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A Pilot PLS-SEM Study on Trust and Knowledge Management for Innovation Performance in University-Industry Collaborations

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ABSTRACT

This study developed and validated a comprehensive scale to assess the influence of trust and knowledge management on innovation performance within university-industry collaborations (UIC). Data collected from 100 industry professionals were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), incorporating Exploratory Factor Analysis (EFA) to evaluate the scale's psychometric robustness. The instrument exhibited high reliability, with composite reliability (CR) values exceeding 0.7 and all factor loadings surpassing 0.5. Convergent validity was confirmed through Average Variance Extracted (AVE), while discriminant validity was also established, affirming the conceptual distinctiveness of the constructs. These findings offer strong empirical evidence for the scale's validity and reliability, presenting a rigorous tool for future investigations into the interplay of trust, knowledge management, and innovation in UIC contexts.

Keywords: PLS-SEM, University-Industry Collaborations, Trust, Knowledge Management, Innovation Performance.

1. Introduction

University-industry collaborations (UICs) have become increasingly important for driving innovation and economic growth in today's knowledge-based economy. These partnerships offer a unique opportunity for businesses to access cutting-edge research and development capabilities, while universities can benefit from industry expertise and resources. UICs play a crucial role in accelerating technological advancements and enhancing national competitiveness. A global trend towards greater collaboration between academia and industry is evident in recent reports and statistics. Per a report from the Chinese Ministry of Science and Technology, the volume of industry-academia collaborative projects in China surged from 180,000 in 2015 to 320,000 in 2020, marking a significant transformation (Esangbedo CO, 2024).

Trust is a critical factor in successful UICs, influencing knowledge transfer, information sharing, and collaborative innovation. Institutional trust, cognitive trust, and affective trust are distinct dimensions that impact various aspects of UICs. Knowledge management capabilities, including knowledge acquisition, knowledge transfer, and knowledge integration, are also essential for effective UICs. Trust and knowledge management interact to create a conducive environment for innovation and knowledge creation within UICs.

Although research on university-industry collaborations (UICs) has grown substantially, a comprehensive and validated scale to measure the impact of trust and knowledge management on innovation performance remains lacking. Developing a rigorous instrument to assess these core constructs and their interrelationships is essential for advancing both academic inquiry and practical implementation. Such a tool would offer significant value to researchers, practitioners, and policymakers engaged in UICs.

To fill this gap, the present study developed and validated a scale to measure the influence of trust and knowledge management on innovation performance within UICs. Employing Partial Least Squares Structural Equation Modeling (PLS-SEM) and data from 100 industry professionals, we evaluated the scale's psychometric soundness.

The paper is structured as follows: First, we present a comprehensive literature review on trust, knowledge management, and innovation in the UIC context. Next, we detail the scale development and validation procedures. We

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Research Article

then report the results of the statistical analysis. Finally, we explore the theoretical and practical implications of our findings.

2. Literature review

Trust is a fundamental relational component of social capital and acts as a "double-edged sword" (Channuwong, et al., 2025; Shen, L., 2019). It exerts a significant influence on the innovation performance of enterprises within university-industry collaboration networks through several key mechanisms: (1) Trust facilitates the transfer of knowledge from academic institutions to businesses, positively impacting the innovation capabilities of the latter. From the perspective of social capital theory, trust catalyzes cooperation, fostering collaboration and encouraging mutual information sharing (Kenikasamanworakhun et al., 2025; Nahapiet & Ghoshal, 1998). (2) Trust reduces the costs associated with managing and maintaining relationships, enabling organizations to allocate more resources to technological innovation, thereby enhancing innovation outcomes. By increasing relational control, trust mitigates organizational investment costs (Adler & Kwon, 2002). (3) However, excessive trust in partners may lead to complacency in monitoring, fostering opportunistic behaviors, such as reducing investments in favor of pursuing more lucrative relationships with other enterprises, or engaging in deceptive and exploitative practices to maximize personal gain (Goel, 2005).

Researchers have primarily concentrated on the impact of trust on specific aspects such as collaborative relationships, knowledge transfer, or performance, yet a comprehensive research framework has yet to be established. While trust undeniably affects collective innovation performance, it is insufficient to link trust to the outcome variables of collaborative innovation merely. There is a pressing need for a deeper exploration of how various dimensions of trust influence outcome variables through mediating mechanisms. Currently, studies on the mediating mechanisms of trust in collaborative innovation performance emphasize affective commitment, calculative commitment, and organizational identification. However, knowledge management capabilities warrant further investigation.

This study examines the relationship between trust, knowledge management (KM), and innovation performance (IP) in industry-academia collaboration. Trust is categorized into three dimensions: institutional trust, cognitive trust, and emotional trust. Knowledge management capabilities are divided into two dimensions: knowledge acquisition and knowledge transfer. The innovation performance of firms is assessed from three perspectives: technological innovation performance, knowledge innovation performance, and management innovation performance. The aim is to provide a comprehensive analysis of how the different dimensions of trust influence the innovation performance of firms. Before using these variables as factors influencing innovation performance, the validity and reliability of the questionnaire must be tested. The study then employs the PLS-SEM methodology and seeks to incorporate knowledge management and other knowledge-based view elements as mediating variables.

A scale, as a standardized questionnaire or list, strictly adheres to management and scoring guidelines. Its primary purpose is to assess latent psychological structures or latent variables that may not be immediately observable (Fabrigar & Ebel-Lam, 2007; Wongmajarapinya et al., 2024). The development of scales is typically driven by practical needs, theoretical advancements, or empirical progress (Irwing & Hughes, 2018). Constructing a scale involves selecting the most appropriate components or aspects from a given framework to serve as test items (Chadha, 2009). This study follows the five-step comprehensive process for scale development outlined by Tripathi (2007) in the Textbook of Social Science Research Methods.

1. Defining the Measured Trait: First, define the trait to be measured, assuming it is unidimensional.
2. Generating Potential Items: Create a pool of 80 potential items, rated on a 5-point Likert scale (from 1 = strongly disagree to 5 = strongly agree).
3. Expert Review: A panel of experts reviews the items and rates them on a 1-5 scale to assess how well each item measures the construct (from 1 = strongly disagree to 5 = strongly agree).
4. Pilot Testing: Conduct a pilot test of the items, including reverse-scored, negatively worded items to measure the construct from the opposite direction.
5. Statistical Analysis: Use statistical analysis software, such as SPSS and Smart PLS, to address issues related to recommended sample size, distribution assumptions, statistical power, and goodness-of-fit tests (Dash & Paul, 2021).

Following the established scale development processes proposed by various studies (Tripathi, 2003; Kyriazos & Stalikas, 2018; Kundu et al., 2023), this study developed and implemented a scale to assess the impact of trust on

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Research Article

industry-academia collaboration innovation performance and the mediating role of knowledge management. The study drew inspiration from previous scale development methods and conducted development. The scale development framework and tool sub-projects are shown in Figure 1.

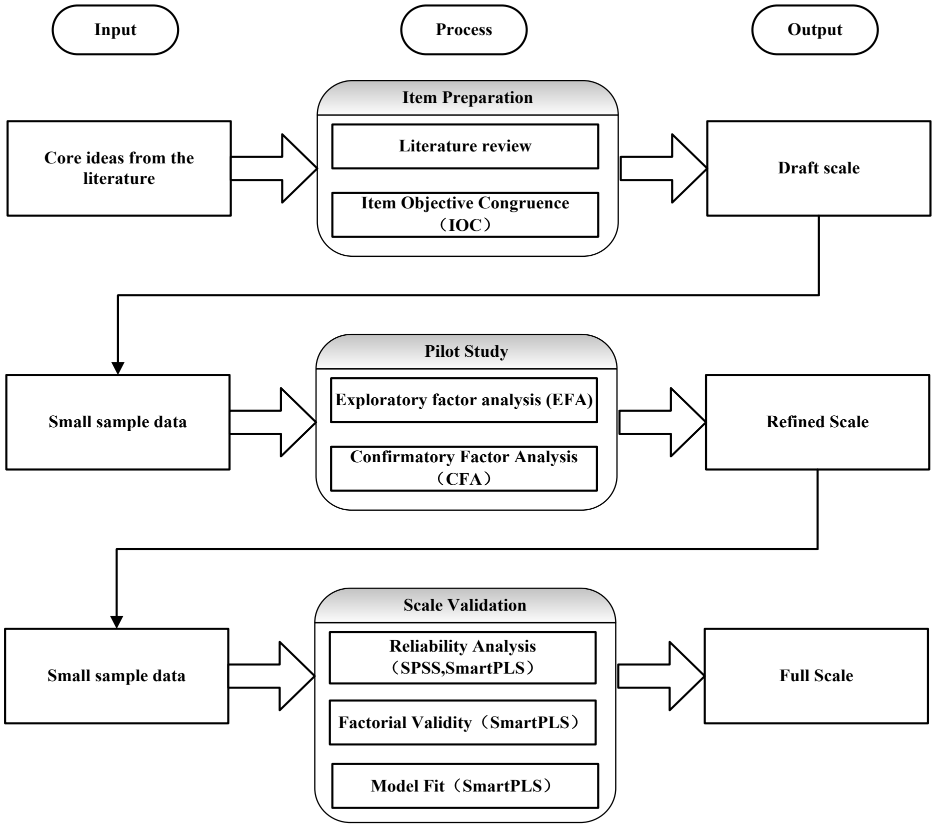

Figure 1 Scale development framework

3. Methodology

3.1 Dimensions of the scale and hypotheses

Before designing the questionnaire, it is essential to establish clear hypotheses regarding the relationships between variables to ensure the effective measurement of each construct. Therefore, prior to developing the questionnaire in this study, an extensive review of relevant literature on inter-organizational emotional trust, cognitive trust, institutional trust, corporate knowledge management capabilities, and corporate innovation performance was conducted. The study draws heavily on theoretical frameworks proposed in authoritative research, selecting well-established scales widely cited in empirical studies. These validated scales were then adapted and refined in alignment with the theoretical foundation of this research to formulate precise measurement items. The model employs variables with measurable indicators. The specific variables and their indicators are as follows:

A. Trust

Institutional Trust (IT): Focuses on the partner's adherence to formal agreements and rules, as well as the firm's confidence in the governance structure of the collaborating academic institution.

Cognitive Trust (CT): Primarily involves the firm's perception of the academic institution's capabilities, including its professionalism and reliability.

Affective Trust (AT): Emphasizes the emotional connection and interpersonal rapport between the firm and the academic institution.

B. Knowledge Management

Knowledge Acquisition (KA): Measures the firm's ability to acquire, absorb, and utilize external knowledge, particularly from partnering academic institutions.

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Research Article

Knowledge Transfer (KT): Focuses on the effectiveness of disseminating and sharing knowledge within the firm and between the firm and its partners.

C. Innovation Performance

Technological Innovation Performance (TIP): Measured through indicators such as the efficiency and quantity of new product development, and the number of patents held, reflecting the firm's technological innovation achievements.

Knowledge Innovation Performance (KIP): Focuses on evaluating the firm's effectiveness in enhancing employee knowledge, mastering new development methods, and shortening the innovation cycle through industry-academia collaboration.

Managerial Innovation Performance (MIP): This metric primarily assesses the firm's internal management innovation achievements, including enhancements in employee creativity, resource utilization efficiency, process optimization, and expedited order delivery.

3.2 Questionnaire Design and Improvement

The questionnaire is divided into two main sections: the first section contains questions regarding the basic information of the enterprise (such as size, position, industry, ownership type, and frequency of cooperation), which is to be filled out directly by the respondents; the second section uses a five-point Likert scale to measure the main variables of this study, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Based on the interrelationships among the variables, the core variables in this study are categorized into three types: independent variables, mediating variables, and dependent variables. The independent variables include institutional trust (3 items), cognitive trust (3 items), and affective trust (3 items); the mediating variables include knowledge acquisition ability (4 items) and knowledge transfer ability (4 items); the dependent variables include technological innovation performance (5 items), management innovation performance (6 items), and knowledge innovation performance (4 items). The measurement of these variables prioritizes scales from relevant empirical studies, with adjustments and revisions made according to the context and actual circumstances of the enterprises, ensuring the reliability and validity of the scales.

After the initial draft of the questionnaire was formed, extensive feedback was solicited from experts within the academic team. Based on their suggestions, adjustments were made to the questionnaire content, item phrasing, and wording. In addition, to ensure the research subjects fully understood the questionnaire, the author engaged in discussions with managers from several companies, including Zhongruan International, China Unicom, and Hikvision, regarding the questionnaire's content. Feedback was gathered on the comprehensibility of the questionnaire items and how well the items reflected the underlying constructions. Based on this feedback, the item content and expression were revised to improve the clarity of the questionnaire, resulting in a draft of a small-sample questionnaire.

3.3 Population and Sample

After determining the structure and items of the questionnaire, a preliminary small-scale distribution will be conducted to assess the reliability and validity of the pre-survey questions. In this phase, 100 questionnaires will be distributed to seven high-tech companies that have established cooperative relationships with the researcher's institution. Data from credible sources and questionnaires using a Chinese questionnaire website called "Questionnaire Star".

3.4 Statistical Analysis

A. Descriptive statistical analysis

This study will use descriptive statistics to assess the percentage of respondent demographics, company size, ownership type, and industry sector in the sample data, as well as the mean, standard deviation, skewness, and kurtosis of the results captured for each question item of the scale.

B. Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) is employed to identify the underlying factor structure of a scale and to determine the initial dimensions of constructs. This technique analyzes the interrelationships among observed variables to uncover latent constructs, facilitating the development of reliable and valid measurement instruments. Exploratory Factor Analysis (EFA) was conducted using SPSS software.

Journal of Information Systems Engineering and Management
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Research Article

C. Reliability Testing

In PLS-SEM, reliability is the extent to which a measurement tool consistently and reliably measures a construct. Key reliability metrics are Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). Cronbach's Alpha and CR both evaluate internal consistency: Cronbach's Alpha gauges the average inter-item correlations, while CR incorporates each item's standardized loading. AVE assesses convergent validity by indicating the average variance extracted by its items. Generally, acceptable reliability and validity are indicated by Cronbach's Alpha and CR values exceeding 0.7 and an AVE value surpassing 0.5.

4. Result and Discussion

4.1 Descriptive statistical analysis

General Information of Respondents: The small-sample data was collected from 123 respondents across seven high-tech enterprises, resulting in 100 valid responses. The results encompass respondent's position, company size, ownership structure, and the frequency of industry-university collaboration. Detailed findings are presented in Table 1.

Table 1 Respondent Profile

General information	option	Number of respondents (n=100)	Percentage (%)
Position	Management Leaders	36	36
	Staff	34	34
	Department Manager	16	16
	Project Manager	11	11
	Company CEO	3	3
Company size	200-500	42	42
	500 and above	29	29
	100-200	16	16
	Below 100	13	13
Ownership structure	Private	66	66
	State-owned	22	22
	Joint Ventures	5	5
	Foreign Investment	5	5
	Other	2	2
frequency of university-industry collaboration	More frequent	64	64
	Yes but not much	34	34
	Partial contact	2	2

This survey collected 100 valid responses, covering enterprises of varying sizes, ownership structures, and collaboration frequencies. In terms of respondent positions, senior management accounted for 36%, employees for 34%, department managers for 16%, project managers for 11%, and CEOs for 3%.

Regarding company size, 42% of the enterprises had 200-500 employees, 29% had more than 500 employees, 16% had 100-200 employees, and 13% had fewer than 100 employees.

In terms of ownership structure, private enterprises comprised 66% of the sample, state-owned enterprises 22%, while joint ventures and foreign-funded enterprises each accounted for 5%, with other types making up 2%.

Additionally, 64% of the enterprises engaged in frequent industry-university collaborations, 34% collaborated occasionally, and only 2% had minimal interaction. Considering that two respondents had no industry-university collaboration experience, the final valid sample size was 98.

Descriptive statistical analysis was conducted to summarize the general characteristics of the sample. This analysis utilized key metrics such as mean, standard deviation, skewness, and kurtosis to assess the distribution of variables. The results of the descriptive statistical analysis are shown in Table 2.

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/
Research Article

Table 2 The results of the descriptive statistical analysis

Item	Indicator	min	max	mean	Std. Dev.	Skewness	Kurtosis
Institutional Trust(IT)	IT1	2	5	4.01	.659	-.443	.747
	IT2	3	5	4.46	.673	-.866	-.387
	IT3	3	5	4.36	.578	-.232	-.695
Cognitive Trust (CT)	CT1	2	5	4.38	.599	-.672	1.101
	CT2	2	5	3.91	.877	-.372	-.619
	CT3	2	5	4.37	.630	-.729	.789
Affective Trust (AT)	AT1	2	5	4.29	.656	-.602	.382
	AT2	2	5	4.28	.740	-1.113	1.670
	AT3	2	5	4.23	.777	-.955	.852
Knowledge Acquisition (KAM)	KAM1	3	5	4.40	.603	-.451	-.639
	KAM2	3	5	4.50	.560	-.529	-.767
	KAM3	2	5	4.18	.687	-.820	1.497
	KAM4	2	5	4.43	.714	-1.191	1.276
Knowledge Transfer (KTM)	KTM1	2	5	4.22	.645	-.470	.420
	KTM2	2	5	4.22	.645	-.470	.420
	KTM3	3	5	4.28	.740	-.502	-1.015
	KTM4	2	5	4.19	.692	-.831	1.445
Technical Innovation Performance (TIP)	TIP1	2	5	4.26	.719	-.767	.496
	TIP2	1	5	4.15	.770	-1.212	2.797
	TIP3	2	5	4.30	.718	-.853	.642
	TIP4	1	5	4.16	.838	-1.469	3.339
Managerial Innovation Performance (MIP)	MIP1	2	5	4.27	.633	-.533	.595
	MIP2	2	5	4.40	.636	-.819	.830
	MIP3	2	5	4.29	.701	-.831	.824
	MIP4	2	5	4.35	.702	-.969	1.029
	MIP5	2	5	4.18	.730	-.611	.166
	MIP6	2	5	4.38	.736	-1.206	1.536
Knowledge Innovation Performance (KIP)	KIP1	2	5	4.21	.640	-.451	.465
	KIP2	2	5	4.42	.755	-1.306	1.499
	KIP3	2	5	4.14	.804	-.736	.171
	KIP4	1	5	4.15	.716	-1.072	3.156
	KIP5	2	5	4.37	.630	-.729	.789

The data demonstrates a strong tendency towards positive evaluations, suggesting that respondents generally hold favorable views regarding the company's trust, knowledge acquisition, transferability, and innovation performance. While some items show slight deviations from a normal distribution, this non-normality may reflect the diverse perspectives and experiences of the respondents, enhancing the depth of the analysis and rendering it more appropriate for empirical research utilizing the PLS-SEM model.

4.2 Exploratory Factor Analysis (EFA)

The Kaiser-Meyer-Olkin (KMO) Measure: The KMO value is a critical indicator for assessing the suitability of data for factor analysis. The closer the KMO value is to 1, the more appropriate the data is for factor analysis. Generally, a KMO value above 0.8 indicates excellent suitability, between 0.7 and 0.8 suggests adequacy, and below 0.6 indicates unsuitability.

Bartlett's Test of Sphericity: Bartlett's test is used to assess whether there is sufficient correlation among variables, ensuring the appropriateness of factor analysis. A significance (Sig.) value of less than 0.05 indicates that the data is suitable for factor analysis.

The results of the KMO and Bartlett's Test for the small sample data of the questionnaire are shown in Table 3.

Journal of Information Systems Engineering and Management
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Research Article

Table 3 The results of the KMO and Bartlett's Test for the small sample data

Variable	Kaiser-Meyer-Olkin (KMO)	Chi-Square	df	Sig
Trust	0.826	188.016	36	0.000
Knowledge Management	0.711	132.763	28	0.000
Innovation Performance	0.798	548.514	105	0.000

The results from the Kaiser-Meyer-Olkin (KMO) Measure and Bartlett's Test of Sphericity indicate that the data for Trust, Knowledge Management, and Innovation Performance are highly suitable for factor analysis. The KMO values of 0.826 for Trust, 0.711 for Knowledge Management, and 0.798 for Innovation Performance suggest that the data is acceptable or excellent for factor analysis. Furthermore, Bartlett's Test of Sphericity shows a significant result ($p < 0.001$) for all three variables, confirming that there are sufficient correlations between the variables, which makes factor analysis appropriate. These results provide a strong foundation for proceeding with the exploratory factor analysis (EFA) for these constructs.

A. Trust

Principal component analysis (PCA) was conducted on 9 trust-related items using a small sample of 98 data points. Based on the criterion of eigenvalues greater than 1 and factor loadings exceeding 0.5, three factors were extracted. The cumulative explained variance of these factors was 59.113%. The exploratory factor analysis (EFA) results for the university-industry collaboration trust items are presented in Table 4.

Table 4 EFA results for trust

Indicator	Component		
	1	2	3
IT1	**.547**	.380	.454
IT2	**.701**	.095	.163
IT3	**.696**	.125	-.105
CT1	.132	**.551**	.341
CT2	.396	**.707**	.030
CT3	-.051	**.813**	.167
ET1	.098	.397	**.657**
ET2	-.051	.167	**.813**
ET3	.374	.105	**.641**

Upon examining the factor loading of all items, the minimum factor loading is 0.547, which exceeds the threshold of 0.5. Furthermore, there is no instance where two or more factor loadings of the items surpass 0.5. The factor analysis results indicate that items IT1-3 assess institutional trust, CT1-3 assess cognitive trust, and AT1-3 evaluate affective trust.

B. Knowledge Management

A principal component analysis (PCA) was conducted on 8 knowledge management-related items using a small sample of 98 data points. Based on the criteria of eigenvalues greater than 1 and factor loadings exceeding 0.5, two factors were extracted. The cumulative explained variance of these factors is 49.238%. The exploratory factor analysis (EFA) results for the company's knowledge management capabilities are presented in Table 5.

Table 5 EFA results for KM

Indicator	Component	
	1	2
KAM1	**.521**	.347
KAM2	**.633**	.040
KAM3	**.799**	.174
KAM4	**.636**	.188
KTM1	226	**.625.**
KTM2	.044	**.852**

Journal of Information Systems Engineering and Management
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Research Article

KTM3	-.151	**.680**
KTM4	.312	**.533**

Based on the principal component analysis conducted on 8 knowledge management items from a sample of 98, two factors were extracted, meeting the criteria of eigenvalues greater than 1 and factor loadings exceeding 0.5. Upon reviewing the factor loadings, the minimum loading is 0.521, which is above the threshold of 0.5, and no items have multiple loadings exceeding 0.5. The results indicate that items KAM1-4 are associated with knowledge acquisition management, while items KTM1-4 are related to knowledge transfer management.

C. Innovation Performance

Principal component analysis (PCA) was conducted on 15 items related to corporate innovation performance using a small sample of 98 data points. Based on the criteria of eigenvalues greater than 1 and factor loadings greater than 0.5, two factors were extracted. The cumulative explained variance of these factors is 55.030%. The results of the exploratory factor analysis (EFA) for corporate innovation performance are presented in Table 6.

Table 6 EFA results for IP

Indicator	Component		
	1	2	3
TIP1	**.643**	.179	.153
TIP2	**.713**	.336	.069
TIP3	**.557**	.177	.228
TIP4	**.697**	.278	.264
MIP1	.308	**.591**	.164
MIP2	.234	**.756.**	034
MIP3	.488	**.604**	-.027
MIP4	-.107	**.733.**	401
~~MIP5~~	~~.431~~	~~.348~~	~~.315~~
MIP6	.424	**.603**	-.008
KIP1	.458	-.070	**.583**
KIP2	.050	173	**.854.**
KIP3	.350	.180	**.528**
KIP4	.292	.024	**.669**
KIP5	.259	.389	**.520**

Based on this, principal component analysis (PCA) was performed on 15 corporate innovation performance items using 98 minor sample data points. Following the standard of eigenvalues greater than one and factor loadings greater than 0.5, three factors were extracted. Upon observing the factor loadings of all items, the item MIP5, "The company can deliver orders faster," had a maximum factor loading of 0.431, which is less than 0.5. Its loadings across multiple factors were significantly low, failing to meet the requirements for discriminant validity. Therefore, this item was removed. The factor analysis results indicate that items TIP1-4 measure technical innovation performance, items MIP1-4 and MIP6 measure managerial innovation performance, and items KIP1-5 measure knowledge innovation performance.

4.3 Reliability Testing

After conducting descriptive analysis and exploratory factor analysis (EFA), the MIP5 items were removed. Import the 98-item small sample dataset into SmartPLS and construct the measurement model. Execute the PLS algorithm, then inspect and evaluate the reliability metrics in the output. This ensures the measurement tool's reliability and validity. The results of the PLS-SEM model in SmartPLS, following item refinement of the small sample data, are illustrated in Figure 2.

Journal of Information Systems Engineering and Management
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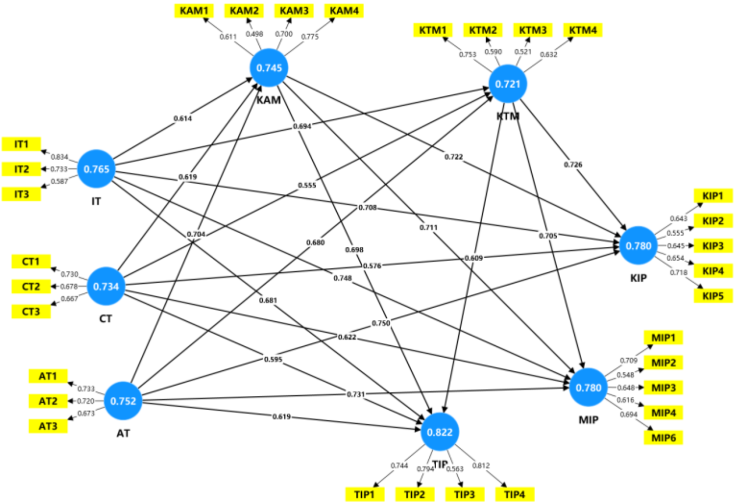

Figure 2. Outer Loading and Cronbach's Alpha values before elimination of indicator

The criterion loading value adopted is 0.50. Consequently, any indicator with an outer loading value below 0.5 must be eliminated. Moreover, the model must be retested following the removal. In the figure above, the loading value of the KAM2 item is less than 0.5 (loading value of 0.498), which is deemed an invalid indicator. Figure 2 below presents the values of convergent validity.

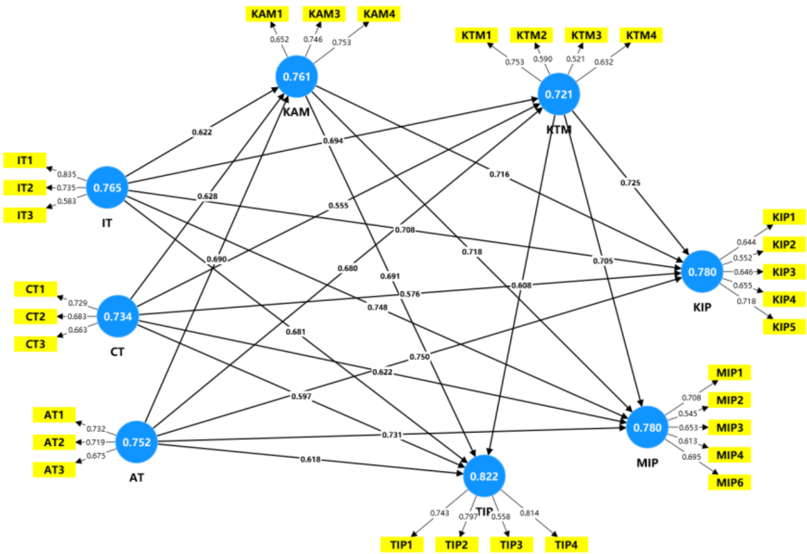

Figure 3. Outer Loading and Cronbach's Alpha values after elimination of the indicator

Retesting is then conducted by eliminating indicators with loading factors and AVE values below 0.5. If any loading factors or AVE values remain below 0.5, the testing process is repeated. The results of the retest are presented in Table 7.

Table 7 The results of construct reliability

Item	Indicator	Outer loading	Cronbach's alpha	CR	AVE
AT	AT1	0.732	0.808	0.752	0.603
	AT2	0.719			
	AT3	0.675			
CT	CT1	0.729	0.857	0.734	0.579
	CT2	0.683			
	CT3	0.663			

Journal of Information Systems Engineering and Management
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Research Article

	IT1	0.835			
IT	IT2	0.735	0.842	0.765	0.526
	IT3	0.583			
	KAM1	0.652			
KAM	KAM3	0.746	0.837	0.761	0.536
	KAM4	0.753			
	KTM1	0.753			
KTM	KTM2	0.590	0.887	0.721	0.697
	KTM3	0.521			
	KTM4	0.632			
	KIP1	0.644			
	KIP2	0.552			
KIP	KIP3	0.646	0.946	0.780	0.616
	KIP4	0.655			
	KIP5	0.718			
	MIP1	0.708			
	MIP2	0.545			
MIP	MIP3	0.653	0.846	0.780	0.717
	MIP4	0.613			
	MIP6	0.695			
	TIP1	0.743			
TIP	TIP2	0.797	0.807	0.822	0.740
	TIP3	0.558			
	TIP4	0.814			

Table 7 presents the outputs of the loading factors, Composite Reliability (CR), and Average Variance Extracted (AVE). All loading factors fall within the range of 0.5 to 0.7. Additionally, the CR values all exceed 0.6. All AVE values are greater than 0.5 and lower than the corresponding CR values.

The reliability analysis reveals that most latent variables exhibit satisfactory external loadings, Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE), all of which meet the established criteria. These results underscore the high level of measurement reliability and validity. The measurement instrument demonstrates robust internal consistency and reliability.

5. Conclusion

This study deepens the understanding of how trust-articulated through institutional, cognitive, and affective dimensions-shapes innovation performance in university-industry collaborations, with knowledge management serving as a critical mediating mechanism. Integrating insights from social capital theory and the knowledge-based view, the findings reveal that trust is not a singular enabler; its impact depends on the effectiveness of knowledge acquisition and transfer. These results resonate with prior research (Nahapiet & Ghoshal, 1998; Adler & Kwon, 2002) while extending it through the empirical validation of a multidimensional trust framework within high-tech enterprises.

Theoretically, this research enriches the literature by constructing and validating a robust measurement scale specifically designed for the university-industry collaboration context. The scale confirms that the various dimensions of trust exert differentiated effects on technological, knowledge, and managerial innovation performance via distinct knowledge management capabilities. This refined understanding offers a more sophisticated analytical model than earlier studies, which often treated trust as a uniform construct.

Practically, the study offers strategic guidance for both universities and enterprises. For universities, the findings emphasize the necessity of fostering institutional and cognitive trust to reinforce long-term alliances and enhance the efficacy of technology transfer. For industry partners, the results highlight that while emotional trust can strengthen mutual commitment, it must be carefully managed to mitigate risks of complacency or opportunism, as cautioned by Goel (2005). The validated scale serves as a practical diagnostic tool to evaluate collaboration readiness, identify deficiencies in trust, and align knowledge management strategies to optimize innovation outcomes.

In conclusion, this research not only advances the theoretical comprehension of trust and knowledge management in collaborative innovation but also delivers a rigorously tested, context-specific instrument for practitioners. The proposed framework bridges academic insight and practical application, laying a solid foundation for future strategies aimed at sustaining and enhancing innovation performance in university-industry partnerships.

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