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The complex role of knowledge diversity in firm's collaborative innovation under inclusive culture

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Collaboration innovation (CI) is increasingly becoming a crucial strategy for enterprises to enhance their technological capabilities. The knowledge base among members and collaborative environment significantly impact on the success of collaboration. However, existing research has overlooked exploration of inter-firm's knowledge diversity and inclusive culture. This study was developed information/decision-making theory and social categorization theory to investigate how knowledge diversity and inclusive culture affect firms' CI. This study collected 5126 annual observations from 712 listed companies in China's high-tech manufacturing industry between 2016 and 2023. Regression analysis through Stata 17.0 was used to test the conceptual model. By employing the fixed effects model, we found that: (1) knowledge variety (KV) positively impacts CI, while knowledge separation (KS) exhibits an inverted U-shaped relationship with CI; (2) KV positively influences collaborative innovation depth (CD) but does not significantly affect collaborative innovation breadth (CB), while KS exhibits an inverted U-shaped relationship with CD; (3) Inclusive culture primarily manifests in relation to KS, which positively moderates the effect of KS on CD. This exploration of when and how the KS promotes or inhibits CI broadens the understanding of the consequences of KS in an inter-firm perspective.

Keywords Knowledge diversity, Collaboration innovation, Collaborative innovation breadth, Collaborative innovation depth, Inclusive culture

In recent year, collaborative innovation (CI) has emerged as a critical strategic response to the escalating complexity of technological development and intensifying global competition. In China, CI has become a national priority, as reflected in the "Innovation-Driven Development Strategy" initiated in 2016, which encourages enterprises to internal and external resources to enhance innovation capability. According to the 2020 Statistical Analysis of Innovation Activities in Chinese Enterprises, among the 279,000 enterprises engaging in technological innovation that year, 188,000 conducted collaborative innovation, accounting for 67.4%. It indicates that collaborative innovation has become a dominant mode for enterprise-level R&D and value creation, especially in high-tech manufacturing sectors that rely heavily on knowledge integration across organizational boundaries.

Despite the growing prevalence of CI in both practice and research, the mechanisms through which firms achieve effective collaboration remain insufficiently understood. One factor that has not been fully explored is knowledge diversity—referring to the heterogeneity of knowledge resources. Since the concept of "knowledge diversity" emerged, most scholars have focused on intra-firm knowledge diversity, focusing on its impact on team creativity[1,2] and internal innovation performance[3]. In contrast, relatively little is known about inter-firm knowledge diversity and its implications for CI. Intra-firm knowledge diversity refers to differences in knowledge among individuals or teams within the same organization, this perspective does not capture the complexities of knowledge diversity across organizations. In contrast, inter-firm knowledge diversity involves the variation in knowledge bases between different firms.

Some scholars have noted the importance of inter-firm knowledge differences by introducing related concepts such as knowledge proximity[4], knowledge distance[5] and knowledge relatedness[6]. These constructs emphasize how the degree of similarity or difference in firms' knowledge bases can significantly shape the effectiveness of collaborative innovation. However, these concepts primarily measure dyadic similarity, that is, how close two firms are in terms of their technological or cognitive domains. In contrast, inter-firm knowledge diversity focuses not on the closeness between two specific firms, but between a focal firm and the broader population

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of firms in the market. Such diversity reflects a firm's position within the broader market and more precisely captures the core purpose of collaborative innovation.

Moreover, existing studies on knowledge diversity yield mixed findings. Based on information/decision-making theory, knowledge diversity enhances innovation by expanding access to heterogeneous information and improving decision quality[7,8]. Conversely, social categorization theory suggests that diversity may exacerbate cognitive conflict, inhibit cooperation, and reduce performance due to ingroup–outgroup distinctions[9,10]. These competing perspectives, typically applied at the team level, have rarely been tested in inter-organizational contexts, leaving a theoretical gap regarding how diversity affects CI across firm boundaries.

To address these inconsistencies, this study decomposes knowledge diversity into two dimensions—knowledge variety (KV) and knowledge separation (KS)—drawing from the framework proposed by Harrison and Klein[11]. KV reflects the breadth of knowledge types shared across firms[12], while KS refers to the degree of difference in knowledge structure between firms[13]. Harrison and Klein[11] argued that KV generally facilitates collaborative innovation by providing diverse information and perspectives, enhancing both the breadth and depth of innovation. In contrast, KS can positively impact innovation by promoting knowledge recombination through knowledge conflict , but it can also negatively affect performance by creating can positively impact innovation by promoting knowledge recombination through knowledge conflict , but it can also negatively affect performance by creating communication and integration barriers when knowledge differences are too large[11]. Therefore we think that knowledge diversity must be examined separately to clarify each effects. In addition, we disaggregate CI into collaboration innovation breadth (CB) and collaboration innovation depth (CD), in line with emerging literature that recognizes their different antecedents and outcomes[14,15].

These inconsistent findings also prompt consideration of their boundary conditions, such as organizational culture[16] (e.g., inclusive culture, learning orientation), leadership style[17] (e.g., transformational leadership), and knowledge management capabilities[18] (e.g., absorptive capacity). Knowledge management theory posits that culture profoundly influences knowledge management activities and processes[19]. From an intra-group collaboration perspective, it is not uncommon to observe an inclusive culture moderating the relationship between knowledge diversity, knowledge sharing, and innovation. An inclusive culture plays a crucial role in integrating, absorbing, and managing knowledge[20]. Similarly, in the context of CI, an inclusive culture may also influence the process from within to outside. However, there is limited research discussing the impact of internal inclusive culture on the CI process. Therefore, there is a need to expand scenario studies of CI from the perspective of inclusive culture.

Given these gaps, it is essential to explore the following research questions: How do different dimensions of inter-firm knowledge diversity (KV and KS) affect collaborative innovation? Do these effects differ between collaborative innovation breadth and depth? How does inclusive culture moderate the relationship between knowledge diversity and CI? To solve those questions, we conduct the theoretical framework in Fig. 1. In summary, this study adopts a cognitive perspective and draws on information/decision-making theory and social categorization theory to examine the CI behavior of 712 high-tech manufacturing companies listed in China from 2016 to 2023. This study explores the relationships among inter-firm knowledge diversity, CI, and inclusive culture.

By answering these questions, this study contributes in three aspects to the innovation literature. First, we extend the application of information/decision-making theory and social categorization theory to the inter-firm level by examining how knowledge diversity influences CI across organizational boundaries. Secondly, we clarify prior inconsistent findings by decomposing knowledge diversity into KV and KS and examining their respective linear and nonlinear effects on CB and CD. It empirically tests the linear effect of KV on CI and the nonlinear effect of KS. Additionally, it decomposes CI into the dimensions of CB and CD, revealing the complex relationships between knowledge diversity and CI, thus expanding CI theory. Lastly, the study deeply explores the moderating role of inclusive culture on the relationship between knowledge diversity and CI, thereby broadening the contextual mechanisms in the study of knowledge diversity and CI.

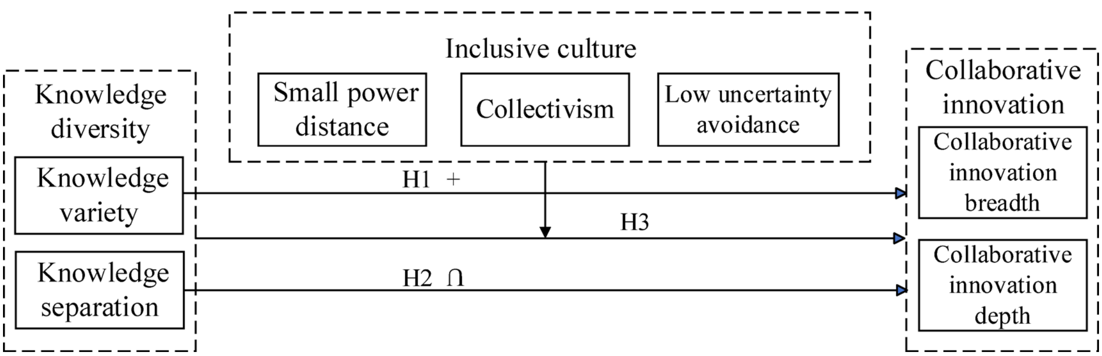

Fig. 1. Theoretical framework.

Theoretical background and hypothesis development

Knowledge diversity

The term "diversity" originated from ecology, referring to the distribution of various species within a community, reflecting both balance and differentiation among species. Management scholars have adapted this concept to describe member internal diversity, where knowledge diversity is one form of deep-level diversity[21]. However, scholars have long conflated diversity, similarity, heterogeneity, and related concepts, leading to inconsistent findings in studies of knowledge diversity. Harrison and Klein[11], from the perspective of internal diversity, delineated diversity into three dimensions: separation, variety, and disparity. Disparity emphasizes the unequal distribution of social expectations such as compensation and power, while separation and variety are more frequently applied in the field of knowledge management. Therefore, following Harrison's approach[11], our study categorizes inter-firm knowledge diversity into two dimensions: variety and separation. Inter-firm knowledge diversity involves comparing and measuring knowledge diversity collectively among all enterprises.

For an individual enterprise, knowledge diversity manifests horizontally as KV, representing the types or scopes of knowledge. Vertically, knowledge diversity signifies KS, which denotes the homogeneity or heterogeneity resulting from differences in knowledge among different enterprises[22]. Such differences can lead to either attraction among similar groups or further repulsion among dissimilar groups. In contrast, the distinction between inter-firm and intra-firm knowledge diversity as defined in our paper lies in two aspects: First, inter-firm KS is not based on the total knowledge quantity of a single enterprise, but rather on the total quantity across all enterprises in one knowledge category. Second, the level of KV is evaluated not from a baseline of zero but from the average level of one category of knowledge across all enterprises. Although KV and KS share similarities in that both can reflect greater quantity as the degree increases, KV reflects more similarity with other enterprises, whereas KS primarily reflects more differences from other enterprises.

In contrast to previous scholars who used patent data to measure explicit knowledge diversity among enterprises, this study employs employee education and profession data to measure tacit knowledge diversity. Knowledge management theory suggests that relative to explicit knowledge, tacit knowledge is considered more valuable due to its contextual dependency, non-replicability, and creativity[23]. From a cognitive perspective, individuals with similar educational backgrounds or within the same occupational categories tend to have similar cognitive frameworks, facilitating easier communication and cooperation, thereby enhancing the efficiency of knowledge creation. This alignment of knowledge is particularly crucial in cross-enterprise projects, as it significantly influences the efficiency of combining explicit knowledge.

Knowledge variety and collaboration innovation

KV refers to the diversity of knowledge sources within an organization, encompassing a wide range of educational backgrounds, work experiences, and areas of expertise among employees. According to the information/decision-making theory, information is the basis of decision-making, and the quantity, scope, and quality of information determine the effectiveness of decision-making[7]. Enterprises with high KV are characterized by a wide range of educational backgrounds or work experiences of their employees as well as a large number of employees. Obviously, enterprises with KV have a variety of and diverse information, which is conducive to enterprises acquiring and processing information from outside.

From the perspective of information acquisition, enterprises with KV can access information from various fields, thereby increasing the potential for collaborative innovation. Employees with diverse knowledge backgrounds act as interfaces between the enterprise and the external environment, using their social networks and personal expertise to access knowledge from various fields[24,25]. Proactively, their diverse knowledge backgrounds not only broaden the scope of the enterprise's knowledge search but also introduce their own social resources, enabling the enterprise to access more potential cooperation opportunities, including cross-field collaborations. Furthermore, KV enhances enterprises' ability to identify and select suitable partners for collaboration. According to information/decision-making theory, decision-makers rely on the quantity and scope of information when facing uncertain or complex situations. Enterprises with high KV can better evaluate the expertise of potential partners, understand their value, and establish complementary partnerships[25].

From the perspective of information processing, enterprises with KV have an advantage in utilizing external knowledge, allowing them to swiftly process the latest information from various fields, enhance their capability to address complex issues, and deliver accurate and timely information for innovative decision-making[26]. Decision-makers are constrained by limitations and biases during information processing and decision-making. Enterprises with high-quality knowledge resources can supply diverse information inputs, mitigate information biases and uninformed decision-making, and enhance the success rate and effectiveness of collaborative innovation projects. The broader the enterprise's range of experience, the stronger its ability to process and absorb heterogeneous information[27]. High-quality knowledge resources can reduce information uncertainty, foster information sharing and coordination among partners, and thereby enhance efficiency and CI performance. We therefore proposed the following hypotheses:

Hypothesis 1 Knowledge variety has a positive impact on collaborative innovation.

Knowledge separation and collaboration innovation

KS further emphasizes external differences in the quantity of knowledge resources across various categories, building upon diversity. According to social categorization theory, individuals typically classify others into "ingroup" and "outgroup"[28]. People tend to be more cooperative and friendly towards ingroup members but exhibit exclusionary behavior towards outgroup members. In the process of CI, enterprise members prioritize internal members and those externally similar, viewing other organizations more as outgroup members compared to internal ones. Therefore, there is a distinction between information/decision theory and social categorization theory: while information/decision theory suggests diversity enhances CI, social categorization theory posits that diversity may cause separation, potentially restraining CI.

The impact of knowledge separation on collaborative innovation can be better understood by examining it from a dynamic perspective. When the level of KS is low, it is easier to find similar external collaboration partners. At this stage, due to the limited knowledge stock and weak risk resistance, there is a higher risk of failure in independent innovation within the enterprise[29]. Therefore, enterprises may rely on appropriate external partners to mitigate the risk of R&D failures. However, a small knowledge stock limits absorption and internalization capacity, and CI may not proceed smoothly[30]. As knowledge stock and R&D experience accumulate, enterprises can acquire more knowledge and technology through CI. When the profits exceed the coordination costs incurred during CI, enterprises demonstrate a strong willingness for collaboration.

At moderate levels of KS, the situation changes. Moderate knowledge separation promotes the exchange, recombination, and integration of diverse knowledge, enhancing CI efficiency. The coordination costs of managing diverse knowledge are balanced by the benefits of knowledge exchange, resulting in a positive net effect on CI performance. This is consistent with the Absorptive Capacity Theory, which suggests that enterprises with moderate knowledge diversity can efficiently identify, assimilate, and apply external knowledge. Studies have shown that moderate KS enhances innovation performance by encouraging diverse idea exchange[31]. Moreover, moderate KS allows firms to benefit from both similar and diverse knowledge without facing significant communication barriers[32].

However, as KS increases beyond a moderate level, the differences in knowledge bases between participants become too significant, leading to high KS. Excessive knowledge separation creates substantial barriers to effective knowledge integration, making it difficult for organizations to align external knowledge with their internal capabilities. This increased complexity in knowledge integration can lead to cognitive overload, where an organization's information processing capacity becomes overwhelmed. And, it could dampen enthusiasm for CI[33]. Under these circumstances, enterprise members may shift towards internal R&D activities. Therefore, moderate KS is beneficial for innovation as it promotes the exchange and integration of ideas. However, excessive KS may create obstacles in understanding and communication, thereby affecting collaboration efficiency and innovation outcomes. We therefore proposed the following hypotheses:

Hypothesis 2 There is an inverted U-shaped relation between knowledge separation and collaborative innovation.

Different dimensions of collaborative innovation

Collaborative innovation is a multidimensional construct, often characterized by variation in both the breadth and depth of inter-firm innovation collaboration[13]. CB refers to the number or variety of innovation partners, reflecting the openness and scope of the firm's external knowledge search. while CD indicates the intensity or frequency of innovation collaboration, representing how deeply knowledge is shared and integrated among partners. This dimensional view of CI captures the dual nature of inter-organizational knowledge integration: firms may pursue broad partnerships to access diverse external knowledge or deep partnerships to co-develop and co-innovate with trusted collaborators. Recognizing this distinction helps us better analyze how knowledge diversity may influence different patterns of collaborative behavior. When CB is higher and CD is lower, the relationship between a company and its partners tends to be a weak tie. Conversely, when breadth is lower and depth higher, the relationship tends to be a strong tie. According to the theory of strong tie and weak ties, weak ties are more effective at bridging social boundaries to acquire information and other resources, with better information dissemination effects than strong ties. Strong ties, although slightly weaker in information dissemination, convey more trust and influence[34].

Given the risk of core knowledge leakage in CI, strong ties are more conducive to building a trusted collaborative innovation environment and reducing opportunistic risks compared to weak ties. Furthermore, weak ties require more initial investment in search capital, which can lead to adverse outcomes due to excessive searching. Deepening strong ties can lower transaction costs, and repeated interorganizational cooperation enhances innovation performance[35]. Ambrosio et al.[36] also argued that CB may harm a company's innovation performance, but deep and long-term relationships are more conducive to corporate innovation. Therefore, when it comes to choosing partners for cooperative innovation, enterprises tend to select partners with whom they can have deep cooperation. Furthermore, while knowledge diversity benefits both the breadth and depth of collaboration, compared to breadth, depth typically involves more complex and specialized knowledge exchanges[14]. Knowledge diversity encompasses knowledge from various professional domains and different perspectives, which particularly facilitates the depth of innovation collaboration—where close integration is essential—more than its breadth. Therefore, we proposed the following hypotheses:

Hypothesis 3 The effect of knowledge diversity on CD is stronger than its effect on CB.

Method

Sample and procedure

We utilized Chinese enterprises to test our hypothesis. The increasing trend of collaborative innovation among Chinese enterprises has provided us with abundant research materials. According to the Chinese Research Data Service Platform, the number of joint patent applications by Chinese listed companies surged from 3088 in 2008 to 26,870 in 2022. Moreover, high-tech enterprises are more active in innovation than traditional enterprises, making them more suitable as research subjects. Therefore, within the framework provided by the "Classification Guidelines for High-Tech Industries (Manufacturing)" and the "Industry Classification Guidelines for Listed Companies" disseminated by the National Bureau of Statistics, we strategically targeted five distinct industries:

pharmaceutical manufacturing; computer, communication, and other electronic equipment manufacturing; chemical raw materials and chemical products manufacturing; instrumentation manufacturing; and railway, shipbuilding, aerospace, and other transportation equipment manufacturing. Furthermore, the impetus provided by China's 2016 unveiling of the "Innovation-Driven Development Strategy" has galvanized a fervent drive for innovation within the corporate sector. Building upon this backdrop, we narrowed our focus to a temporal scope spanning from 2016 to 2023, encompassing publicly listed companies on the Shanghai and Shenzhen stock exchanges.

Regarding sample selection, adherence to the following criteria is essential. First, considering the disparities between the two industry classification standards, the National Bureau of Statistics defines high-tech industries (manufacturing) as those characterized by a relatively high intensity of R&D investment. Hence, based on the recent three-year average (2020–2022) of R&D investment intensity within high-tech industries (2.67%, 2.71%, and 2.91%, respectively), publicly listed companies were chosen from industries where the R&D investment intensity over the past three years exceeds the annual industry average. Second, samples potentially afflicted with financial data anomalies were excluded, including ST, *ST, and PT category companies, as well as those companies delisted before 2019 and listed after 2020. Third, companies with severely incomplete information disclosure or significant financial data deficiencies were also excluded from the sample pool.

Following the screening process, data from 712 listed companies were collected, comprising a total of 5126 annual observations. The primary data sources included the China Stock Market and Accounting Research Database (CSMAR), Patyee Database, and Wind Database. In instances where individual years within the sample lacked data, we supplemented with annual report data or the mean of the nearest two years. To mitigate the influence of extreme values, tail truncation at the 1st and 99th percentiles was applied to the continuous variables. Data processing and analysis for this study were conducted using Stata 17.0 and Excel 2021.

Measure

*Collaboration innovation***.** A joint patent application is a technological innovation outcome achieved through collaboration by multiple innovative entities[37], which can largely reflect the level of CI. Therefore, we used the logarithm of (the number of joint patent applications plus one) of enterprises to measure the level of CI. Drawing on the approach by Kobarg et al.[15], we further processed the data on joint patent applications. CB was characterized by the number of collaborating organizations involved in joint patent applications, while CD was represented by the average collaboration frequency with organizations, calculated as the total number of joint patent applications divided by the number of collaborating organizations. Compared to design patents, invention patents and utility model patents more effectively demonstrate a company's innovation capability. Therefore, we only examined invention and utility model patents.

*Knowledge diversity***.** Since our dependent variable is based on patent data, we intentionally avoid using patent-based classifications (e.g., IPC codes) as independent variables, in order to prevent common method bias and measurement redundancy. Moreover, patents primarily represent explicit knowledge, which is codified, standardized, and publicly disclosed. However, our study focuses on implicit knowledge diversity, which reflects the uncodified, experience-based knowledge embedded within organizations. According to Nonaka[38], implicit knowledge—deeply rooted in individual experience and context—is often more valuable and inimitable than explicit knowledge, and plays a central role in organizational learning and innovation. Implicit knowledge is stored in the minds of employees and cannot be easily codified or transferred. Prior research suggests that the heterogeneity of implicit knowledge is closely related to the educational background[39] and professional functions of employees[40], which influence their cognitive perspectives and absorptive capacity. Following this logic, we utilized the following coding rules for educational background: graduate, undergraduate, associate, high school, and other levels. For professional background, it is classified based on departmental functions into production, finance, sales, technology, and other categories. This approach allows us to capture the input side of knowledge diversity and provides a conceptually appropriate alternative to patent-based measures of innovation inputs.

In general, business partners tend to focus more on an enterprise's high-quality knowledge resources, which better reflect the strength of the enterprise's core technology. To highlight the importance of individuals with higher education and relevant professional backgrounds for enterprise innovation, our study represented KV as the number of categories with high-quality knowledge resources exceeding a threshold. Specifically, we used two measures—graduate personnel and technical personnel—that are more conducive to innovation performance. Here, we defined the threshold as the mean value of the entire sample's data. For example, if a company's sample data for technical personnel exceeds the overall sample mean in this dimension, KV score for this category is defined as 1, and so on. Therefore, KV is defined as a discrete variable ranging from 0 to 2.

To avoid the cross-impact of educational and professional backgrounds, which makes it difficult to clearly distinguish differences in various types of knowledge, when considering KS, we chose to focus solely on the dimension of professional background, and make educational background as robustness test. Drawing from the approach of Chen and Liang[41], we used the entropy index method to measure differences between different types of knowledge, denoted as $TKS = -\sum p_{it} * lnp_{it}$, where p_{it} represents at t time the proportion of knowledge resources that an enterprise sample possesses in category i out of the total number of categories. A higher value of KS indicates stronger KS. Both intra-firm diversity and inter-firm diversity use the entropy index, but the meanings are very different. For example, we have companies A and B, both of which have X and Y knowledge. Company A has 1 unit in X and 1 unit in Y, and company B has 5 units in X and 5 unit in Y. In the calculation of intra- firm diversity, p is equal to the ratio between the amount of a certain type of knowledge and the total amount of knowledge within the enterprise. Therefore, the p value of company A and company B is the same ($p_a = 1/(1+1) = 0.5$, $p_b = 5/(5+5) = 0.5$). But for third-party cooperative institutions, the knowledge diversity of company B is obviously better than that of company A, which is caused by inter-firm knowledge diversity.

Control variables. In order to accurately assess the impact of corporate knowledge diversity on CI, we introduced relevant control variables, including firm size, firm age, financing constraints, and ownership type. Although these variables are not the main focus of our study, previous research has demonstrated their relevance to CI. Therefore, controlling for these variables is crucial to mitigate potential confounding effects on the dependent variable (CI) and clarify relationships between variables.

Size. Large-scale enterprises may have more resources and capabilities to implement knowledge management and innovation activities, thereby influencing research outcomes[31]. Therefore, we controlled for firm size using the logarithm of total assets.

Age. Established enterprises with longer operating histories often have accumulated extensive knowledge and experience in knowledge combination and utilization, which can affect innovation[42]. Hence, this study measured firm age using (current year—year of establishment).

Financing constraints (SA). CI allows firms to benefit from knowledge spillovers from other innovators, but converting this external knowledge into internal innovation output requires high financial costs. Firms facing severe financing constraints may struggle to provide the necessary financial support for collaborative research and development activities, thereby reducing their propensity to engage in collaborative R&D[43]. Therefore, this study used the SA index to measure financing constraints[44], $SA = 0.737*Size + 0.043*Size^2 - 0.040*age$.

Ownership. In China, ownership type can influence the extent of advantages in funding, technology, and policies, playing a significant role in firms' strategic choices and innovation activities[45]. Thus, this study controlled for ownership type, where state-owned enterprises are defined as 1 and non-state-owned enterprises are defined as 0.

Empirical model

This study constructs econometric models to examine the impact on collaborative innovation(CI), collaborative innovation breadth (CB), and collaborative innovation depth (CD). Taking CI as an example, the models are presented below, while the models for CB and CD follow a similar structure and are therefore omitted here for brevity. Specifically, Eqs. (1, 2, 3) represent the models used to investigate the determinants of CI.

$$CI_{it} = \alpha_0 + \sum \alpha_2 CVs_{it} + \sum Year + \sum Ind + \varepsilon_{it} \tag{1}$$

$$CI_{it} = \beta_0 + \beta_1 TKV_{it} + \sum \beta_2 CVs_{it} + \sum Year + \sum Ind + \theta_{it} \tag{2}$$

$$CI_{it} = \gamma_0 + \gamma_1 TKS_{it} + \gamma_2 TKS_{it}^2 + \sum \gamma_3 CVs_{it} + \sum Year + \sum Ind + \mu_{it} \tag{3}$$

Here, i represents individual firms, t represents time. KS^2 represents the squared term of KS. *CVs* represent the aforementioned control variables. To prevent potential influences from economic cycles, policy changes, and unexpected events on the model, this study also controls for time (Year) and industry (Ind) fixed effects, with random error terms denoted by ε, θ, and μ.

According to the theoretical analysis in the preceding sections, if β_1 is significantly positive, it aligns with Hypothesis 1. If γ_2 is significantly negative and of opposite sign to γ_1 it aligns with Hypothesis 2. However, Haans, Pieters and Visconti[46] pointed out limitations in solely judging U-shaped or inverted U-shaped relationships based on the squared term coefficient. They outlined three criteria to determine the presence of an inverted U-shape in the model: first, the significance of the squared term coefficient; second, the significance of the coefficients at the minimum and maximum of the independent variable within the sample range, aligning with the slopes at the left and right extremes of the inverted "U-shape"; and third, the 95% confidence interval of the critical value within the sample data range. Therefore, this study further verifies these relationships using the U-test in Stata.

Results

Preliminary analyses

We calculated the means, standard deviations, and correlations of our focal variables. The results are exhibited in Table 1.

The mean of CI is 0.59, indicating that the level of enterprise CI is low. The CI standard deviation is 1.06, indicating significant variation among enterprises. The correlation between KS and KV is relatively high, approaching 0.7. To avoid collinearity, these two variables are not included in the same model in this study. The correlations among other variables are moderate, with many being statistically significant, suggesting that the research hypotheses in this study are reasonably supported. Furthermore, due to the relatively high correlation between Size and KS, Age and SA, we conducted further tests for multicollinearity and found that without including quadratic terms, the variance inflation factors (VIF) for each variable do not exceed 10, indicating the absence of severe multicollinearity issues. Because of the large differences in measurement scales between variables, and to minimize inter-variable collinearity, continuous variables are standardized prior to regression analysis in this study.

The regression results for collaboration innovation

The variable data passed Hausman test, therefore this study employed a fixed effects panel model. To mitigate heteroscedasticity effects, heteroscedasticity-robust standard errors were used in the regression model. Table 2 presents the direct effect analysis of knowledge diversity on CI. Model 1 serves as the base model with only

Variable	CI	CB	CD	KV	KS	Size	Age	SA	Mean	SD
CI	1								0.59	1.05
CB	0.76***	1							0.87	1.88
CD	0.74***	0.44***	1						1.37	4.01
KV	0.21***	0.24***	0.17***	1					0.42	0.70
KS	0.19***	0.27***	0.15***	0.64***	1				0.04	0.05
Size	0.21***	0.29***	0.14***	0.59***	0.72***	1			9.48	0.44
Age	0.04**	0.09***	−0.03**	0.10***	0.07***	0.17***	1		2.94	0.30
SA	−0.02	−0.04***	0.05***	−0.05***	0.06***	−0.18***	−0.92***	1	−3.89	0.24
Ownership	0.03**	0.04**	0.00	0.26***	0.18***	0.22***	0.21***	−0.20***	0.22	0.42

Table 1. Descriptive statistics and correlations. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level; CI = collaboration innovation; CB = collaborative innovation breadth; CD = collaborative innovation depth; KV = knowledge variety; KS = knowledge separation; Size = firm size; Age = firm age; SA = financial constraint.

Variables	Model 1	Model 2	Model 3
Size	0.168*** (3.69)	0.140*** (3.12)	0.113 (2.03)
Age	0.037 (0.40)	0.025 (0.28)	0.032 (0.35)
SA	0.033 (0.35)	0.042 (0.45)	0.041 (0.45)
Ownership	0.012 (0.18)	0.010 (0.15)	0.016 (0.25)
KV		0.079** (2.44)	
KS			0.195* (1.66)
KS^2			−0.134** (−1.99)
Constant	−0.116 (−1.32)	−0.133 (−1.53)	−0.152* (−1.70)
Ind/year FE	YES	YES	YES
Adj.R^2	0.027	0.030	0.028
F	6.111	5.703	5.394

Table 2. The regression results for collaboration innovation. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

control variables included. Model 2 adds KV to Model 1 to examine the linear relationship between KV and CI. Model 3, also based on Model 1, includes KS and KS^2 to examine the nonlinear relationship between KS and CI.

From Model 2, it is evident that the regression coefficient of KV is statistically significant at the 5% level ($\beta = 0.079, p < 0.05$), indicating that higher levels of KV are associated with higher levels of CI, thereby confirming Hypothesis 1. Combining with the theoretical analysis in the previous sections, higher KV enhances knowledge search and integration capabilities, thereby increasing opportunities for enterprise CI. This result suggests that when firms engage with a broader range of knowledge sources, such as partners from diverse industries, disciplines, or technological domains, they are more likely to access complementary knowledge and novel perspectives.

According to Model 3, the regression coefficient of KS^2 is significantly negative at the 5% level ($\beta = -0.134$, $p < 0.05$). This study further conducted a test for an inverted U-shaped relationship, and the regression results are reported in Table 3.

From Model 3 of Table 3, it can be observed that the critical point of 0.730 falls within the data range of −0.846 to 7.236. Moreover, the slope of KS is significantly positive at the minimum and significantly negative at the maximum, rejecting the null hypothesis of "no inverted U-shaped relationship" and further supporting Hypothesis 2. Based on the regression analysis, this study concludes that, under unchanged conditions, an intermediate level of KS is most favorable for enterprise CI, while excessively low or high levels of KS are detrimental to enterprise CI. It tells us, if knowledge separation is too low, collaboration may become stagnant due to a lack of complementary knowledge and intellectual challenge. Conversely, if the cognitive gap is too large, mutual understanding, communication, and coordination become increasingly difficult, which can hinder effective knowledge integration and reduce innovation efficiency.

The result of different collaboration innovation type

The impact of knowledge diversity on the breadth and depth of collaboration is depicted in Tables 4.

Models 5 and 6 show that knowledge diversity has no significant impact on CB. While Model 8 and 9 indicate knowledge diversity exhibits a significant effect on CD. And model 9 also indicates a significant inverted U-shaped relationship between KS and both collaborative innovation depth at the 10% significance level, which also have been proved in the Table 5. These confirm Hypothesis 3, emphasizing that knowledge diversity has a stronger impact on collaborative innovation depth. This suggests that collaborative innovation depth requires

Test model	Model 3		Model 11		Model 13	
Item	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Internal	−0.846	7.236	−0.824	7.980	−0.848	6.566
Slope	0.421	−1.737	0.681	3.245	0560	−2.000
t-value	1.903	−1.982	2.268	−2.441	1.878	−2.013
$p>\|t\|$	0.028	0.024	0.012	0.007	0.030	0.022
Extreme point	0.730		0.702		0.774	
Overall t-value	1.90		2.27		1.88	
Overall $p>\|t\|$	0.029		0.011		0.031	

Table 3. The result of U-test for collaboration innovation.

	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Variables	CB	CB	CB	CD	CD	CD
Size	0.165***	0.164***	0.148***	0.075	0.021	−0.024
	(3.23)	(3.11)	(2.67)	(1.38)	(0.40)	(−0.33)
Age	0.029	0.028	0.030	0.007	−0.016	−0.008
	(0.33)	(0.32)	(0.34)	(0.07)	(−0.15)	(−0.08)
SA	0.214*	0.204*	0.229**	−0.174*	−0.157*	−0.186**
	(1.89)	(1.91)	(2.13)	(−1.80)	(−1.67)	(−1.90)
Ownership	−0.054	−0.054	−0.052	0.005	0.001	0.011
	(−0.87)	(−0.87	(−0.84)	(0.05)	(0.02)	(0.22)
KV		0.004			0.155***	
		(0.12)			(3.16)	
KS			0.073			0.323*
			(0.72)			(1.90)
KS^2			−0.079			−0.157*
			(−1.03)			(−1.86)
Constant	−0.246**	−0.247**	−0.262***	0.074	0.040	0.020
	(−2.53)	(−2.56)	(−2.72)	(0.83)	(0.46)	(0.21)
Ind/year FE	YES	YES	YES	YES	YES	YES
Adj.R^2	0.066	0.066	0.067	0.012	0.022	0.015
F	9.251	8.525	7.912	4.530	4.314	4.110

Table 4. The regression results for collaborative innovation breadth and depth. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

Test model	Model 9	
Item	Lower bound	Upper bound
Internal	−0.840	7.134
Slope	0.590	−2.034
t value	1.778	−1.862
$p>\|t\|$	0.038	0.032
Extreme point	0.953	
Overall t value	1.78	
Overall $p>\|t\|$	0.038	

Table 5. The results of U-test for collaborative innovation depth.

a higher level of mutual trust, absorptive capacity, and sustained engagement, all of which are more likely to be activated and enriched when partners bring heterogeneous knowledge resources to the table.

This discrepancy may be attributed to the nature of CB and its relatively lower sensitivity to knowledge characteristics. CB reflects the number or variety of external partners involved in innovation, which is often driven by strategic motives such as access to resources, market expansion, or policy incentives, rather than the internal knowledge structure of the firm. In contrast, CD emphasizes the intensity and depth of interaction with existing partners, which relies more heavily on mutual understanding, knowledge integration, and cognitive alignment. Given this, KV and KS are more likely to influence CD, where close collaboration requires effective communication and absorptive capacity. In shallow or broad collaborations, such deep-level knowledge interaction may be limited, thereby weakening the observable effect of knowledge diversity. Consequently, we do not provide empirical evidence that knowledge diversity exerts a stronger influence on CD than on CB, but our findings suggest that it has a more direct impact on CD.

Robustness tests

To further examine the robustness of the empirical results, this study conducted robustness tests from two aspects[47]. First, independent variable replacement. To assess whether KV processing affects the results, KV is defined as 1 and 5, representing the mean. Additionally, KS is replaced with educational background rather than professional background. The results are presented in Table 6 as Model 10 and Model 11.

Second, Sample size reduction. To mitigate the potential influence of enterprises with no CI behavior on the results, enterprises are excluded if they did not hold joint patents during the period from 2016 to 2023, leaving only enterprises engaged in CI. The results are shown in Table 6 as Model 12 and Model 13. Furthermore, in both of these robustness tests, a U-test is conducted on KS in Table 3. In sum, KV still has a positive effect on CI, KS has an inverted U-shaped effect on CI, remaining consistent with the earlier findings. Therefore, Hypotheses 1 and Hypothesis 2 are robust.

Moderator of inclusive culture

Establishing a culture of open innovation and knowledge sharing can facilitate ent erprises in acquiring and managing external knowledge[48]. Many scholars agree that an inclusive culture helps unleash the creative potential of diversity[49]. The most classic cultural framework in cultural studies is proposed by Hofstede[50], which encompasses six dimensions at the national and ethnic levels: power distance, individualism versus collectivism, uncertainty avoidance, masculinity versus femininity, long-term versus short-term orientation, and indulgence versus restraint. Currently, many scholars have gradually applied these cultural dimensions to the organizational level[51]. However, these cultural dimensions do not specifically differentiate inclusive characteristics.

However, Nishii[52] summarized the essence of an inclusive culture at the team level, comprising three dimensions: employment equity, difference integration, and decision making. Employment equity emphasizes respect and equality in resource allocation and the exercise of power within the organization. Difference integration emphasizes the integration of employees' cognition and values through a shared vision and compatible goals. Decision making reflects the organizational willingness to tolerate risks and employees' trial-and-error approach in innovation.

Comparing the cultural dimensions of these two scholars, Nishii's employment equity, difference integration, and decision making are akin to Hofstede's small power distance (SPD), collectivism (CM), and low uncertainty avoidance (LUA), representing the concretization of national cultural concepts at the organizational level. Therefore, combining insights from Hofstede and Nishii, we explored organizational inclusive culture through the dimensions of SPD, CM, and LUA. We posit that SPD, CM, and LUA positively moderate the effects on both CB and CD.

Building upon the previous step of categorizing CI, we further examined the moderating effect of an inclusive culture on the relationship between knowledge diversity and CI. To demonstrate the moderating effect on the linear relationship, the interaction coefficient between the moderator variable and the independent variable must be significant. For the moderating effect on the inverted U-shaped relationship between the independent variable and the dependent variable, we drew from Haans et al.[46] two-step test method first, examining the shift direction of the inverted U-shaped curve caused by the moderator variable to determine whether the inflection point of the inverted U curve shifts leftward or rightward; second, examining whether the moderator variable causes the inverted U-shaped curve to become flatter or steeper, indicating the change in the slope's absolute value of the inverted U-shaped curve.

Type	Independent variable replacement		Sample size reduction	
Model	Model 10	Model 11	Model 12	Model 13
Size	0.119** (2.65)	−0.018* (−0.26)	0.153** (2.22)	0.119 (1.44)
Age	0.010 (0.11)	−0.019 (−0.18)	0.172 (1.02)	0.200 (1.18)
SA	0.010 (0.11)	−0.195 (-1.99)	− 0.081 (− 0.56)	−0.040 (−0.27)
Ownership	0.015 (0.23)	0.012 (0.22)	−0.052 (−0.50)	−0.046 (−0.44)
KV	0.118*** (2.50)		0.141** (2.16)	
KS		0.313 (2.01)		0.345* (1.87)
KS^2		−0.223***(−2.42)		−0.228**(−2.43)
Constant	−0.128 (−1.46)	0.028 (0.32)	0.008 (0.05)	−0.035
Ind/Year FE	YES	YES	YES	YES
Adj.R^2	0.031	0.015	0.053	0.052
F	5.730	4.305	6.130	5.798

Table 6. Robust tests for collaboration innovation. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

Since he main effect of KV and KS on CB is not significant, this pathway is omitted in the subsequent moderation analysis. Taking the moderating effect of SPD as an example, the models are specified in Eqs. (4 and 5). The tests for the moderating effects of CM and LUA follow the same structure and are therefore not repeated.

$$CD_{it} = \delta_0 + \delta_1 TKV_{it} * SPD + \sum \delta_2 CVs_{it} + \sum Year + \sum Ind + \rho_{it} \tag{4}$$

$$CD_{it} = \chi_0 + \chi_1 TKS_{it} * SPD + \chi_2 TKS_{it}^2 * SPD + \sum \chi_3 CVs_{it} + \sum Year + \sum Ind + \sigma_{it} \tag{5}$$

The results are shown in Table about the moderating effect of inclusive culture on the relationship between knowledge diversity and CD.

The moderator of small power distance

Power distance refers to individuals' perception of power distribution within the organization, reflecting their psychological acceptance of supervised management. When individuals perceive relatively equal power distribution and closer psychological distance between themselves and higher-ups, they are more willing to express their opinions and ideas, and engage in active communication and collaboration, thereby promoting CI[53]. Conversely, when individuals perceive a greater psychological distance from higher-ups, they may feel their opinions and ideas are not valued, leading to distrust or defensiveness toward leadership and colleagues, thus inhibiting communication and collaboration[54]. Additionally, the difficulty of knowledge transfer necessitates knowledge workers' demand for autonomy in management and decision-making, urging organizations to gradually decentralize decision-making authority[55].

Power distance reflects employees' psychological acceptance of supervised management. The higher the number of supervisory managers, the stronger the perceived power of higher-ups by employees[56]. Therefore, we represented power distance using the ratio of the number of senior managers to the number of employees, reverse-coded in our study.

We examined the moderating effect of SPD on the relationship between knowledge diversity and CD. Model 14 and 15 present the results in the Table 7.

As we can see, only Model 15 indicates that the coefficient of KS^2 multiplied by SPD is negatively significant at the 10% level ($\beta = -1.250, p < 0.1$). To illustrate the moderating effect more intuitively, we also depict the moderating curve of inclusive culture based on the regression results (See Figs. 2 and 3).

From Fig. 2, it can be observed that as the level of SPD increases, it is an inverted U-shaped relationship between KS and CI. Conversely, when the level of SPD is lower, the relationship curve between KS and CD flips from an inverted U-shaped relationship to a U-shaped relationship. Therefore, SPD intensively enhances the inverted U-shaped relationship between KS and CD.

The moderator of collectivism

Individualism emphasizes the realization of individual freedom, interests, and self-value, while collectivism emphasizes team cooperation, coordination, and collective interest achievement. In a collectivist culture, individuals must conform to team goals and ideas, fostering knowledge sharing and CI, mutually inspiring and achieving, maximizing the utilization efficiency of knowledge resources and team innovation efficiency, thereby promoting improvement in overall innovation performance[57]. In a collectivist culture, organizational members

	SPD moderation		CM moderation		LUA moderation	
Variables	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19
Size	0.015	−0.016	0.016	−0.032	0.025	−0.035
Age	−0.016	−0.007	−0.016	−0.007	−0.015	−0.012
SA	−0.160*	−0.163*	−0.159*	−0.180*	−0.147	−0.186*
Owneiship	0.003	0.010	0.002	0.013	0.013	0.022
KV	0.139***		0.154***		0.155***	
Inclu	0.023	−0.501**	−0.016	−0.015	0.006	−0.033
KV* Inclu	0.035		0.029		0.028	
KS		0.684***		0.341*		0.370**
KS2		1.078*		−0.184**		−0.243**
KS*Inclu		−0.470**		0.03		0.072**
KS2*Inclu		−1.250*		−0.024		−0.137**
Constant	0.024	0.424*	0.04	0.021	0.034	0.005
Ind/Year FE	YES	YES	YES	YES	YES	YES
Adj.R2	0.022	0.016	0.022	0.015	0.022	0.019
F	4.014	3.42	3.785	3.398	3.795	3.407

Table 7. Regression results of moderating effect of inclusive culture. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level. Inclu = Inclusive culture, in different models, Inclu is represented by SPD, CM, or LUA.

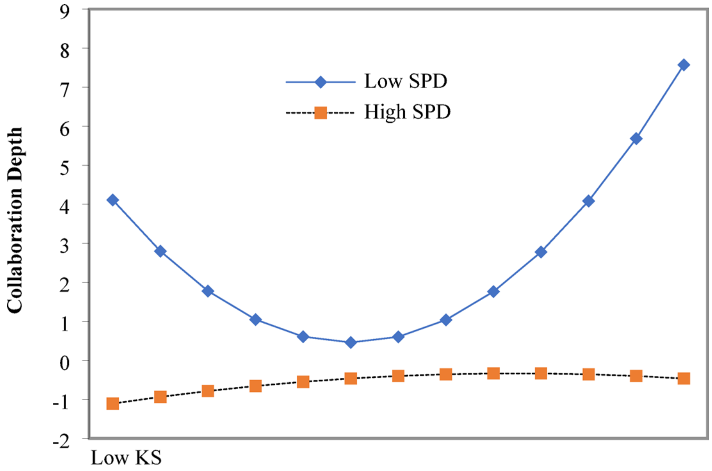

Fig. 2. Moderating role of SPD on the relationship between KS and CD.

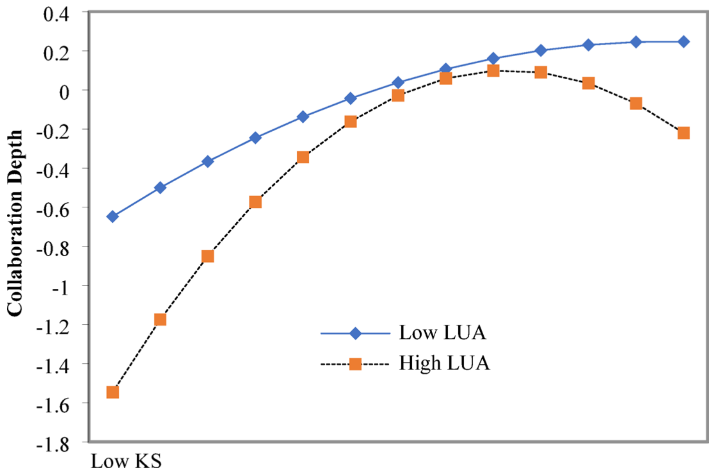

Fig. 3. Moderating role of LUA on the relationship between KS and CD.

pay more attention to cohesion and stability, further enhancing trust and cooperation among members, thereby forming a virtuous cultural system and knowledge ecology, promoting the health and sustainable development of innovation ecosystems[58].

The distinction between collectivism and individualism lies in whether the organization aims to incentivize the majority's interests, which are manifested through compensation, among other factors[59]. Hence, we used the ratio of average management salary to average employees' salary as a measure of individualism/collectivism, reversed in coding in our study.

Our study examined the moderating effect of CM on the relationship between knowledge diversity and CD. The result is presented in the Table 7. Model 16 and 17 shows that CM does not significantly moderate the relationship, whether the independent variable is knowledge variety (KV) or knowledge sharing (KS). One possible explanation is that, while collectivism emphasizes group orientation and shared goals, the formation of deep collaborative ties may rely more on interpersonal trust, mutual commitment, or organizational routines, which are not necessarily enhanced by high collectivism.

The moderator of low uncertainty avoidance

Uncertainty avoidance refers to an organization's conservative attitude towards uncertain risks. When an organization exhibits high uncertainty avoidance, diverse resources are identified as critical assets for maintaining business profitability and competitive advantage. Such organizations are less willing to undertake additional technological and operational risks associated with innovation, which hinders knowledge sharing and dissemination[60]. Conversely, when an organization exhibits low uncertainty avoidance (LUA), diverse resources are perceived as key assets supporting innovative development, reinforcing the organization's inclination towards innovation strategies, and enhancing innovation capability, level, and performance.

Uncertainty avoidance represents an organization's conservatism towards unknown risks. The attitudes of senior management determine the organization's risk aversion; studies show that the older the CEO, the more risk-averse they tend to be[61]. Therefore, we use CEO age as a measure of uncertainty avoidance, reverse-coded in our study.

Our study examined the moderating effect of LUA on the relationship between knowledge diversity and CD. The result is presented Model 18 and 19 in Table 7. Model 19 shows that the coefficient of KS^2 multiplied by LUA is negatively significant at the 5% level. From Fig. 3, it can be seen that as the level of LUA increases, the critical point of KS shifts leftward, and the inverted U-shaped curve becomes steeper. Therefore, LUA enhances the inverted U-shaped relationship between KS and CD.

Discussion

Theoretical implications

Three significant theoretical implications can be drawn from this study. First, it demonstrates the impact of inter-firm knowledge diversity on CI, which not only supplements the literature on inter-firm knowledge diversity but also expands the application of information/decision-making theory and social categorization theory. Previous studies have rarely explored how knowledge diversity functions in inter-firm settings. Bodla et al.[20] find intra-firm knowledge diversity consistently enhances innovation in intra-firm contexts. However, our study reveals that even deep-level diversity, specifically in the form of knowledge separation (KS) between firms, may produce negative effects on collaborative innovation when it exceeds an optimal level. Furthermore, our results contrast with Wang et al.[4], who adopt a proximity-based network perspective and argue that greater knowledge proximity facilitates the growth of innovation networks. While their study suggests that similarity in knowledge bases fosters collaboration, speciously KV. Together, we offer a more nuanced understanding of knowledge diversity in inter-firm collaboration, revealing that both the content and structure of knowledge relationships must be carefully balanced to maximize innovation outcomes.

Second, this study delves into the complexities of knowledge diversity and CI, elucidating the intricate impacts of knowledge diversity on CI. On the one hand, KV and KS have distinct impacts on CI. The results indicate that the multi-dimensional characteristics of knowledge diversity are a significant reason for its inconsistent influence on CI. We demonstrate the inverted U-shaped effect of KS on CI, which aligns with Choi[22]. However, unlike Choi[22], we also discover the positive impact of KV on CI. Most scholars elaborate on the characteristics of knowledge diversity from a single dimension, while this paper divides it into two dimensions and demonstrates the multi-level connotation of knowledge diversity. On the other hand, based on the sub-dimensions of knowledge diversity, we further segment CI into CB and CD. The findings show that the inconsistent effect of knowledge diversity also extends to CB and CD, with its impact on CD being more apparent. CB and CD are pivotal dimensions of CI, with scholars often discussing their divergent effects on firm innovation performance but less frequently exploring their antecedents to CI behavior. Thus, this study extends the relevant literature on CI.

Third, this study elucidates the impact mechanism of knowledge diversity on CB and CD from the perspective of inclusive culture, exploring the partial positive moderating effects of SPD, CM, and LUA on the relationship between knowledge diversity and CI. Previous literature has recognized that inclusive culture can influence knowledge diversity and internal cooperation within enterprises but has not explored its impact on CI. Furthermore, scholars have discussed the mediating or moderating roles of abilities such as knowledge recombination, absorption, and integration in the CI process but have not focused on their relationship with the internal environment closely associated with these abilities. Particularly in the context of these cultural dimensions on innovation, which are often considered double-edged swords[62], their inherent connections from the perspective of inclusive culture have not been fully integrated. By focusing on CI, this study not only further elucidates the essence of inclusive culture but also expands its application scenarios.

Practical implications

The findings of this study have significant practical implications for managers, policymakers, and innovation leaders seeking to enhance CI in organizations. Based on our results, we provide the following targeted recommendations.

First, we suggest that managers should address the deficiencies in managing knowledge diversity. Our findings reveal that many firms still face challenges in effectively managing knowledge diversity. Specifically, firms often struggle to balance KV and KS. In practice, some organizations overly emphasize knowledge variety, encouraging a broad range of expertise without sufficient integration, leading to confusion and communication barriers. Conversely, some firms maintain collaborations where KS between partners is too low, meaning that partners possess highly similar knowledge bases. This lack of knowledge disparity can lead to redundant perspectives, limit the introduction of new ideas, and reduce the potential for creative problem-solving. Such deficiencies are often due to a lack of strategic planning in knowledge management, insufficient assessment of partner knowledge diversity, and an overemphasis on maintaining cognitive alignment rather than leveraging diverse expertise. To address these issues, managers should prioritize the strategic management of knowledge diversity. This involves not only expanding the range of KV but also carefully managing KS to maintain an optimal balance. Specifically, we recommend the following strategies: (1) choose partners with complementary knowledge rather than vastly different expertise, ensuring that knowledge differences are manageable and beneficial; (2) establish knowledge-sharing platforms, such as regular cross-functional meetings and digital knowledge-sharing systems, to facilitate understanding between partners with different knowledge bases; (3) regularly assess the knowledge diversity of teams using tools such as a "knowledge matrix" or "knowledge radar," which can help managers identify gaps in knowledge variety and excessive knowledge separation.By strategically managing KV and KS, firms can optimize their collaborative innovation performance, leveraging diverse perspectives while minimizing cognitive conflicts.

Second, we suggest that firms and policymakers should prioritizing collaborative innovation depth over breadth. we find that compared to CB, knowledge diversity has a more significant impact on CD. This may be due to the different roles that breadth and depth play. Specifically, it highlights the need to prioritize the quality of collaborative relationships over the mere quantity of partners. While CD reflects the intensity of knowledge exchange, problem-solving, and co-creation among partners, CB merely indicates the number of partners involved. Simply expanding the network of collaborators does not guarantee effective knowledge integration or meaningful innovation outcomes. Many firms aim to expand their collaborative networks, believing that a larger number of partners will automatically enhance innovation. However, this approach often results in "partnership overload," where firms maintain numerous superficial relationships with limited knowledge exchange. To address these deficiencies, we propose several strategic recommendations for firms and policymakers. (1) innovation policies, such as *Made in China 2025* and the *High-Quality Development Guidelines*, should be refined to prioritize the quality of partnerships over their quantity. Performance indicators should measure not only the number of partners but also the depth of collaboration, the quality of knowledge integration, and the sustainability of relationships. (2) firms should adopt a more strategic approach to partner selection, choosing partners with complementary knowledge rather than merely increasing the number of partnerships. (3) firms should regularly monitor collaborative quality using qualitative metrics, such as a Knowledge Integration Index (measuring the extent of knowledge integration), a Collaboration Intensity Score (assessing the frequency of joint activities), and a Relational Quality Metric (evaluating trust, commitment, and mutual understanding between partners).

Third, our study emphasizes the importance of an inclusive corporate culture. Enterprises should cultivate an organizational culture that promotes SPD and LUA to foster an inclusive collaborative environment. Such a culture helps mitigate cognitive barriers between partners, enhancing collaborative innovation depth and fostering successful innovation cooperation. However, many firms still maintain hierarchical structures with high power distance, where decisions are concentrated at the top, and lower-level employees hesitate to voice their ideas. Such environments hinder open communication and limit the effective exchange of diverse knowledge. Similarly, high uncertainty avoidance leads to rigid rules, standardized procedures, and risk-aversion, which discourage experimentation, adaptive problem-solving, and creative thinking. These cultural barriers prevent firms from fully leveraging the benefits of knowledge diversity, resulting in superficial collaboration rather than meaningful co-creation. To address these challenges, we propose several strategic recommendations for firms and policymakers: (1) Firms should minimize hierarchical barriers by adopting a flat organizational structure where all employees, regardless of rank, feel comfortable expressing their views. This can be achieved through mentorship programs, open-door policies, and participatory leadership practices that encourage two-way communication. (2) To reduce uncertainty avoidance, firms should promote a culture that values experimentation, calculated risk-taking, and adaptive problem-solving. This can include pilot projects for testing new ideas, "innovation labs" for creative experimentation, and flexible project management practices that allow teams to pivot when necessary. (3) Organizations should provide training for managers on how to cultivate an inclusive culture, including techniques for managing diverse teams, facilitating open dialogue, resolving conflicts constructively, and encouraging calculated risk-taking. Such training can help managers support a culture of psychological safety where diverse perspectives are valued.

Limitations and future directions

This study has several limitations, presenting opportunities for future research. First, this study only compares the level of knowledge diversity between enterprises, neglecting the knowledge diversity between enterprises and different types of organizations or specific partners. Some scholars have investigated the impact of knowledge differences on CI performance in specific scenarios such as enterprise-school or parent company-subsidiary relationships. Due to methodological and data constraints, this study was unable to examine knowledge diversity among different types of innovation entities.

Second, while this study supplements an external perspective on knowledge diversity, internal knowledge diversity is equally important. Previous scholars have found that internal and external knowledge diversity have distinct effects on innovation performance and that their combination provides complementary and balancing effects on innovation performance[63]. Therefore, future research should further explore the motivations and mechanisms of CI by integrating internal knowledge diversity.

Finally, this study has not explored the mediating mechanisms through which knowledge diversity impacts CI. Previous scholars have indicated that absorptive capacity and connective ability act as bridges linking knowledge to innovation[64]. Future research should introduce these capacities as mediating factors to enrich the theoretical findings.

Conclusion

Drawing on information/decision-making theory and social categorization theory, our study offers new insights into how inter-enterprise knowledge diversity and inclusive culture impact collaborative innovation (CI). As organizations increasingly recognize the importance of knowledge diversity for driving innovation, our research provides a nuanced understanding of the relationship between knowledge variety (KV), knowledge separation (KS), and inclusive culture within CI.

Our findings demonstrate that knowledge diversity has distinct impacts on CI. Specifically, KV positively influences CI, expanding the scope of knowledge exchange and enhancing collaborative innovation performance. In contrast, KS exhibits an inverted U-shaped relationship with CI, indicating that moderate levels of KS foster innovation by promoting diverse perspectives, while excessive cognitive differences can hinder communication and trust among partners.

Furthermore, our findings reveal that knowledge diversity has varied impacts on collaborative innovation breadth (CB) and collaborative innovation depth (CD). Specifically, KVpositively influences CD but has no significant impact on CB. This indicates that a wide range of knowledge types primarily contributes to deep, intensive knowledge exchange, fostering in-depth collaboration rather than simply expanding the number of partners. Conversely, KS exhibits an inverted U-shaped relationship with CD, where moderate levels of KS enhance CD by promoting diverse perspectives, but excessive cognitive differences hinder effective knowledge exchange and integration. Notably, neither KV nor KS shows a significant impact on CB, suggesting that the breadth of collaboration is less sensitive to knowledge diversity.

Beyond the direct effects of knowledge diversity, our study also emphasizes the critical role of inclusive culture in moderating the relationship between KS and CI. Specifically, small power distance and low uncertainty avoidance positively moderate the inverted U-shaped relationship between KS and CD, promoting a collaborative environment where diverse knowledge can be effectively integrated. However, collectivism does not show a significant moderating effect, suggesting that shared goals alone are insufficient to leverage knowledge diversity without an inclusive organizational culture.

These insights have significant theoretical and practical implications. Theoretically, our study advances the application of information/decision-making theory and social categorization theory to the context of inter-firm collaboration, providing a deeper understanding of how knowledge diversity shapes collaborative outcomes. Practically, we recommend that firms strategically balance knowledge diversity, avoid excessive cognitive separation, and foster an inclusive culture characterized by low power distance and low uncertainty avoidance. These strategies can help firms optimize their collaborative innovation efforts, and transforme diverse knowledge into valuable innovation outcomes.

We hope that these findings will guide managers and policymakers in designing collaborative environments that promote knowledge integration and innovation. Future research can further explore the impact of knowledge diversity in different contexts, such as cross-industry collaboration, and examine additional cultural dimensions that may influence collaborative innovation.

Data availability

All data included in the current study can be obtained from the corresponding author through their email address upon reasonable request.

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Declarations

Competing interests
The authors declare no competing interests.

Ethics approval
The study procedures were approved by the Ethics Committee of Nanchang University and were in line with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. Informed consent was signed and obtained from all individual participants included in the study.

Additional information
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