73)	(-0.70)	(-2.78)	(-0.45)	(0.52)	(-0.02)
fix	-0.032	-0.049	-0.034	-0.001	-0.101	-0.004
	(-0.94)	(-0.18)	(-1.02)	(-0.02)	(-0.42)	(-0.14)
soe	0.003	0.016	0.004	0.011	0.018	0.012
	(0.26)	(0.15)	(0.32)	(0.93)	(0.18)	(1.03)
cur	-0.001	0.015	-0.001	-0.002 **	0.021 **	-0.001
	(-1.11)	(1.49)	(-0.64)	(-1.98)	(2.45)	(-1.17)
lnsub	-0.017	-0.012	-0.018	-0.01	0.067	-0.008
	(-1.37)	(-0.12)	(-1.61)	(-0.93)	(0.65)	(-0.76)
rd	0.098	-8.761 ***	-0.185	0.197	-7.959 ***	-0.074
	(0.6)	(-5.74)	(-1.13)	(1.15)	(-5.49)	(-0.43)
Constant	0.405 ***	12.406 ***	0.804 ***	0.424 **	11.856 ***	0.827 ***
	(2.81)	(9.81)	(5.56)	(2.03)	(8.69)	(4.29)
Observations	7550	7548	7548	6163	6161	6161
R − squared	0.084	0.199	0.129	0.139	0.228	0.173
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Sobel Z			-0.009 ***			-0.004 ***
SZ mediation effect ratio			37.42%			30.95%

Table V (1) - (3) reports the mediation effect of R&D human capital in collaborative innovation and sustainable innovation. Extreme value exclusion analysis is conducted by using the middle 80% of the data on patent application quantity, which is shown in (4) - (6). Both steps will be complemented by Sobel tests to ensure robustness. The dependent variables are the measurement of R&D human capital (*lnApatnt*) and sustainable innovation (*Aqua*). The variables of interest are *lnJinv* and *lnApatnt*, the mediating effect coefficient $\alpha_1 * \varphi$. We control for the firm and year fixed effects. Robust t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

In the regression results of the control variables, it can be observed that during the process of mediating effect transformation, the significance of variables such as R&D expense ratio (*rdrc*) and cash flow (*Cash*) decreases from column (2) to column (3). This is because, in column (2), the effect of collaborative innovation on

R&D human capital efficiency is more driven by resource investment, while in column (3), patent application efficiency is more dependent on the efficiency of converting innovative outcomes. The change in significance highlights the complexity of transitioning to sustainable innovation. Additionally, data heterogeneity may be one of the reasons for the insignificance of certain variables (such as *Cash* and *Lev*). Differences between companies in terms of innovation capacity, financing methods, and resource allocation may obscure the significance of some variables. Overall, our control variables show results similar to the baseline analysis. This reflects how innovation works in our sample. It also points to indirect effects of some factors in companies with strong capital.

4.4 Robustness Tests

To validate the robustness of the mediating effect analysis, we conducted a series of robustness tests. These included the Sobel test, the Bootstrap method, and Two-Stage Least Squares (2SLS) regression to address potential endogeneity issues. We also performed analyses using alternative measurements of the mediator. Through these multi-faceted in-depth analyses, we strengthened the causal inference of the mediating mechanism and demonstrated the robustness of the theoretical framework proposed in this paper.

4.4.1 Sobel and Bootstrap Tests

First, we conducted Sobel and Bootstrap tests to examine the significance and robustness of the mediating effect of R&D human capital. Sobel test is used to examine the mediating role of R&D human capital in the relationship between collaborative innovation and sustainable innovation. The Sobel coefficients of -0.009 and -0.004 in Table VI are both statistically significant at the 1% level, with mediating effect proportions of 37.42% and 30.95%, respectively. These results confirm that the mediating effects pass the Sobel test, indicating that approximately one-third of the impact of collaborative innovation on sustainable innovation is mediated through R&D human capital, highlighting its crucial role.

However, if the data do not follow a normal distribution (for example, if there is a concentration of R&D investment among many firms at either low or high values), the results of the Sobel test may not be reliable. In such cases, the Bootstrap method can be used to conduct repeated sampling and expand the sample size, simulating the distribution and range of the mediating effect. This approach effectively addresses this limitation. We applied a bootstrap analysis by constructing 500 samples through repeated sampling to ensure this condition is met.

Table VI shows that neither the direct effect coefficient γ_1 nor the indirect effect coefficient $\alpha_1 * \varphi$ estimated intervals that crossed zero, indicating a significant mediating effect in both baseline regression and the 80% truncated model. These two tests reinforce the conclusions of the baseline regression regarding the mechanism of action.

Table VI: Bootstrap Tests

VARIABLES		*Observed Coef.*	*Bootstrap Std. Err.*	*Normal-Based [95% Conf. Interval]*	
Baseline	γ_1	-0.009 ***	0.0013273	-0.0120695	-0.0068666
	$\alpha_1 * \varphi$	0.035 ***	0.0078817	0.0193256	0.0502211
***Trim* (10–90%)**	γ_1	-0.004 ***	0.0011496	-0.0060551	-0.0015487
	$\alpha_1 * \varphi$	0.016 ***	0.005911	0.0045012	0.0276721

Table VI reports the Bootstrap test of the transmission coefficient γ_1 represents direct effect; The coefficient $\alpha_1 * \varphi$ represents the indirect effect. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

4.4.2 2SLS Regression

Second, to more robustly validate the causal logic of the indirect path from collaborative innovation to sustainable innovation, we used the 2SLS method, accounting for potential biases or endogeneity issues. We introduce R&D human capital as an instrumental variable in the regression of collaborative cooperation and sustained innovation, forming a two-stage regression: collaborative cooperation to R&D human capital in the first stage and R&D human capital to sustainable innovation in

the second stage. This approach controls for the endogeneity issue between variables. It further demonstrates that the effect of *lnJinv* on *Aqua* is indirectly realized through *lnApatnt*.

The results of the first-stage regression (1) of Table VII, the coefficient of *lnJinv* on *lnApatnt* is positive. In the second-stage regression, the coefficient of *lnApatnt* on *Aqua* is also positive. This result eliminates the interference of potential biases in causal inference and further validates the mediating role of *lnAptant*. The 2SLS results not only confirm that the effect of *lnJinv* on *Aqua* includes an "indirect path," but also support the causal assumptions in the mediation effect model, demonstrating that *lnApatnt* plays a crucial role in the transmission process.

Table VII: 2SLS Regression

	lnApatnt **(1)**	***Aqua*** **(2)**
$lnJinv$	0.292***	
	(7.71)	
$lnApatnt$		0.086***
		(2.76)
$Observations$	7,218	7,218
$R-square$	0.470	0.470
$Control\ variables$	YES	YES
$Firm\ FE$	YES	YES
$Year\ FE$	YES	YES

Table VII presents the 2SLS regression results, where the endogenous variable is *lnJinv*, and the instrumental variable is *lnApatnt*. Column (1) shows the first-stage regression of the 2SLS model, while column (2) reports the second-stage regression. The variables of interest are *lnJinv* and *lnApatnt*. Firm and year fixed effects are controlled for. Robust t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

4.4.3 Alternative Measurement of Mediator

Third, in this section, we attempt to enrich the research dimensions of R&D human capital. Specifically, we replace the original mediating factor (R&D human efficiency) with alternative variables such as the number of R&D personnel, the proportion of R&D personnel, and per capita R&D expenditure, and then conduct further robustness analysis.

The results show that the number of R&D personnel, the proportion of R&D personnel, and per capita R&D expenditure were used as alternative mediating variables. The regression results in columns (1), (3), and (5) of Table VIII indicate that *lnJinv* has no significant effect on these alternative variables. The mediation effect cannot be established. The *lnJinv* coefficient in columns (2), (4), and (6) is approximately 0.025, indicating the direct effect of collaborative innovation on sustainable innovation.

Table VIII: Alternative Measurement of Mediator

VARIABLES	*RDstuff (1)*	*Aqua (2)*	*RDsratio (3)*	*Aqua (4)*	*lnAinv (5)*	*Aqua (6)*
$lnJinv$	0.004	0.025***	0.000	0.025***	0.006	.025***
	(0.00)	(3.21)	(0.68)	(3.21)	(0.49)	(3.22)
$RDstuff$		0.000				
		(1.44)				
$RDsratio$				0.062*		
				-1.73		
$lnAinv$						-0.003
						(-0.68)
$Observations$	7,550	7,550	7,550	7,550	7,548	7,548
$R-squared$	0.199	0.084	0.088	0.084	0.334	0.084
$Control\ Variables$	YES	YES	YES	YES	YES	YES
$Firm\ FE$	YES	YES	YES	YES	YES	YES
$Year\ FE$	YES	YES	YES	YES	YES	YES

Table VIII presents the mediation effect regression results by replacing the original mediating variable *(lnApatnt*) with *RDstuff, RDsratio*, and *lnAinv,* which serve as proxies for the number of R&D personnel, the proportion of R&D personnel, and per capita R&D expenditure, respectively. The results omit the first step of the mediation model (Model 1) and only display the regression results for the subsequent two steps (Models 2 and 3). The variables of interest are *lnJinv*. Firm and year fixed effects are controlled for. Robust t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***.

From a definitional perspective, the impact of the collaborative innovation mechanism, with the three alternative variables as mediators, is not significant. This further illustrates that the core of sustainable innovation lies in the efficiency and output of R&D activities, with the measurement of input quantity being more indirect in capturing the influence mechanism. "Per capita patent applications by R&D personnel" as an indicator of R&D human capital can better capture the innovation output efficiency of R&D personnel. This efficiency-oriented indicator aligns with

the mechanism of continuous R&D enhancing innovation output efficiency, and more effectively reflects the actual impact path of collaborative innovation on sustainable innovation.

4.5 Further Analysis

After confirming the robust mediating role of R&D human capital, we explore this mechanism further in different cases. This part covers cooperation types, innovation levels, major industries, and changing effects to deepen our understanding.

4.5.1 Cooperation Types

In this section, we conducted a group analysis on different cooperation types, specifically focusing on industry-university-research (IUR) and inter-enterprise collaboration, to explore the presence and functioning of the transmission mechanism within these types.

In China, universities play a significant role in theoretical research. Collaboration among academia, industry, and research institutes fosters innovation and benefits enterprises (Wei *et al*., 2013; Jiang *et al*., 2020; Fan *et al.*, 2011; Zeng, 2023). Meanwhile, as shown in the descriptive statistics of Table II, the proportion of enterprises engaging in collaborative innovation is 43%, with 12% of all enterprises participating in IUR cooperation. Clearly, the collaborative type of IUR has become an important collaboration method for enterprises.

As a traditional types of cooperation, we anticipated that the R&D human capital transmission role presented in inter-enterprise collaboration would be generally consistent with the results of transmission mechanism (Table V). However, we are interested in whether the transmission mechanism of the IUR cooperation mode is effective.

Table IX: Cooperation models

VARIABLES	***Industry–University–Research***			***Enterprise Cooperation***		
	(1)	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***

	Aqua	*lnApatnt*	*Aqua*	*Aqua*	*lnApatnt*	*Aqua*
lnApatnt			-0.028 ***			-0.032 ***
			(-2.88)			(-10.07)
lnJinv	0.036 **	0.143	0.040 **	0.023 **	0.299 ***	0.032 ***
	(2.25)	(1.12)	(2.49)	(2.54)	(7.36)	(3.55)
Constant	-0.228	14.793 ***	0.139	0.387 ***	12.476 ***	0.784 ***
	(-0.60)	(3.68)	(0.37)	-2.58	(9.43)	(5.2)
Observations	947	949	947	6601	6601	6601
Control variables	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Soble Z			-0.004			-0.010 ***
SZ/mediation effect		-10.87%			-41.46%	
Bootstrap − bdiff of (3) and (6): lnApatnt				-0.005		
Bootstrap − bdiff of (3) and (6): lnJinv				-0.008		

Table IX reports the IUR ((1) - (3)) and Enterprise-Cooperation ((4) - (6)) model of the transmission mechanism. oth steps are complemented by Sobel tests to ensure robustness. The dependent variables are the measurement of R&D hu- an capital and sustainable innovation. The variables of interest are *lnJinv* and *lnApatnt*, the mediating effect coefficient ı∗φ. We control for the firm and year fixed effects. Robust t-statistics are reported in parentheses. Significance at the 10%, 5%, nd 1% levels is indicated by *, **, and ***, respectively.

As shown in Table IX, in the grouped analysis of IUR collaboration, the coefficients of *lnApatnt* is significant in column (3), indicating the primary existence of the R&D human capital mediating effect. However, when Sobel and Bootstrap tests are conducted, the mediating effect of R&D human capital cannot be confirmed. In inter-company cooperation, the R&D human capital exhibits a masking effect, which is -0.01 ($\alpha_1 * \varphi = (-0.299) * (-0.032)$). This result passes both the Sobel and Bootstrap tests, confirming the robustness of the mediating effect. To further investigate the comparative relationship between IUR cooperation and inter-company cooperation in transmission mechanism performance, model (3) was used to test the inter-group coefficient differences. Bootstrap analysis reveals that the inter-group coefficient differences in *lnApatnt* (-0.005) and *lnJinv* (-0.008) are not significant, showing that there is no comparative relationship between the two collaboration modes.

This answer was elucidated in the study by Belderbos *et al.* (2014) about the technological activities and financial performance of European, US, and Japanese firms. Partners in inter-firm collaboration focus more on inventions in current application areas, while IUR cooperation emphasizes the market value of related connections.

In the short term, the value of this collaboration is more evident among firms. Therefore, there is reason to believe that due to time lags and the lag in the reflection of research value, the mechanism of IUR collaboration may not be significant.

4.5.2 Quantile Regression

This study focuses on Chinese A-share enterprises and does not cover non-listed (small and medium-sized) enterprises or non-local firms, which limits the generalizability of the conclusions. As shown in the descriptive analysis in Table II, there is significant heterogeneity in the number of patent applications across firms of different sizes. Therefore, this section employs quantile regression to examine how different firms (such as large or small ones, or those with varying levels of innovation activity) affect innovation. It can reveal that the impact of collaborative innovation on sustainable innovation varies across different contexts.

We use the number of patent applications and asset size as conditioning variables. With these variables, we examine the pathway strength of R&D human capital in collaborative innovation across different quantiles (e.g., high- and low-R&D investment firms) and its potential masking effect. For the sake of brevity in table presentation, Table X omits the results of the first two regression stages of the mediation effect and only presents the regression results of model (3) for discussion.

Panel (a) in Table X shows the regression analysis based on the quartiles of application quantity. In the quantile regression of patent application numbers, all *lnApatnt* coefficients are significant. That indicates a significant mediating effect of R&D human capital. In terms of the direct impact of collaborative cooperation. Collaboration level (*lnJinv)* has a strong effect, matching the main findings in Table V. In column (2), it weakens. In columns (3) and (4), it turns negative, which is opposite to the results in Table V. This confirms the conclusion that more applications are not necessarily better; excessive applications can have a negative impact on the application success rate, thus reducing the efficiency of sustainable innovation in enterprises.

Table X: Quantile Regressions

			(a)	
VARIABLES	***(1)***	***(2)***	***(3)***	***(4)***
			Aqua	
lnApatnt	-0.033 ***	-0.030 ***	-0.035 ***	-0.021 **
	(−3.49)	(−2.84)	(−4.07)	(-2.31)
lnJinv	0.076 *	0.016	-0.031 **	-0.016 *
	(1.83)	(0.90)	(-2.39)	(-1.80)
Constant	1.108 ***	0.762 **	0.665 ***	0.584 **
	(2.84)	(2.45)	(2.74)	(2.57)
Observations	1803	1978	1844	1923
Control variables	YES	YES	YES	YES
FIrm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
			(b)	
VARIABLES	***(1)***	***(2)***	***(3)***	***(4)***
			Aqua	
lnApatnt	-0.030 ***	-0.037 ***	-0.038 ***	-0.032 ***
	(-4.89)	(-4.95)	(-5.36)	(-5.01)
lnJinv	0.024 *	0.049 ***	0.034 ***	0.025 **
	(1.87)	(2.92)	(3.18)	(2.10)
Constant	0.389	1.672 **	1.419 *	1.097 **
	(1.02)	(2.54)	(1.88)	(2.55)
Observations	1874	1893	1894	1887
Control variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table X reports the quantile regressions of patent application number (a) and enterprise asset scale (b). The dependent variables are the measurement of R&D human capital and sustainable innovation. The variables of interest are *lnJinv* and *lnApatnt*, the mediating effect coefficient $\alpha_1 * \varphi$. We control for the firm and year fixed effects. Robust t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

In the regression analysis based on quartiles of enterprise capital scale, panel (b) in Table X indicates that the regression results for all four quartile segments are consistent with Table V's main findings, fluctuating around -0.35. The coefficient of the *lnJinv* for the direct effect is also significant and is more pronounced within the 25–75% quantile range. This suggests that the mediating effect of R&D human capital is relatively evenly distributed across different asset sizes.

These results indicate that the mediating effect of R&D human capital exhibits a masking effect across different asset sizes and patent application numbers. However, in the patent application numbers grouping, the direct effect of collaborative innovation is negatively impacted by an excessive number of cooperative R&D projects. This further clarifies the argument that quality takes precedence over quantity in collaborative innovation.

4.5.3 Group Study of the Three Major Sectors

Now, we explore the mediating effect across major industries. The path dependencies of sustainable innovation vary across different industries. For example, the secondary industry (manufacturing) may rely more on technological research and process innovation, while the tertiary industry (services) depends on service innovation and improvements in user experience. Breaking down the transmission mechanism by specific industries helps reveal the differences in the demand for R&D human capital across industries. It also clarifies the impact of these differences on sustainable innovation.

In the analysis of the impact mechanism in the primary industry, column (1) in Table XI shows that collaborative innovation in agriculture can effectively promote the growth of R&D human capital. This, in turn, significantly enhances R&D efficiency. However, in column (2), there is no evidence to suggest that R&D human capital plays a significant role in promoting sustainable innovation. In the secondary and tertiary industries, the mediating effects of R&D human capital are significant, with values of -0.009 and -0.011($\alpha_1 * \varphi$), respectively. These results consistent with the conclusions in Table V.

This is because innovation in the primary industry tends to focus on areas such as production technology, resource management, and environmental protection. These innovations focus on better production and lower costs. Their R&D often depends on industry internal industry collaboration, like farms, fisheries, and research groups working together (Lu *et al*., 2024). Sustainable innovation (especially patent application success rates) often requires a high level of originality and technological

breakthroughs, while primary industry innovations focuses on practical improvements. Compared to the manufacturing or information technology sectors, technological innovation in the primary industry tends to be more fundamental.

4.5.4 Conditional mediation effect

The mediation effect model typically assumes that the mediating effect is universally present and fixed. However, in reality, the strength and direction of the mediating effect of R&D human capital may change under different conditions.

By using a conditional mediation effect model and adding an interaction term (*lnJinv*∗*lnApatnt*) to the regression model, we can further examine how the mediating variable (*lnApatnt*) affects the relationship between collaborative innovation input and innovation performance under different conditions.

The results in column (2) of Table XII show that the coefficient of *lnJinv* is largely consistent with the results in Table V. The mediating effect coefficient has slightly decreased, to -0.007 ($\alpha_1 * \varphi$). The coefficients of *lnApatnt* and *lnJinv* have the same sign, further validating the robustness of the mediation model. The coefficient of the interaction term is -0.016, indicating that R&D human capital plays a moderating role in the relationship between collaborative innovation and sustainable innovation. Specifically, an increase in *lnApatnt* somewhat suppresses the positive effect of *lnJinv* on *Aqua*. This conclusion further emphasizes the importance of prioritizing R&D efficiency for the development of collaborative innovation.

Table XI: Group Study of the Three Major Sectors

VARIABLES	***Primary Sector***		***Secondary Sector***		***Tertiary Sector***	
	(1)	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***
	lnApatnt	***Aqua***	***lnApatnt***	***Aqua***	***lnApatnt***	***Aqua***
lnApatnt		-0.051		-0.032***		-0.032***
		(-1.35)		(-10.19)		(-4.18)
lnJinv	0.925***	0.145	0.282***	0.025***	0.330***	0.035***
	(3.11)	(1.54)	(6.11)	(3.62)	(4.58)	(2.91)
Constant	28.240***	3.159*	12.311***	0.881***	8.475***	0.255

	(3.75)	(1.74)	(7.84)	(5.35)	(4.17)	(0.94)
$Observations$	94	94	5,618	5,618	1,781	1,781
$R-squared$	0.509	0.292	0.201	0.142	0.164	0.133
$Control\ variables$	YES	YES	YES	YES	YES	YES
$Firm\ FE$	YES	YES	YES	YES	YES	YES
$Year\ FE$	YES	YES	YES	YES	YES	YES

Table XI presents the mediation effect regression results by the three major sectors. (1)(2) are for primary sector, (3)(4) are for second sector and (5)(6) are for tertiary sector respectively. The results omit the first step of the mediation model (Model 1) and only display the regression results for the subsequent two steps (Models 2 and 3). The variables of interest are *lnJinv* and *lnApatnt*. Firm and year fixed effects are controlled for. Robust t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***.

Table XII: Conditional Mediation Effect

VARIABLES	*lnAptant*	*Aqua*
$lnApatnt$		-0.024***
		(-8.59)
$lnJinv$	0.292***	0.036***
	(7.67)	(3.01)
$lnJinv * lnApatnt$		-0.016***
		(-7.42)
$Constant$	12.406***	0.901***
	(9.81)	(6.04)
$Observations$	7,548	7,548
$R-squared$	0.199	0.155
$Control\ Variables$	YES	YES
$Firm\ FE$	YES	YES
$Year\ FE$	YES	YES

Table XII presents the results of the conditional mediation effect model. The results omit the first step (Model 1) of the mediation effect model and only display the regression results of the subsequent two steps (Models 2 and 3). The variables of interest are *lnJinv, lnApatnt*, and *lnJinv*lnApatnt*. Firm and year fixed effects are controlled for. Robust t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

5. Conclusion

5.1 Discussion of Findings

This study explores the relationship between collaborative innovation and sustainable innovation, introducing a new perspective on the impact pathway by incorporating R&D human resources. It systematically explains the mediating role of R&D human capital between the two. The results indicate that collaborative innovation

enhances firms' sustainable innovation capabilities by integrating internal and external resources, thereby improving the efficiency of R&D human capital. This impact mechanism holds across firms of different asset sizes but does not function effectively in industry-university-research collaborations or the primary sector. However, the masking effect of R&D human capital partially weakens the positive impact of collaborative innovation on sustainable innovation, with this effect being particularly pronounced in R&D-intensive firms.

This masking effect has been observed in British manufacturing (Laursen and Salter, 2006) and European technology and energy collaboration cases (Ghobakhloo and Fathi, 2021). Take it a step further, we elucidate the mediating role of R&D human capital within this phenomenon. Specifically, if a company misjudges market dynamics, resulting in R&D objectives that deviate from demand, even a significant increase in R&D outputs may fail to align with actual market needs, thus undermining the efficiency of collaborative innovation. This finding indicates that if R&D focuses on quantity rather than quality, the low efficiency of R&D may offset some of the benefits of collaboration.

The discovery of the masking effect within the collaborative and sustainable innovation pathway system challenges the conventional view. This view holds that R&D investment always has a positive impact on innovation. From a deeper mechanistic perspective, it highlights the complexity of the sustainable innovation mechanism and advocates for a resource-collaborative innovation approach that prioritizes quality over quantity.

Theoretically, the masking effect deepens the understanding of R&D human capital efficiency, suggesting that innovation research should shift from a quantity-based to a quality-focused perspective. Practically, it advises firms to avoid blindly expanding R&D scale and instead optimize resource allocation. Particularly in cross-departmental collaboration, integrating technological expertise or introducing diverse technological support can effectively reduce redundant investment and enhance innovation quality.

These findings not only confirm the role of R&D human capital as a pathway in collaborative innovation but also enrich innovation theory by highlighting the masking effect. Furthermore, they provide empirical evidence and practical guidance for firms to optimize R&D strategies in complex environments.

5.2 Practical Implications

In collaborative efforts, leveraging the R&D efficiency of human capital is crucial for sustainable innovation in enterprises. Enterprises of different sizes can adopt differentiated strategies accordingly: large enterprises can enhance R&D patent efficiency by integrating internal resources with high-end partners. By learning from the experience of BMW and Daimler in jointly establishing ShareNow, they can focus on high-quality patent outputs through technological collaboration to address competition in the shared mobility market. Although the analysis did not reveal a significant effect of IUR, universities still offer strong research and talent advantages, which are especially beneficial for SMEs. For instance, a textile enterprise in Zhejiang optimized its R&D talent configuration by leveraging a collaborative network while developing environmentally friendly dyes in partnership with a university.

Policymakers can support this transformation through targeted incentives. The experience of Shenzhen’s "Peacock Plan" is worth promoting, which focuses on attracting high-end talent, optimizes the human resource structure and significantly improves enterprise patent R&D efficiency through knowledge spillovers. The Digital platforms further amplify this effect: Jiangsu’s "IUR Collaborative Innovation Cloud Platform" integrates resources and demands, not only shortening collaboration cycles but also improving the output efficiency of high-quality patents, which is an approach that aligns with the interactive logic between human capital and network collaboration outlined in intellectual capital theory. At the industry level, the government plays a leading role through technological support and promotion. The smart agriculture pilot in an agricultural region in Shandong has proven beneficial for focusing on resource optimization and enhancing patent quality. In manufacturing, R&D centers should adopt intelligent manufacturing production lines to boost the precision and application efficiency of patent technologies; in the service sector,

innovation labs can be leveraged to develop green financial services, emphasizing the practicality of digital patents. Overall, all three sectors should embrace open innovation and cross-industry collaboration to optimize R&D human capital efficiency and drive sustainable innovation through high-quality patents.

At the same time, policymakers should pay attention to the ethical dimension of collaborative innovation. In existing cases, the Zhejiang textile industry has enhanced brand trust by showcasing environmental protection technologies, while the service sector in Shanghai has shaped an ethical image through carbon neutrality projects. This indicates that sustainable production and technological progress can help enterprises gain public recognition, and governments can enhance social acceptance of sustainable innovation through public education and engagement initiatives.

5.3 Future Perspectives

When exploring the role of R&D human capital in the collaborative and sustainable innovation mechanisms, we found that this field still has potential for further development in terms of dimensional expansion. Sustainable innovation is a dynamic process, involving the accumulation effect of innovation capabilities, knowledge spillovers, and the ability to convert results into profits.

In this study, we attempted to use intangible assets as representative variables for sustainable innovation analysis. However, due to the complexity of path analysis, the effects of intangible assets did not directly emerge. According to the resource-based view (Barney, 1991), intangible assets (such as intellectual property, brand value, and organizational culture) are considered key resources that, when combined with human capital, form the basis for sustainable innovation. In the manufacturing industry, patent sharing increases the technology adoption rate (Eppinger, 2021). Corporate culture can also moderate the collaborative effect rate, influencing sustainable innovation (Linnenluecke and Griffiths, 2010). These perspectives suggest that multi-dimensional factors, such as intangible assets, new product market performance, and others, can comprehensively assess the causes of sustainable innovation (Nejjari and Aamoum, 2022; Medeiros *et al*., 2014).

External environmental factors may further moderate the observed effects. For example, changes in economic policies (such as intellectual property protection) may enhance the role of collaborative innovation by optimizing resource allocation or technology sharing. Meanwhile, global innovation trends (such as green technologies or multinational R&D alliances) may amplify the mediating effect of R&D human capital through knowledge spillovers (Eppinger *et al*., 2021; Chesbrough, 2020). Although we conducted a heterogeneity analysis of firms based on R&D quantity and asset scale using quantile regression in Section 4.5.2, which to some extent broadened the applicability of our research scope. However, these factors were not directly tested in this study. This reminds us that when interpreting the masking effect, we need to take a broader context into account.

Furthermore, the open innovation environment in developed countries may weaken the masking effect through diversified knowledge and resource flows, while policy instability and resource constraints in developing countries may amplify its impact (De Marchi, 2012). Therefore, the impact of the masking effect on global industries or innovation ecosystems may vary depending on the external environment.

This study reveals the relationship between collaborative innovation, R&D human capital, and sustainable innovation, as well as the masking effect mechanism. However, the limitations in dimensional expansion, external environmental factors, and global applicability provide room for improvement in future research. First, measuring sustainable innovation should shift from single indicators to multidimensional perspectives, integrating intangible assets (e.g., IP, brand), market performance (e.g., sales, share), and knowledge spillovers (e.g., tech diffusion) to build a comprehensive evaluation system reflecting innovation dynamics. Second, future research could include SMEs and startups to analyze their collaborative innovation effects under resource constraints or greater flexibility, enhancing universality. Finally, the applicability of the findings needs to be validated through studies on non-local firms and multi-country data comparisons. Additionally, case studies of multinational firms, combining qualitative and quantitative methods, can help explore the varying roles of R&D human capital across different contexts. This approach can uncover heterogeneity in global industrial ecosystems and align with SDG 17.

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