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Research article

Investigating the effect of university enterprise collaboration on individual innovation in underdeveloped regions

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Abstract: The innovation capability index of underdeveloped regions lags far behind that of the eastern coastal areas. This imbalance in innovation capability poses a critical challenge for underdeveloped regions in implementing its innovation-driven development strategy and economic transformation. Individual collaborative innovation ability is an essential skill that allows individuals to transform knowledge and resources into economic value. Presently, research on individual collaborative innovation capability focuses only on the external environment, cooperation mode and benefit allocation. This approach fails to reveal how organizational factors affect individual collaborative innovation capability, and there is a lack of research on underdeveloped regions. Collaborative innovation theory proposes that deep cooperation between industries or institutions through acquiring resources and knowledge can have a positive impact on other environments. Improving individual collaborative innovation capabilities must be achieved through the integration of heterogeneous innovation resources owned by the two core innovation entities, to achieve full integration of innovation elements. Therefore, collaborative innovation theory can effectively address this problem. This article adopts a quantitative research method. A sample of 911 teachers was selected from thirty vocational colleges in Inner Mongolia. The data were analyzed using the Hierarchical Linear Modeling (HLM) model and the proposed relationship was validated. The research findings indicate that cognitive, social and geographical proximity have significant positive effects on collaborative behavior. Collaborative behavior has a significant positive impact on individual collaborative innovation ability. Collaborative behavior plays a mediating role between multidimensional proximity and individual collaborative innovation ability. This study will add information on the collaborative innovation theory, help to understand the formation and impact mechanism of cooperative relationships in school-enterprise cooperation in underdeveloped regions, and thus promote the development of STEM education in underdeveloped areas.

Keywords: collaborative innovation, multi-dimensional proximity, collaborative behavior, STEM education, individual collaborative innovation ability

1. Introduction

In September 2016, the US Institute of Research and the US Department of Education jointly released the STEM 2026: A Vision for Innovation in STEM Education, which divided education into five categories: students, teachers, schools, school enterprise partnerships and evaluation databases, clarifying STEM's plans in the education field for the next 10 years [1].

STEM, as an organic whole, is task-driven with real problem solving, applying and acquiring knowledge in practice, and cultivating students' problem-solving abilities [2]. Additionally, reality (real situation, real world) has also become the focus of attention as a keyword in STEM connotation. Real situations refer to the real problems that exist or arise from our daily life practices captured from the real world and the context of this problem [3].

In line with its definition, enterprises are constantly facing and solving problems in an environment, thus possessing unique conditions for creating real situations. Moreover, the real context provided by school enterprise cooperation expands the participants in the context to include teachers. The cooperation process between schools and enterprises is full of difficulties and obstacles [4]. There are significant differences between schools and enterprises in terms of background, culture and mode of action, and both parties are not clear about how to properly handle each other's affairs. Therefore, ensuring the cooperative relationship between the two remains stable, healthy and efficient has become the key.

Collaborative behavior can promote the cooperative relationship between schools and enterprises, and more effectively improve teachers' innovation ability by sharing enterprise resources and technology. "Promoting STEM education to the whole community in rural and remote (RR) areas, not only in the RR schools, is the top priority in terms of improving the awareness of career prospective in STEM" [5], Inner Mongolia belongs to a remote area in China, and also an underdeveloped region. It is necessary to improve STEM education in Inner Mongolia.

The current state of Innovation in enterprises and universities in underdeveloped regions is characterized by a lack of collaboration and integration. Enterprises are in a passive position in the industry-academia collaborative innovation system, and the research activities of universities are separated from the new product development activities of enterprises. This results in low collaborative innovation capabilities between schools and enterprises, with research funds being invested mainly in higher education institutions and research institutes, focusing on pure scientific research rather than industrialization. As a result, universities have not been able to effectively support independent innovation in enterprises, leading to low conversion rates of scientific and technological achievements and limited contribution to the strategic adjustment of underdeveloped regions' economic structure and transformation of economic growth modes. By implementing STEM education, it becomes feasible to enhance collaboration and integration between universities and enterprises, ultimately fostering a culture of innovation and facilitating the exchange of technology and knowledge between academia and industry. This collaboration plays a crucial role in supporting enterprise'' independent innovation capabilities. Moreover, STEM education equips students with practical skills, problem-solving abilities and an innovative mindset. By nurturing a workforce educated in STEM disciplines, underdeveloped regions, such as Inner Mongolia, can expedite technological advancements, stimulate entrepreneurship and facilitate the transition towards a more innovation-driven economic growth model [6].

In this context, universities assume a critical role in enhancing regional innovation capabilities and promoting industrial development within the region. Governments in underdeveloped regions are increasingly prioritizing effective cultivation and utilization of school and enterprise resources, integrating these resources to foster industrial innovation and enhancing the innovation capabilities of both educational institutions and enterprises. By facilitating collaboration and integration between schools and enterprises, regional innovation systems can be strengthened, resulting in substantial economic and social development in underdeveloped regions of China. Current theoretical and empirical research has consistently demonstrated the pivotal role of individual innovation ability in organizational innovation and effectiveness [7–9]. Additionally, employee innovation capabilities are crucial for enterprises to gain a competitive advantage, thereby enhancing regional innovation capabilities. Scholars have extensively researched the factors that influence an individual's innovation ability. Previous studies have identified multiple factors that contribute to an individual's capacity for innovation [7,10,11], these studies has not yet taken into account the collaborative behavior of external subjects in the innovation network, and how external innovation knowledge is transformed into individual collaborative innovation capability.

Some scholars [12–14] have noted that collaborative innovation between schools and enterprises needs to be achieved through their behavioral interactions, which are influenced by regional, institutional, technological and environmental differences. However, these factors' impact on behavior is often not comprehensively considered. In the case of Inner Mongolia, the region's large geographical span, with a straight east-west distance of 2400 kilometers, and significant differences in resource endowments and cultural customs across regions result in varying economic development conditions [15]. Therefore, a comprehensive consideration of the impact of these factors on collaborative innovation behavior is crucial, and multidimensional proximity can offer a valuable explanation for the complex relationship between schools and enterprises. Geographical, cognitive and social proximity between higher vocational colleges and enterprises is called multidimensional proximity, which has a significant impact on the efficiency and efficiency of collaborative innovation [16]. The Chinese government has recently launched a series of plans and laws to encourage joint innovation between higher vocational colleges and enterprises.

Vocational schools and enterprises collaborate to identify relevant research areas in the sector and develop practical and transferable solutions [17]. In Inner Mongolia, thirty vocational colleges have established partnerships with high-tech enterprises, primarily focusing on electronic information technology and advanced manufacturing industries (as shown in Table 1). These collaborations significantly contribute to enhancing the innovation capabilities of vocational college teachers. The partnerships involve cooperative forums, conferences, technology transfer, internship and work-study programs, as well as research and development initiatives. These initiatives effectively bridge the gap between theory and practice, providing students with enhanced real-world training and fostering the creation of new technologies and products applicable to the field of education. The current study aims to investigate the influence and mechanism of multi-dimensional proximity between schools and enterprises on collaborative innovation within higher vocational colleges located in underdeveloped regions.

Table 1. Data characteristics of high-tech Enterprises in Inner Mongolia.

Enterprise Attribute	Category	Percentage (%)	Enterprise Attribute	Category	Percentage (%)
Enterprise Type	Electronic Information Technology	19.8	Located	Hulunbuir	7.6
	High Tech Services	8.2		Manzhouli	2.3
	Aerospace	3.3		Tong Liao	8.4
	Resources and Environment	14.6		Xilingol	3.2
	New Materials	12.7		Xing'an	3.4
	Advanced Manufacturing and Automation	17.3		Wu hai	8.4
	Biology and New Medical Technology	9.4	Located	Wu lan cha bu	7.2
	New Energy and Energy Conservation	14.7		Bayannur	6.7
Years of Establishment	With in 5 years	2.4		Hohhot	16.6
	6-10 years	32.0		Baotou	16.1
	11-15 years	30.9		Ordos	8.3
	16-20 years	24.1		Chifeng	7.5
	More than21 years	10.6		Alxa	4.3

Data source: Statistics of Inner Mongolia Science and Technology Bureau [18]

2. Literature review

2.1. Collaborative innovation theory

The theory of "collaborative innovation" posits that extensive cooperation between industries or institutions, which involves the acquisition of resources and knowledge, can have a positive impact on various environments [19]. This suggests that resources and knowledge obtained in one setting can contribute to collaborative innovation and improve other settings, regardless of the initial intent. The theory of collaborative innovation holds significant importance for innovation policies as it facilitates a better understanding of enterprise needs and market development. It promotes practicality in university research and encourages exploration of research fields that align with market demand. Additionally, through partnerships with enterprises, universities can secure research funding, leading to increased academic achievements [16,20]. Collaborative behavior can be classified into three dimensions from a process perspective: partner selection behavior, collaborative relationship maintenance behavior and risk monitoring behavior [21].

STEM education plays a vital role in fostering collaborative innovation by providing teachers and students with the essential skills and knowledge required to support enterprise and market development. For instance, STEM education enables teachers to enhance their technological and innovative capabilities, which are crucial for addressing the needs of enterprises and driving innovation. Additionally, STEM education promotes collaborative behavior among students by offering opportunities to work on projects, participate in competitions and engage in research practices. These activities cultivate the necessary skills for deep collaboration between educational institutions and enterprises [22].

Collaborative innovation theory highlights the significance of cooperation and resource sharing in driving innovation and economic growth. Collaboration among diverse industries and institutions can foster the generation of new ideas and breakthroughs, thereby stimulating the development, enhancement and diffusion of innovative technologies that contribute to prosperity and well-being [23]. As per the theory of collaborative innovation, social, cognitive and geographic proximity can facilitate the exchange of information and collaboration among different individuals or groups, ultimately boosting innovation outcomes. Collaborative behavior serves as a specific pathway for collaborative innovation between educational institutions and enterprises and may act as a potential mediator in this interaction [16]. In the context of higher vocational colleges in Inner Mongolia, collaborative behavior can support cooperation and knowledge sharing among various educational institutions and enterprises, creating a platform for commercialization and innovation. This collaborative environment can lead to improved outcomes and increased innovation in the field of higher vocational education. STEM education plays a crucial role in equipping students with the necessary technological and innovative capabilities required to address enterprise needs and drive innovation forward [24].

2.2. Social proximity and collaborative behavior

Social proximity refers to the degree of closeness among individuals or organizations in a given social context, based on factors such as close friendships, shared interests, or cooperation experiences [25]. Social distance can affect the partner selection behavior of higher vocational colleges in Inner Mongolia, promoting the establishment of networks and relationships that contribute to education and career development [26]. Cooperative experience enhances trust between organizations through mutual communication and adjustment. Previous cooperative experiences can lead to the emergence of social capital and work regulations and procedures in the cooperative process, which stabilize the interaction mode between subjects and facilitate the transfer of knowledge between cooperative subjects [27,28]. The experience and value created in previous collaborations are helpful for both parties to choose partners again, and the view that past collaborations significantly increase the likelihood of future collaborations has been confirmed by some scholars [29,30].

A closer social relationship between schools and enterprises in collaborative endeavors corresponds to higher social proximity, resulting in increased trust and willingness to invest effort in joint projects [31]. High levels of trust facilitate effective communication and interaction, removing barriers and sustaining collaborative relationships. In the context of collaborative innovation, higher social proximity between parties corresponds to higher levels of trust. This trust mechanism mitigates risks during scientific research cooperation [32]. Conversely, when there is a significant social gap between schools and enterprises, trust may be lower, increasing the likelihood of opportunistic risks and cooperation challenges [33]. A high level of social proximity in collaborative innovation signifies a strong and high-quality relationship between the parties.

Social proximity enhances trust between organizations through past communication and exchanges, serving as a crucial foundation for cooperative relationships. Additionally, social proximity contributes to the generation of social capital, which is instrumental in forming cooperative relationships. Furthermore, work regulations and procedures play a pivotal role in the cooperation process. They facilitate the transfer of knowledge among collaborating entities and are more likely to emerge in relationships characterized by strong social proximity. As a result, individuals with close social relationships are better equipped to navigate collaborative relationships due to the existing regulations and procedures in place.

H1: *Social proximity significantly affects partner selection behavior.*

H2: *Social proximity significantly affects collaborative relationship maintenance behavior.*

H3: *Social proximity significantly affects risk monitoring behavior.*

2.3. Geographic proximity and collaborative behaviour

Geographical proximity, also known as spatial proximity or physical proximity, refers to the close spatial distance between entities and is considered an important factor in establishing partnerships between vocational colleges and enterprises in China [34]. In the context of China's vocational education, the country has been vigorously expanding its vocational education system over the past few decades, and the concept of geographical compactness is particularly important [35].

Geographical proximity plays an important role in establishing partnerships between schools and enterprises. Geographical proximity is considered an important element in STEM education. For example, the geographical proximity between schools and enterprises can promote students' participation in on-site learning and practical activities, in order to better understand industry and market demands [36]. In addition, the geographical proximity between schools and communities can promote cooperation between students and local businesses and organizations, thereby gaining practical experience and obtaining more employment opportunities [37]. Compared to other regions, the transportation in the western region of Inner Mongolia is not developed, and collaborative behavior between schools and enterprises is hindered. For example, large geographical distances and inability to communicate face to face can lead to schools and enterprises failing to pay attention to issues such as intellectual property protection and risk financing channels [35].

Collaborative relationship maintenance behavior may be significantly affected by geographical proximity. Institutions with close geographical distances can obtain more resources, thereby bringing higher educational outcomes to higher vocational colleges [20]. With the reduction of transportation costs and the development of information technology, the blocking effect of geographical proximity on cooperation has become increasingly blurred and has been questioned and challenged by a large number of scholars [38–40]. Face-to-face communication and contact are required in the process of collaborative innovation and innovation. Compared to other communication methods, face-to-face communication has the most prominent advantages. First, it is an efficient communication technology, and second, it can enable partners to trust each other and abide by commitments, thereby reducing incentive issues in uncertain environments. Geographical proximity can easily achieve frequent face-to-face communication, which is important for the maintenance of relationships between organizations and can achieve the acquisition and integration of heterogeneous resources among collaborative entities [41,42]. Therefore, in the context of STEM, geographical proximity can play a significant role in promoting collaborative behavior and facilitating the acquisition and integration of diverse resources to promote collaborative innovation.

H4： *Geographical proximity significantly affects partner selection behavior.*

H5： *Geographical proximity significantly affects collaborative relationship maintenance behavior.*

H6： *Geographical proximity significantly affects risk monitoring behavior.*

2.4. Cognitive proximity and collaborative behaviour

The degree to which people or institutions share information, capabilities and expertise is known as cognitive proximity and is a crucial factor for collaborative innovation processes [34].

In the context of STEM education, cognitive proximity plays a crucial role in establishing a collaborative learning environment that facilitates the transfer of knowledge and technology. The closer the cognitive proximity between enterprises, the higher the likelihood of establishing cooperative relationships [43]. Maintaining a certain level of diversity and complementarity in the knowledge base is particularly important for generating new ideas, avoiding cognitive stagnation and ensuring the sustainability of collaborative relationships [44].

Collaborative innovation entities require a certain level of cognitive distance to ensure a difference in knowledge base, which is beneficial for the generation of new knowledge and technology in school-enterprise cooperation, thus promoting the maintenance of cooperative relationships [44]. According to Wang Haihua (2017), a certain degree of technological proximity facilitates effective communication and interaction between innovation entities, maintains the stable development of cooperative relationships and enhances collaborative innovation performance [45].

The stability of cooperation resulting from cognitive proximity promotes mutual trust between entities, thereby reducing obstacles in knowledge sharing and transfer and helping to overcome limitations and barriers encountered in collaboration [46], thus influencing cooperation risks.

When an organization realizes that its own knowledge and technology are insufficient to meet its development needs, it seeks external partners. In this scenario, cognitive proximity has an impact on the organization's choice of partners. Differences in technological foundations can significantly affect the maintenance of relationships among collaborating entities, increasing costs. Meanwhile, cognitive proximity fosters increased communication and enhances mutual trust and understanding among collaborative innovation entities, thereby promoting the effectiveness of cooperation and reducing risks.

H7： *Cognitive proximity significantly affects partner selection behavior.*

H8： *Cognitive proximity significantly affects collaborative relationship maintenance behavior.*

H9： *Cognitive proximity significantly affects risk monitoring behavior.*

2.5. Cooperative behaviour and individual collaborative innovation ability

In recent years, China has placed significant emphasis on promoting collaborative innovation in vocational colleges to cultivate a more innovative and entrepreneurial workforce [47]. Collaborative innovation entails the joint efforts of schools and enterprises to develop new products, services and processes. To achieve successful collaborative behavior, it is essential to identify potential partners, evaluate and screen them, maintain collaborative relationships and acquire necessary resources [32]. However, collaboration also involves risks that need to be identified and mitigated.

Partner selection behavior is crucial for individual collaborative innovation capability as it involves the active engagement of individuals in innovative services, integrating resource knowledge and transforming innovative elements and services into innovative results through exchange, sharing and cooperation [48]. Partner selection is an essential step that can help companies identify opportunities for technological knowledge spillovers from external knowledge sources, integrate and restructure cross-domain technologies and resources, achieve maximum synergy and further affect their collaborative innovation capabilities [49].

Higher vocational colleges play a critical role in providing talent support for collaborative innovation between schools and enterprises. Higher vocational colleges can establish multifaceted cooperation with enterprise groups, where enterprises can provide corresponding heterogeneous resources, such as equipment, funds, etc., to provide prerequisite guarantees for scientific researchers to successfully complete cooperative projects [50]. Furthermore, the deepening of collaborative relationships between schools and enterprises presents opportunities to integrate real-world learning, enhance teachers' STEM abilities and enable students to proactively discover the connection between the knowledge learned in school and their career pursuits.

The maintenance of cooperative relationships is crucial for school enterprise cooperation, as it can generate shared values that are beneficial to both parties and have a positive impact on the organization's innovative social capital [51]. Moreover, social capital has a positive impact on organizational collaborative innovation capabilities [52,53]. Therefore, cooperative relationship maintenance behavior may have a positive impact on individual collaborative innovation ability.

The process of collaborative innovation is accompanied by the emergence of different types of risks and varying degrees of risks, and the process of risk monitoring assesses the uncertainty in the collaborative innovation process to avoid the occurrence of greater risks, cooperative conflicts and even accidents in the future. Through risk monitoring behavior, it is ensured that resources can be shared among organizations, preventing the occurrence of uncontrollable behaviors that may lead to the risk of organizational technology leakage, thereby ensuring the smooth output of innovation achievements and promoting the improvement of individual collaborative innovation capabilities.

***H10*：** *Partner selection behavior significantly affects individual collaborative innovation capabilities.*

***H11*：** *Collaborative relationship maintenance behavior significantly affects individual collaborative innovation capabilities.*

***H12*：** *Risk monitoring behavior significantly affects individual collaborative innovation capabilities.*

2.6. Mediation of collaborative behaviour

Collaborative behavior plays a crucial role in facilitating the interaction between social cohesion, cognitive proximity, geographic proximity and individual collaborative innovation capabilities in higher vocational colleges in Inner Mongolia. Collaborative innovation, which involves multiple institutions working together to develop new goods, services, or technologies that benefit society, is affected by geographical proximity, social proximity and cognitive proximity [54–56].

When organizations face collaborative innovation, they choose to collaborate with partners with similar social backgrounds, experiences and values in order to better understand each other and form highly coordinated and cooperative relationships in collaboration. In addition, geographical proximity also plays an important role, as it can provide more convenient opportunities for communication and face-to-face cooperation, which is conducive to establishing cooperative relationships of mutual trust and collaborative innovation. At the same time, cognitive proximity reflects the similarity of technology between organizations [57–60]. By selecting partners with high cognitive proximity for collaboration, organizations can better understand each other's technological backgrounds, promote knowledge sharing and the generation of innovation.

Collaborative relationship maintenance behavior involves interaction and relationship maintenance between partners, including mutual support, information sharing, conflict resolution and collaborative coordination. Organizations with high social, geographical and cognitive proximity are more likely to exhibit positive collaborative relationship maintenance behavior because they have better communication and understanding abilities, can better solve problems and conflicts in cooperation, and thus promote the realization of collaborative innovation [61].

Collaborative innovation involves certain risks and uncertainties, and vocational colleges will pay attention to the management of risks and uncertainties when selecting partners and maintaining collaborative relationships. Social proximity, geographical proximity and cognitive proximity can affect an organization's perception and management of risks, thereby affecting its collaborative innovation ability. By monitoring and managing risks, organizations can better adapt to and respond to the uncertainty in the process of collaborative innovation and improve the effectiveness and outcomes of individual collaborative innovation [53].

***H13*：** *Partner selection behavior mediates the relationship between social proximity and individual collaborative innovation capabilities.*

***H14*：** *Partner selection behavior mediates the relationship between cognitive proximity and individual collaborative innovation capabilities.*

***H15*：** *Partner selection behavior mediates the relationship between geographic proximity and individual collaborative innovation capabilities.*

***H16*：** *Collaborative relationship maintenance behavior mediates the relationship between social proximity and individual collaborative innovation capabilities.*

***H17*：** *Collaborative relationship maintenance behavior mediates the relationship between cognitive proximity and individual collaborative innovation capabilities.*

***H18*：** *Collaborative relationship maintenance behavior mediates the relationship between geographic proximity and individual collaborative innovation capabilities.*

***H19*：** *Risk monitoring behavior mediates the relationship between social proximity and individual collaborative innovation capabilities.*

***H20*：** *Risk monitoring behaviors mediate the relationship between cognitive proximity and individual collaborative innovation capabilities.*

***H21*：** *Risk monitoring behaviors mediate the relationship between geographic proximity and individual collaborative innovation capabilities.*

Figure 1 depicts the framework we created using the above aspects.

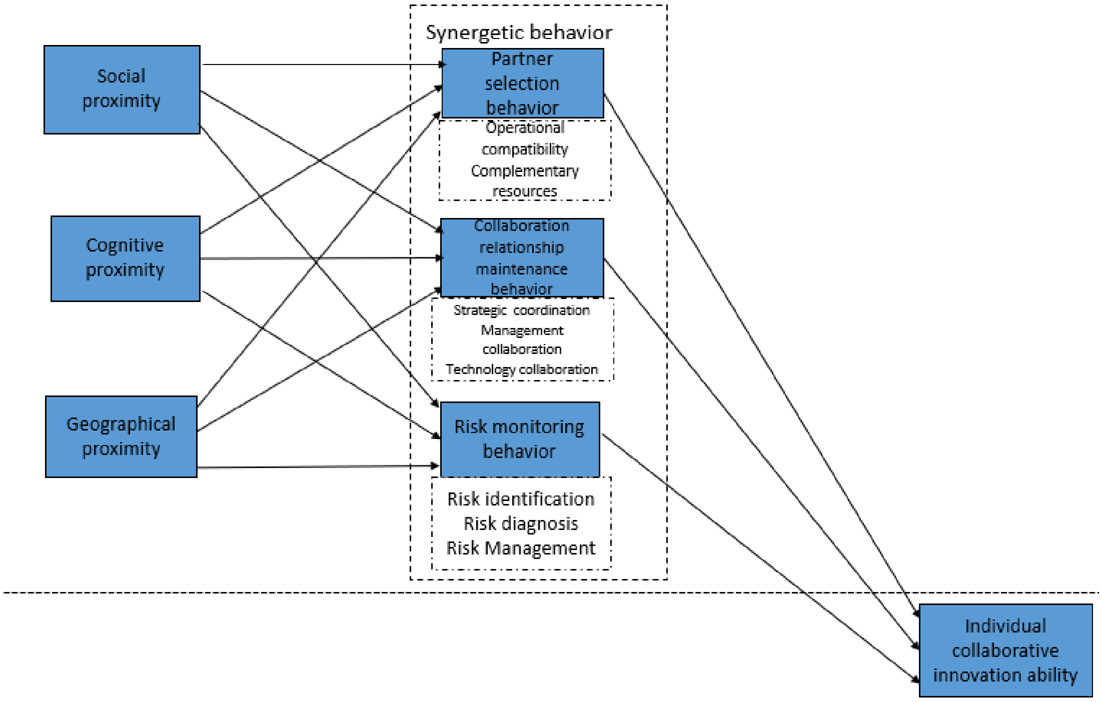

Figure 1. Conceptual framework.

3. Methodology

The model of the study was developed using the collaborative innovation theory. The main objective of the study was to determine the influence and mechanism of school-enterprise multi-dimensional proximity on collaborative innovation in higher vocational colleges.

We incorporate both organizational and individual-level analyses using multi-level linear analysis (HLM). The researchers uphold a strong commitment to ethical standards, ensuring the strict confidentiality of the questionnaires collected from participants, which are exclusively used for the purposes of this study. Following the recommendation by Kreft (1995), a universal 30/30 rule for HLM sample size was employed, suggesting a minimum of 30 sample groups, each consisting of 30 participants [62]. Consequently, 30 higher vocational colleges in Inner Mongolia were selected as sample groups using random sampling, with each vocational college requiring 30 participants.

3.1. Participants

Participants of this study comprise teachers and researchers directly involved in school-enterprise collaborative innovation in 30 higher vocational colleges in Inner Mongolia. Additionally, it includes management personnel responsible for industry-university cooperation, achievement transfer in universities and innovation service support department management personnel. A total of 1000 participants completed the questionnaire, and 911 valid questionnaires were returned. Table 2 presents the demographic analysis of teachers who participated in the questionnaire survey conducted in vocational colleges. The analysis primarily focuses on gender, age, length of work experience, major and school nature.

Table 2. Frequency analysis.

Statistical items	Category	Number of people	Percentage	Statistical items	Category	Number of people	Percentage
Gender	Male	491	53.9%	Unit nature	Public school	626	68.7%
	Female	420	46.1%		Private schools	285	31.2%
Age	20-30 years old	142	5.6%	Major	Electronic Information Technology	138	15.1%
	31-40 years old	358	39.3%		Public Service and Logistics	61	6.8%
	41-50 years old	285	31.3%		Biological and Medical Technology	72	7.9%
	51-60 years old	126	13.8%		Materials	201	22.0%
Years of work experience	6-12 months	151	16.5%		Energy	141	15.5%
	1-2 years	167	18.4%		Resources and Environment	98	10.7%
	2-3 years	384	42.1%		Machinery/Advanced Manufacturing	179	19.7%
	3 years and above	219	24.0%		Aerospace Technology	21	2.3%

Source: By Author

3.2. Measurement scale

Prior to the formalization and distribution of the final questionnaire, one of the authors developed a pre-survey questionnaire to assess the suitability of the questionnaire design and wording. The pre-survey questionnaire was distributed to 50 respondents, and their feedback and suggestions were collected. Based on the input received from the pre-survey respondents, the questionnaire was revised and modified to improve its clarity and effectiveness. This iterative process ensured that the final questionnaire was appropriately designed and well-suited for data collection.

The questionnaire was administered in this study to collect data on seven variables, including three independent variables and four mediating and dependent variables. The first independent variable is Social Proximity (SP), which was measured using a five-item measurement scale [40]. The second independent variable is Geographic Proximity (GP), which was measured using a six-item scale [25]. The third independent variable is Cognitive Proximity (CP), which was measured using a six-item scale [34]. Mediating variables were measured using the scale [41], which includes partner selection behavior (PB), relationship maintenance behavior (CB) and risk monitoring behavior (RB) and consists of a total of sixteen items. The scales mentioned above were completed by management personnel responsible for industry university research cooperation, transfer of university achievements and management personnel from innovation service support departments. The dependent variable is Individual Collaborative Innovation Ability (ICIA), which has been adjusted for seven projects and was measured using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) [35]. The scale was completed by teachers and researchers who are directly involved in school-enterprise collaborative innovation.

3.3. Data collection

With the assistance of a team, the researchers distributed 1000 questionnaires to thirty vocational colleges in Inner Mongolia. To ensure that the respondents had a clear understanding of the research purpose, they first communicated and exchanged information with the tested organizations and employees before the study, provided explanations, so that the surveyed organizations and individuals fully understood the purpose of this study, and invited them to participate in this study. The questionnaire is distributed and collected through two channels: paper questionnaire and questionnaire star. Subsequently, the collected data was analyzed using the Mplus software, employing the specified method for hypothesis testing.

4. Results

The current research determines the impact and mechanism of collaborative behavior on individual collaborative innovation capabilities in higher vocational colleges in Inner Mongolia from a multi-dimensional approach perspective.

4.1. Analysis of reliability and validity

In the present study, the HLM (Hierarchical Linear Modeling) structural equation model is employed to examine the evolution of the model. The measurement process is conducted using Mplus, a statistical software program. The "average variance extracted (AVE), confirmatory factor analysis (CFA), convergent validity and discriminant validity" are taken into consideration while calculating this quality score. PLS analysis uses two primary criteria: validity and reliability. This is true since the main objective of model measurement is to ascertain the model's quality. Evaluations of the construct under investigation's convergent and discriminant validity were conducted. The convergent validity, also known as the internal consistency of the variables, was examined using the average variance extracted (AVE) values and item loading values. In this convergent validity analysis, the items' dependability was assessed [60]. A statistical method for analyzing and estimating intricate interactions between variables is structural equation modelling (SEM). In the social sciences, psychology, economics and other disciplines, it is a sort of multivariate analysis that is frequently employed. In SEM, a theoretical model that explains the connections between numerous observable and latent variables is specified, and the model is then tested using data. A collection of equations that express the relationships between the variables serves as the model's representation. The equations are commonly stated as matrices, with measured variables for the observable variables and unseen variables for the latent variables.

4.1.1. Composite reliability and validity

Internal consistency of a measurement tool, or the degree to which the items on a scale or measure are measuring the same underlying construct or concept, is referred to as composite reliability [63]. Higher numbers denote more internal consistency or dependability. Composite reliability has a range of 0 to 1. The degree to which a measurement tool accurately assesses the construct it is designed to measure is referred to as validity. Convergent validity and discriminant validity are two techniques that can be used to assess construct validity. PLS-SEM was also used to assess the factor loadings, validity and reliability of the data collected from 911 teachers at higher vocational institutions. Table 2 provides information on the item factor loading, validity and reliability of the PLS measurement model. To assess an item's internal reliability, Cronbach's alpha test value, which must be 0.70 or higher, is generally utilized [64]. For the variables under examination, Cronbach's Alpha and composite reliability values were both greater than 0.70. Convergence validity and high reliability were shown because the average variance extracted (AVE) values for discriminant validity were higher than 0.50 [65]. The composite dependability values ranged from 0.787 to 0.896, exceeding the cutoff range of 0.70. Table 3 Composite Reliability displays values for Cronbach’s alpha and average extracted variance.

Table 3. Composite reliability, Cronbach’s Alpha and AVE values.

Variable	Items	Factor loadings	CA	CR	AVE
GP	5	0.794~0.935	0.896	0.836	0.505
CP	6	0.657~0.899	0.905	0.909	0.628
SP	6	0.702~0.749	0.731	0.878	0.545
CR	5	0.669~0.770	0.836	0.865	0.562
SC	5	0.652~0.782	0.812	0.890	0.619
MC	5	0.685~0.731	0.816	0.857	0.545
TC	5	0.594~0.768	0.923	0.846	0.528
RI	5	0.817~0.897	0.916	0.890	0.619
RD	5	0.550~0.882	0.830	0.884	0.609
RC	5	0.624~0.830	0.874	0.832	0.598
ICIA	7	0.778~0.804	0.903	0.892	0.542

“Note: CR=composite reliability; AVE=average variance extracted; CA= Cronbach’s Alpha”
Source: By Author

4.1.2. Discriminant validity

Each research method must also show that it is discriminant valid. One predictor variable's discriminant validity explains why it stands out from some of the other latent variables [60]. The associated factor variability, AVE value and other range of fundamental values must all be lower than the AVE of the independent factors in order to evaluate the discriminant validity [65]. A notion is validated using discriminant validity, which involves contrasting it with different concepts. Once we were confident in the consistency and validity of the variables, further research was done for structural analysis.

We employ the average extracted variance (AVE) method for testing, with a measurement criterion stating that if the average variance of a variable exceeds 0.5, it passes the test for aggregation validity. Additionally, the square root of AVE for each variable should be higher than its correlation coefficient with other variables to establish discriminant validity. The test results, as shown in Table 4, indicate that the square root of AVE values for all latent and observable variables (highlighted in bold on the diagonal) surpass the critical value of 0.5 and exceed the correlation coefficients among variables. This signifies that all variables in the study exhibit satisfactory discrimination validity.

Table 4. Discriminant validity.

	GP	CP	SP	OC	CR	SC	MC	TC	RI	RD	RC	ICIA
GP	**.801**											
CP	.216**	**.790**										
SP	.236**	.599**	**.725**									
OC	.419**	.478**	.484**	**.796**								
CR	.333**	.360**	.500**	.743**	**.711**							
SC	.388**	.429**	.380**	.385**	.318**	**.786**						
MC	.354**	.495**	.428**	.432**	.352**	.709**	**.781**					
TC	.381**	.503**	.442**	.422**	.308**	.744**	.783**	**.876**				
RI	.353**	.336**	.257**	.331**	.274**	.274**	.249**	.234**	**.833**			
RD	.316**	.336**	.279**	.272**	.214**	.258**	.266**	.254**	.545**	**.724**		
RC	.289**	.325**	.232**	.247**	.228**	.260**	.248**	.241**	.281**	.626**	**.803**	
ICIA	.456**	.565**	.541**	.695**	.608**	.678**	.686**	.683**	.508**	.515**	.462**	**.756**

Source: By Author

4.2. Regression analysis

The structural model route coefficients representing the hypothesized correlations were statistically determined using the Mplus bootstrapping technique. The Mplus evaluation of research on the influence and mechanism of school-enterprise multi-dimensional proximity on collaborative innovation in higher vocational colleges in Inner Mongolia. A statistical method used to examine intricate interactions between observed and unobserved factors is structural equation modelling (SEM). Even in the presence of measurement errors, numerous interdependent linkages and latent constructs that cannot be directly observed, SEM enables the testing of theoretical models and the assessment of the strength and direction of relationships between variables [61]. About bootstrapping, ratings of assumptions' correctness, predictability, measurement variation, coefficient of determination and other features are given [61]. Almost any statistic that uses the survey technique may be estimated using the sample distribution of this method. It can also be used to create tests for hypotheses. When a modelling approach is unreliable, difficult to implement, or necessitates the use of complex formulas to determine standard errors, an alternative to statistical processes is frequently used [66].

4.2.1. Aggregation test

Aggregation test is the internal consistency test of data from individual level to higher level, with internal consistency γ_{wg}, relevant ICC (1) and ICC (2) in the group. Among them, γ_{wg} it is used to measure the extent to which different individuals within an organization have the same perception of a concept. The value range is from 0 to 1. Generally, it requires more than 0.70 to have enough consistency for aggregation [67]; ICC (1) is used to test whether there is sufficient inter-group difference between different organizations before aggregating individual perceived data to the organizational level. Generally, if it is greater than 0.10, there is inter-group difference. ICC (2) is used to measure the reliability of the organizational average of this variable when aggregating individual level variables into organizational level variables, and the value should preferably reach 0.7 [68].

The results show that (Table 5), γ_{wg} it is 0.744, ICC (1) and ICC (2) are 0.394 and 0.753, respectively, which meet the requirements of data aggregation, which can indicate that the team variance is different, and multi-level linear analysis can be carried out.

Table 5. Aggregation test.

	γ_{wg}	ICC (1)	ICC (2)
Standard	> 0.7	> 0.1	> 0.7
	0.744	0.394	0.753

Source: By Author

4.2.2. Direct relation

The study findings revealed a significant positive relationship between social proximity and partner selection behavior ($p < .05$), collaborative relationship maintenance behavior ($p < .05$) and risk monitoring behavior ($p < .05$). Thus, supporting H1, H2 and H3. Similarly, there was a significant positive relationship between geographic proximity and partner selection behavior ($p < .05$), collaborative relationship maintenance behavior ($p < .05$) and risk monitoring behavior ($p < .05$). Hence, H4, H5 and H6 were supported. Moreover, cognitive proximity showed a significant positive relationship with partner selection behavior ($p < .05$), collaborative relationship maintenance behavior ($p < .05$) and risk monitoring behavior ($p < .05$). Thus, supporting H7, H8 and H9. Furthermore, partner selection behavior ($p < .05$), collaborative relationship maintenance behavior ($p < .05$) and risk monitoring behavior ($p < .05$) had significant positive relationships with individual collaborative innovation ability, confirming H10, H11 and H12. Table 6 illustrates the direct relationships between independent and dependent variables.

Prior to examining interactions, this study presents the R^2 value, a main regression model that indicates the goodness of fit. According to Hamdollah & Baghaei (2016), an R^2 value of 0.13 is considered poor, 0.33 as moderate and 0.67 as strong [69]. The assessment coefficient of determination is displayed in the table. Partial Least Squares (PLS) regression frequently employs R square (R^2) as a statistical metric to evaluate the goodness of fit. R^2 is determined separately for each endogenous latent variable in Mplus, which corresponds to the dependent variables in the model [69]. The individual collaborative innovation ability value was 0.587.

Table 6. Direct relation.

	Dependent Variable	Independent Variable	Estimate	S.E.	Est./S.E.	P-Value
Between	ICIA	GP	-0.139	0.104	-1.326	0.185
		CP	-0.138	0.142	-0.972	0.331
		SP	0.045	0.101	0.447	0.655
		PB	0.491	0.127	3.860	0.000
		CB	0.921	0.316	2.916	0.004
		RB	0.496	0.201	2.472	0.013
	PB	GP	0.240	0.087	2.772	0.006
		CP	0.254	0.113	2.252	0.024
		SP	0.317	0.099	3.204	0.001
	CB	GP	0.355	0.045	7.964	0.000
		CP	0.411	0.055	7.424	0.000
		SP	0.170	0.059	2.862	0.004
	RB	GP	0.337	0.044	7.691	0.000
		CP	0.308	0.056	5.496	0.000
		SP	0.165	0.059	2.811	0.005
Within	ICIA	Variance	0.394	0.081	4.862	0.000

Source: By Author

4.2.3. Mediation effect

After introducing synergy as an intermediary variable, we found that the indirect effects of social neighbor partner selection behavior, cooperative relationship maintenance behavior and risk monitoring behavior on individual collaborative innovation ability are significant, while the direct effects do not exist. This indicates that these factors are completely mediating, fully mediating the relationship between social proximity and individual collaborative innovation ability, supporting H13, H14 and H15.

Similarly, in the context of geographical proximity, we observed that the indirect effects of partner selection behavior, relationship maintenance behavior and risk monitoring behavior on individual collaborative innovation ability exist, while the direct effects are not observed. This indicates that geographic proximity is a complete intermediary that supports H16, H17 and H18.

In addition, in terms of cognitive proximity, our research results indicate that the indirect effects of partner selection behavior, cooperative relationship maintenance behavior and risk monitoring behavior on individual collaborative innovation ability are significant, while the direct effects have not yet been established. This supports the concept of complete mediation, indicating that cognitive proximity plays a complete mediating role in the relationship between cognitive proximity and individual collaborative innovation ability, supporting H19, H20 and H21.

Table 7. Mediation effect.

	Estimate	S.E.	90%CI		95%CI	
			lower	upper	lower	upper
GP-PB-ICIA(IE)	0.118	0.045	0.044	0.192	0.030	0.207
CP-PB-ICIA(IE)	0.125	0.066	0.016	0.233	-0.004	0.254
SP-PB-ICIA(IE)	0.156	0.072	0.038	0.274	0.015	0.296
GP--ICIA(DE)	-0.139	0.104	-0.310	0.033	-0.343	0.066
GP-CB-ICIA(IE)	0.327	0.127	0.119	0.535	0.079	0.575
CP-CB-ICIA(IE)	0.378	0.136	0.154	0.602	0.111	0.645
SP-CB-ICIA(IE)	0.156	0.079	0.027	0.286	0.002	0.311
CP--ICIA(DE)	-0.138	0.142	-0.372	0.096	-0.417	0.140
GP-RB-ICIA(IE)	0.167	0.076	0.043	0.292	0.019	0.315
CP-RB-ICIA(IE)	0.153	0.066	0.044	0.261	0.024	0.282
SP-RB-ICIA(IE)	0.082	0.048	0.003	0.161	-0.012	0.176
SP--ICIA(DE)	0.045	0.101	-0.121	0.211	-0.153	0.243

Source: By Author

5. Discussion

The findings of this research have theoretical and practical ramifications. This study could be very useful to administrators, policymakers and decision-makers.

The result of this paper emphasizes the value of social proximity, cognitive proximity and geographical proximity in promoting individual collaborative innovation capabilities in vocational colleges. For the purpose of creating effective networks that foster cooperation and knowledge sharing, these three proximities are crucial. Quantitative research shows that social proximity, cognitive proximity and geographical proximity can promote the sharing of implicit information and the emergence of norms and values, thus encouraging cooperation and trust between various stakeholders [40]. The key to successful creativity is to establish trust between two partners and team members. Only by helping each other to compensate for each other's shortcomings can we maximize mutual trust between members, promote knowledge and information sharing and accelerate the generation of creativity [70]. In addition, geographical proximity can provide users with new ideas, materials and financial opportunities, which can encourage the creation of creative entrepreneurship and partnerships. Social proximity can make it easier for institutions to cooperate and share information, which can promote the improvement of individual collaborative innovation ability. Cognitive proximity can help organizations improve their innovation capabilities by encouraging cooperation, understanding and communication among many stakeholders.

The study also believes that collaborative behavior is the key link between mediating proximity and individual collaborative innovation capabilities. High quality collaborative behavior can facilitate smooth communication and interaction between vocational colleges in forward-looking technical fields, accelerate the interaction and feedback process between knowledge elements from different backgrounds. The rich resources and training activities provided by enterprises can help teachers connect real practical activities with classroom content and understand the role of STEM skills in the labor market, deepen teachers' understanding of STEM in real situations and enhance their collaborative innovation ability.

By examining the role of collaborative behavior in the mediating relationship between social proximity, cognitive proximity, geographical proximity and individual collaborative innovation ability in Inner Mongolia vocational colleges, this study will increase the literature volume of collaborative innovation theory. This study will reveal factors that encourage or inhibit information exchange and team cooperation among different personnel or groups in Inner Mongolia higher vocational colleges. This study will enhance our understanding of the role of collaborative behavior in cultivating creativity in vocational education and training. Collaborative behavior is a way to promote cooperation and knowledge exchange between higher vocational colleges and enterprises. Collaborative behavior can promote the exchange of knowledge and ideas among different disciplines or institutions by providing a shared platform for commercialization and innovation, thereby improving innovation outcomes.

6. Limitations and future research

Based on the perspective of multi-dimensional proximity, this paper studies the three levels embedded in school-enterprise collaborative behavior. However, the study of school-enterprise collaborative behavior can also be analyzed from other perspectives. Future research can analyze and verify the conclusions of this study through other perspectives. For example, we can analyze school-enterprise collaborative behavior from the perspective of ecology, complex adaptability theory, game theory, transaction cost theory, etc.

7. Conclusions

This research has yielded significant theoretical and practical implications in the field of collaborative innovation within vocational colleges. The findings emphasize the importance of social proximity, cognitive proximity and geographical proximity in promoting individual collaborative innovation capabilities. Through quantitative analysis, it has been demonstrated that these proximities facilitate the sharing of implicit information, the establishment of norms and values and the development of cooperation and trust among stakeholders.

Collaborative behavior emerges as a key factor in mediating the relationship between proximity and individual collaborative innovation capabilities. It plays a crucial role in fostering smooth communication and interaction between vocational colleges, thereby facilitating the exchange and feedback process between knowledge elements from diverse backgrounds. By leveraging the resources and training activities provided by enterprises, collaborative behavior enables teachers to bridge the gap between theoretical knowledge and practical applications, enhancing their understanding of STEM skills in real-world contexts and empowering their collaborative innovation abilities.

In summary, this research contributes to the knowledge base surrounding collaborative innovation in vocational colleges and highlights the significance of social, cognitive and geographical proximities. The study underscores the pivotal role of collaborative behavior in facilitating effective cooperation and knowledge sharing, leading to enhanced individual collaborative innovation capabilities. By addressing the limitations and considering avenues for future research, this study sets the stage for further exploration and advancements in the field of collaborative innovation within vocational education.

Conflict of interest

All authors declare no conflicts of interest in this paper.

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