



The Impact of Competitive Intelligence on Institutional Innovation in Chinese Higher Education: The Mediating Role of Knowledge Sharing

O Impacto da Inteligência Competitiva na Inovação Institucional no Ensino Superior Chinês: O Papel Mediador do Compartilhamento de Conhecimento

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ABSTRACT | Purpose: This study examines whether perceived competitive-intelligence capability is associated with institutional innovation in Chinese higher education and whether knowledge sharing accounts for part of that association. It responds to a fragmented literature in which university information needs, recruitment intelligence, digital transformation, knowledge exchange, and institutional innovation have largely been examined as separate research streams. **Methodology/Approach:** The study used a de-identified cross-sectional dataset comprising 240 complete responses collected from a geographically concentrated group of universities in Wuhan, Hubei Province. The questionnaire included 24 competitive-intelligence items, eight knowledge-sharing items, and 12 institutional-innovation items, all measured on seven-point Likert scales. The analysis employed composite scores, internal-consistency diagnostics, construct-correlation analysis, HTMT assessment, HC3-robust regression models, and a nonparametric bootstrap procedure with 10,000 resamples. The dataset was finalized for analysis on 3 August 2026. **Originality/Relevance:** The study brings together the competitive-intelligence cycle, the knowledge-based view, and dynamic-capabilities theory within a higher-education setting. Its relevance lies in examining how intelligence practices may be translated into institutional innovation through internal knowledge-sharing processes, an issue that remains underexplored in Chinese higher education. It also provides an institutionally focused framework that can inform strategic planning, information use, and innovation management in universities. **Key Findings:** Competitive intelligence was positively associated with both knowledge sharing and institutional innovation. The standardized indirect association through knowledge sharing was .240, with a 95% bootstrap confidence interval of [.133, .345]. The direct association between competitive intelligence and institutional innovation remained positive after knowledge sharing was included in the model. However, the very high interconstruct correlations, HTMT ratios, and predictor collinearity indicated substantial overlap among the three measures. The findings therefore support the proposed sequence at the composite-score level but do not establish a causal or fully measurement-distinct

mediation process. **Theoretical/Methodological Contributions:** The study extends competitive-intelligence research by positioning knowledge sharing as a potential mechanism linking intelligence capability with institutional innovation. It also demonstrates an important methodological point: high reliability, significant regression paths, and a non-zero bootstrap interval do not, on their own, establish construct distinctiveness. By combining structural estimates with discriminant validity and collinearity diagnostics, the study offers a more cautious and reproducible analytical framework for future multi-source and time-lagged research.

Keywords | Competitive Intelligence. Institutional innovation. Knowledge sharing. Higher education. China. Mediation. Measurement validity

RESUMO | Objetivo: Este estudo examina se a capacidade percebida de Inteligência Competitiva está associada à inovação institucional no ensino superior chinês e se o compartilhamento de conhecimento explica parte dessa associação. O estudo responde a uma literatura fragmentada, na qual as necessidades informacionais das universidades, a inteligência aplicada ao recrutamento, a transformação digital, a troca de conhecimentos e a inovação institucional têm sido, em grande medida, examinadas como linhas de pesquisa separadas. **Metodologia/Abordagem:** O estudo utilizou um conjunto de dados transversal e desidentificado, composto por 240 respostas completas coletadas em um grupo geograficamente concentrado de universidades em Wuhan, província de Hubei. O questionário incluiu 24 itens de Inteligência Competitiva, oito itens de compartilhamento de conhecimento e 12 itens de inovação institucional, todos mensurados por meio de escalas Likert de sete pontos. A análise empregou escores compostos, diagnósticos de consistência interna, análise de correlação entre construtos, avaliação HTMT, modelos de regressão robustos HC3 e um procedimento de *bootstrap* não paramétrico com 10.000 reamostragens. O conjunto de dados foi finalizado para análise em 3 de agosto de 2026. **Originalidade/Relevância:** O estudo integra o ciclo de Inteligência Competitiva, a Visão Baseada em Conhecimento (*Knowledge-Based View – KBV*) e a Teoria das Capacidades Dinâmicas (*Dynamic Capabilities Theory*) no contexto do ensino superior. Sua relevância reside na análise de como as práticas de inteligência podem ser convertidas em inovação institucional por meio de processos internos de compartilhamento de conhecimento, uma questão ainda pouco explorada no ensino superior chinês. O estudo também apresenta um framework com foco institucional que pode contribuir para o planejamento estratégico, a utilização de informações e a gestão da inovação nas universidades. **Principais Resultados:** A Inteligência Competitiva apresentou associação positiva tanto com o compartilhamento de conhecimento quanto com a inovação institucional. A associação indireta padronizada por meio do compartilhamento de conhecimento foi de 0,240, com intervalo de confiança *bootstrap* de 95% de [0,133; 0,345]. A associação direta entre Inteligência Competitiva e inovação institucional permaneceu positiva após a inclusão do compartilhamento de conhecimento no modelo. Entretanto, as correlações muito elevadas entre os construtos, os índices HTMT e a colinearidade entre os preditores indicaram uma sobreposição substancial entre as três medidas. Portanto, os resultados oferecem suporte à sequência proposta no nível dos escores compostos, mas não estabelecem um processo de mediação causal nem plenamente distinto do ponto de vista da mensuração. **Contribuições Teóricas/Metodológicas:** O estudo amplia a pesquisa em Inteligência Competitiva ao posicionar o compartilhamento de conhecimento como um mecanismo potencial de ligação entre a capacidade de inteligência e a inovação institucional. O estudo também demonstra um aspecto metodológico importante: alta confiabilidade, relações de regressão estatisticamente significativas e um intervalo *bootstrap* diferente de zero não são, isoladamente, suficientes para estabelecer a distinção entre construtos. Ao combinar estimativas estruturais com diagnósticos de validade discriminante e colinearidade, o estudo apresenta um framework analítico mais cauteloso e reproduzível para futuras pesquisas com múltiplas fontes de dados e desenhos com defasagem temporal (*time-lagged*).

Palavras-chave | Inteligência Competitiva. Inovação institucional. Compartilhamento de conhecimento. Ensino superior. China. Mediação. Validade de mensuração.



1. INTRODUCTION

Universities no longer make strategic decisions in a stable educational environment. Enrolment patterns shift with demographic change; labor-market expectations often evolve faster than programme-review cycles; digital technologies reshape teaching and administration; and governments increasingly require evidence of economic and social relevance. These pressures are especially pronounced in China, where rapid expansion has been accompanied by demands for academic quality, institutional differentiation, digital modernization, graduate employability, research impact, and regional contribution. Digital transformation is therefore an organizational challenge rather than a narrow technology project: institutions must decide which signals matter, how those signals should be interpreted, who should act on them, and how experience should inform subsequent decisions (Akour & Alenezi, 2022; Benavides et al., 2020; Hashim et al., 2022; Knox, 2020).

CI provides a systematic approach to the information-to-action issue. In more advanced accounts, competitive intelligence isn't only about gathering data from competitors. It is a process of decision-making that a given organization determines its needs, examines its surroundings, collects authorized and trustworthy information, evaluates implications, informs responsible users, feeds information into decision-making, and monitors the results (Calof & Wright, 2008; Dishman & Calof, 2008; Herring, 1999). This definition is helpful in higher education because higher education is a competitive multiple-stage, multiplayer, partly-cooperative process. While they vie for students, faculty, research dollars, partners, legitimacy and attention to policy, they also share knowledge, join consortia, and fulfil public missions. Rather, the question to consider is not whether a university mimics a competitor. It is whether the institution can interpret external change and coordinate an informed response without compromising ethical, academic, or public-interest obligations.

Recent work confirms that competitive intelligence is beginning to enter higher-education research, but the empirical base remains thin. Oraee et al. (2021) mapped the information needs of higher-education managers; Oraee (2023) examined information behavior within the competitive-intelligence process of medical-sciences universities; Mgweba et al. (2024) considered competitive intelligence in public-university student recruitment; and Mogale et al. (2025) examined its significance in selected higher-education institutions. These studies establish sectoral relevance. They do not yet offer a settled explanation of how intelligence becomes institutional innovation. The broader competitive-intelligence literature supplies evidence that intelligence routines can support innovation, responsiveness, and value creation (Bao et al., 2020; Hamilton, 2024; Olszak et al., 2023), but much of that evidence comes from firms, startups, tourism, logistics, or manufacturing.

A second literature examines knowledge sharing. Its central insight is straightforward but often underdeveloped in competitive-intelligence models: intelligence held by one office does not become institutional capability merely because it exists. Admissions may observe changing student preferences, industry-relations staff may detect new skill requirements, research managers may see emerging funding priorities, and information-technology units may understand platform constraints. Innovation requires these partial perspectives to be exchanged, challenged, integrated, and made usable. Knowledge donation and knowledge collection provide the social infrastructure for that work. Prior research connects knowledge sharing with organizational innovation and performance



(Azeem et al., 2021; Olan et al., 2022; van den Hooff & de Ridder, 2004), but the mechanism has rarely been placed between a directly measured university competitive-intelligence capability and a multidimensional institutional-innovation outcome.

The separation of these literatures produces four linked gaps. The theoretical gap is that competitive-intelligence scholarship explains organized environmental interpretation, whereas knowledge-management scholarship explains the movement and integration of expertise; few higher-education models specify how the latter translates the former into innovation. The empirical gap is the scarcity of manager- or knowledgeable-employee data that directly measure the full intelligence cycle rather than using digital literacy, analytics, or general information use as a proxy. The methodological gap concerns the tendency to treat high reliability and significant paths as sufficient evidence, even when constructs are so strongly correlated that their distinctiveness is doubtful. The contextual gap concerns Chinese higher education, where digital and innovation policies are prominent but institution-level competitive-intelligence routines are not well represented in peer-reviewed survey evidence.

This study fills these gaps by adopting a measurement-cautious mediation model. Competitive intelligence consists of 24 items covering intelligence planning, environmental scanning, collection, analysis, dissemination, utilization, governance and feedback. Knowledge sharing is operationalized through knowledge donation and knowledge collection. Institutional innovation covers academic programmes, administrative processes, digital services, and external partnerships and research initiatives. The individual response is the unit of analysis; therefore, the constructs are interpreted as perceptions of institutional practice and not as objective scores on the institution level. This distinction matters. The records are not available for aggregation or claims of the differences between universities without institutional identifiers and without statistics of agreement.

This study therefore adopts a measurement-cautious, mechanism-based perspective. It examines whether knowledge sharing accounts for an indirect component of the association between competitive intelligence and institutional innovation, while also testing whether the three constructs are empirically distinguishable. In light of these gaps, the study addresses three research questions:

- RQ1. Is perceived competitive-intelligence capability positively associated with perceived institutional innovation in Chinese higher education?
- RQ2. Does knowledge share account for a positive indirect component of this association?
- RQ3. Do the measurement results support discriminant validity among competitive intelligence, knowledge sharing, and institutional innovation? The first two questions are related to the proposed mechanism and the third to the question of whether the mechanism is empirically identifiable. The paper has three contributions to make. First, it connects the competitive-intelligence cycle to the knowledge-based view and the dynamic-capabilities theory in a more concise model of the university. Institutional innovation involves coordinated application and reconfiguration, while knowledge sharing involves sharing and interpretation, and competitive intelligence involves organized sensing and interpretation. Second, it brings in a more operational level where it directly uses eight domains of the institutions rather than being dependent on the technology ownership or personal digital skill. Third, it illustrates a methodological lesson of practical impact: positive bootstrapped indirect association does

not exclude problems with discriminant validity, high degrees of collinearity and common factor dominance. In such a case, the coefficient is reproducible but is not in itself proof of three different organizational processes.

The rest of the article presents the theoretical framework and hypotheses, the study design and reproducible analysis, the diagnostics supporting the hypotheses, the diagnostics that disconfirm the hypotheses, and the conclusions that can be drawn from the results – and those that cannot be drawn.

2. THEORETICAL FRAMEWORKS

2.1 Competitive intelligence as a governed information-to-action capability

There is a wide range of definitions of competitive intelligence. A few highlight competitors monitoring and others add market, technology, customer, regulatory, and stakeholder intelligence. The common denominator is more defensible, however, at a procedural than a topical level: Intelligence is information interpreted for a decision. Calof and Wright (2008) and Dishman and Calof (2008) see competitive intelligence as a cyclical process between information needs, information gathering and analysis, dissemination, and strategy development. Herring (1999) also suggests that the initial topics of key intelligence should be presented at the beginning of the cycle since the topics collected without a need for a decision will only be volumes of information. The field has been enriched by knowledge, information-processing, resource and dynamic-capability theories in the contemporary period, but there are also inconsistent definitions of constructs and maturity measures (Madureira et al., 2023; Maungwa & Laughton, 2023). The bibliometric analysis also indicates that the study of competitive intelligence (CI) is increasingly focused on innovation and decision support (De las Heras-Rosas & Herrera, 2021).

The eight-domain architecture follows this process logic. Intelligence planning identifies the decisions that require evidence and assigns responsibility. Environmental scanning tracks regulation, student demand, labour-market developments, technology, and comparable institutions. Collection concerns source breadth, credibility, timeliness, and lawful access. Analysis converts observations into implications and options. Dissemination directs intelligence to relevant academic and administrative users. Utilization captures its use in programme, resource, risk, and opportunity decisions. Governance establishes ethical, legal, confidentiality, quality, and accountability standards. Feedback assesses usefulness and outcomes and informs subsequent improvement.

These domains aren't mutually exclusive. A university can scan but lack analytical ability; it can have good analysis, but it is late; it can have good analysis but it is not used by the decision makers; or it can make decisions without checking if the intelligence was correct. Research on open-source intelligence (OSINT) and professional-generated content offers some examples of the diverse ways information can be articulated as stakeholder or expert insight (Lutz & Bodendorf, 2020; Qian et al., 2024). The role of integrating the dispersed high volume information and merging the analytical capacity and emerging technologies is another of the analytics enabled intelligence applications



(Hossain et al., 2022; Ranjan & Foropon, 2021). Research on digital startups further suggests that competitive intelligence creates value when it guides strategic pivots rather than merely increasing the volume of reports (Sadeghiani et al., 2022). The results of these include a measure in higher education that is implemented at every stage.

For many universities, the word “competitive” is also open to multiple interpretations because of the public nature of many of these institutions. Intelligence is no justification for any type of covert competition or for gaining the advantage at any social price. In the higher education sector, it can be used for academic quality, policy responsiveness, public accountability, and student outcomes. Governance is thus not an add-on, but an integral part. All intelligence practices should be compliant with privacy, source protection, rules for access to data, and the distinction between benchmarking and imitation. This moral line is particularly important when staff from different disciplines and external partners at the university share information.

In this study, sustainable competitive advantage does not mean short-term positional dominance over other universities. It refers to an institution's continuing capacity to anticipate environmental change, renew programmes and services, and preserve academic quality, legitimacy, and public value over time. Information asymmetry arises when external signals or internal expertise remain concentrated in particular offices or hierarchical levels. A governed competitive-intelligence cycle can reduce this imbalance by converting dispersed evidence into traceable intelligence that is available to operational teams, middle managers, and senior decision makers. At the operational level, intelligence supports service and process adjustment; at the middle-management level, it informs programme coordination and resource allocation; and at the executive level, it supports institutional positioning, partnership, portfolio, and risk decisions. Intelligence governance should therefore function as a permanent mechanism, supported by defined responsibilities, source-quality standards, access controls, decision logs, feedback routines, and periodic review of intelligence outcomes.

2.2 Institutional innovation in higher education

Institutional innovation is broader than the introduction of a digital platform. It includes new or substantially improved academic programmes, teaching or assessment arrangements, administrative processes, student services, digital systems, research configurations, and external partnerships. Reviews of higher-education transformation repeatedly warn against treating technology purchase as transformation. Innovation occurs when institutions redesign work, governance, competencies, and stakeholder relationships around new possibilities (Akour & Alenezi, 2022; Benavides et al., 2020; Hashim et al., 2022).

This is important for measurement purposes. It is possible to have a technically competent organization that is institutionally rigid. On the other hand, a university might change its programme approach, collaborate with others across disciplines, or redesign programmes without investing in a major technology acquisition. In the present study, then, the outcome scale is divided into four categories, namely academic and programme innovation, administrative and process innovation, digital-service innovation, and research, partnership, and external-engagement innovation. The

multi-dimensional definition supports the concept that there could be multiple kinds of institutional reactions to the intelligence.

Generally, competitive-intelligence research predicts that there will be a positive association between competitive intelligence and innovation, since competitive intelligence will minimize unnecessary uncertainty and increase the options to be explored. Bao et al. (2020) found a positive relationship between competitive intelligence and innovation in the field of Chinese tourism; Hamilton (2024) found a relationship between competitive-intelligence practices and innovation performance in the logistics industry; and Olszak et al. (2023) named competitive intelligence as the lever of added value. Although each of the above sectoral settings are different, the process is transferable: if an organization fails to detect and interpret change it cannot react intelligently to change.

2.3 The knowledge-based view and the translation problem

The knowledge-based view is the reason that intelligence gathering is not enough. In Grant's (1996) view, organizations create value by combining the specialized know-how that is de-centralized in individuals and units. The problem is embodied most clearly in universities. Academic departments have disciplinary knowledge, policy and finance central offices have policy, finance and quality information, digital teams have systems understanding and admissions and careers units have an understanding of demand, while external-relations staff interact with partners. There is no single actor who has the entire vision and picture needed to achieve institutional change.

Knowledge sharing comprises two reciprocal behaviors. Knowledge donation refers to providing colleagues with relevant insights, lessons, and information, whereas knowledge collection refers to actively seeking advice, expertise, or evidence from colleagues and shared repositories (van den Hooff & de Ridder, 2004). Donation can carry the dissemination of interpretation of environment, and collection can take the discovery of dispersed expertise by analysts and decision makers in the competitive-intelligence cycle. Validation is also made possible through knowledge sharing; claims can be scrutinized, contrasted with local experiences and improved prior to action.

This exchange is scientifically supported with empirical work. Azeem et al. (2021) correlated organization culture to knowledge sharing and organizational innovation while Olan et al. (2022) demonstrated that technology and knowledge sharing are correlated to organizational performance together. However, don't romanticize knowledge sharing. Exchange can spread false information, perpetuate agreement or lead to overload. It is related to the source credibility, psychological safety, incentives, boundary-spanning roles, and to the presence of decision processes that can leverage the shared knowledge. This is why knowledge sharing is represented as a mechanism (and not an alternative) to the competently managed CI.

2.4 Dynamic capabilities and the role of knowledge sharing

The knowledge-based view (KBV) has been complemented by dynamic-capabilities theory (DCT) in terms of time and action. Dynamic-capabilities theory distinguishes sensing opportunities

and threats, seizing them through decisions and commitments, and reconfiguring resources and routines (Teece, 2007). The four activities of competitive intelligence: planning, scanning, collection, and analysis, are closely related to the four activities of sensing: planning, scanning, collection, and analysis of change that focuses managerial attention on external change. Collective interpretation is facilitated by dissemination and knowledge sharing. Utilization relates interpretation to seizing. Governance and feedback shape the path of reconfiguring and repeating the process, not simply as a one-off response to adaptation.

Evidence from manufacturing SMEs, digitally mediated firms, and Chinese companies links analytics, competitive intelligence, and dynamic capabilities with organizational responsiveness and responsible innovation (Hassani & Mosconi, 2022; Wu et al., 2023; Chen et al., 2024). However, these studies do not establish that the same mechanism operates in universities, where authority is distributed, professional autonomy is stronger, and innovation must satisfy public-value as well as performance objectives. The knowledge-based view and dynamic-capabilities theory therefore make complementary but non-interchangeable contributions: the knowledge-based view explains why dispersed expertise must be integrated, whereas dynamic-capabilities theory explains how sensing is translated into seizing and reconfiguration. The present model connects these perspectives by treating competitive intelligence as governed sensing, knowledge sharing as cross-unit integration, and institutional innovation as coordinated application. The relationship is conditional rather than automatic: intelligence that is not shared may remain local, while knowledge sharing that is not linked to governance and decision authority may increase communication without producing strategically coherent change.

2.5 Competitive intelligence and institutional innovation

There are three reasons that a positive relationship between competitive intelligence and institutional innovation is anticipated. For one, systematic scanning increases the institution's opportunity set. The more universities are able to track the emergence of needs through policy, technology, the labor market and other comparable institutions, the more likely they are to anticipate such needs before they become urgent. Secondly, analysis increases selectivity. Not all trends require a response and not all innovation is cheap. Structured interpretation aids to differentiate between weak evidence and material change. Third, dissemination, utilization, and feedback diminish the gap between information and implementation.

However, in a cross-sectional survey, the association is to be interpreted as a relationship. For innovative institutions, investments in intelligence could be higher, and for respondents, visible outcomes of the innovation could imply higher intelligence. Both constructs may be impacted by common leadership, culture, or digital maturity. The first hypothesis is thus formulated in a predictive-associational way.

H1. Perceived competitive-intelligence capability is positively associated with perceived institutional innovation in Chinese higher education.

2.6 Competitive intelligence and knowledge sharing

Competitive intelligence should be positively associated with knowledge sharing because several stages of the intelligence cycle require cross-boundary exchange. Planning benefits from diverse decision needs, collection draws on multiple internal and external sources, and analysis improves when assumptions are challenged. Dissemination constitutes an organized form of knowledge donation, while utilization often requires employees to obtain additional contextual knowledge before acting. Oraee (2023) shows that information seeking, evaluation, sharing, and use are embedded in university competitive-intelligence processes.

This relationship is not self-fulfilling. Dissemination is one part of the competitive intelligence and knowledge sharing is a more general term for disseminating and acquiring knowledge among employees. A university may disseminate official reports on intelligence while at the same time, the employees do not feel inclined to share their practical experience; it is possible to share knowledge informally without an institutionalized intelligence process. The constructs should be related, but not identical, and empirically different.

H2. Perceived competitive-intelligence capability is positively associated with knowledge sharing.

2.7 Knowledge sharing and institutional innovation

To understand the positive connection between knowledge sharing and institutional innovation, Knowledge sharing should be understood as the process that makes dispersed knowledge combinable. Innovation in the programmes requires academic, market and regulatory knowledge, innovation in administration requires process and user knowledge, innovation in the digital services requires technical and service knowledge and innovation in partnerships requires knowledge on institutional capabilities and external needs. Donation brings others the insights and collection provide employees with the knowledge they need to understand and enact change.

The relationship may weaken where knowledge is low quality, where sharing is ceremonial, or where governance does not connect conversation with decisions. It may also be inflated in same-source surveys because respondents who view their institution positively tend to rate both collaboration and innovation highly. These qualifications do not remove the theoretical expectation, but they make discriminant-validity and common-method diagnostics central to interpretation.

H3. Knowledge sharing is positively associated with perceived institutional innovation after competitive-intelligence capability is considered.

2.8 The mediating role of knowledge sharing

The mediation proposition combines the two theories. Competitive intelligence organizes environmental sensing and creates decision-relevant interpretations. Knowledge sharing distributes those interpretations, combines them with local expertise, and enables coordinated application. Institutional innovation reflects the resulting changes in programmes, processes, digital services,

and partnerships. The indirect path is therefore not intended to imply that all intelligence effects pass through informal exchange. Formal governance, leadership, resources, and implementation capability may support a continuing direct association.

A positive indirect effect would be consistent with complementary partial mediation when both the indirect and direct paths are positive. However, the interpretation requires three distinct constructs. When competitive intelligence, knowledge sharing, and innovation are nearly indistinguishable statistically, the product term may reflect decomposition of a common evaluative factor rather than a substantive mechanism. The mediation hypothesis is consequently paired with an explicit measurement question.

H4. Knowledge sharing carries a positive indirect component of the association between perceived competitive-intelligence capability and perceived institutional innovation.

Figure 1 Conceptual framework linking competitive intelligence, knowledge sharing, and institutional innovation.

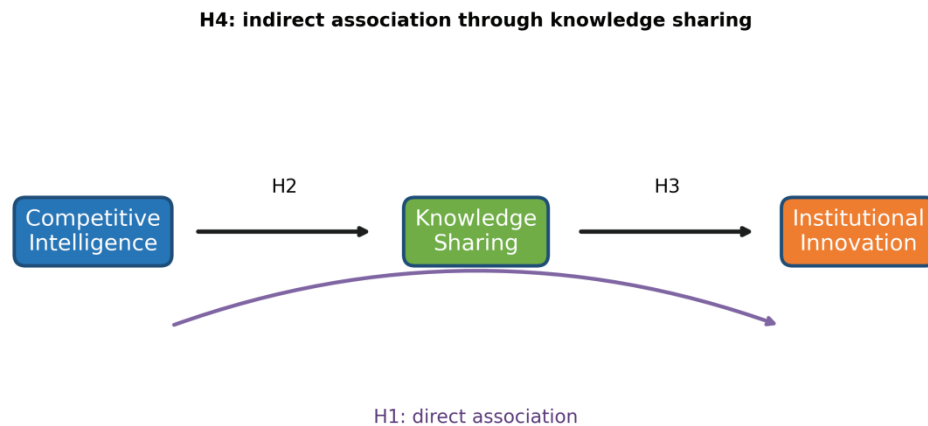


Figure 1. Conceptual framework linking competitive intelligence, knowledge sharing, and institutional innovation.

Table 1 summarizes the alignment among the fixed title, the available variables, the unit of analysis, and the limits of inference.

Table 1. Topic–dataset–theory alignment

Element	Operational decision	Alignment and boundary
Independent variable	Competitive Intelligence (CI1–CI24)	Directly measured through eight three-item domains; treated as perceived institutional capability.
Mediator	Knowledge Sharing (KS1–KS8)	Knowledge donation and collection; employee-perceived sharing practices.
Dependent variable	Institutional Innovation (II1–II12)	Academic, process, digital-service, and partnership/research innovation.
Controls	Gender, age category, qualification	Only documented covariates available in the workbook; not interpreted as causal confounder control.
Unit of analysis	Individual response	Institution identifiers were removed after quota monitoring; the analysis was conducted at the individual-response level.



Element	Operational decision	Alignment and boundary
Sample	N = 240 complete response records	All documented scale items were complete and within the 1–7 range.
Time period	Cross-sectional dataset finalized on 3 August 2026	Collection timestamps were not retained; temporal ordering cannot be tested.
Geographic scope	Wuhan, Hubei Province, China	Twenty-four usable responses were retained from each participating institution; university identifiers were removed before analysis.
Theoretical frame	Knowledge-based view + dynamic capabilities	CI supports sensing; knowledge sharing supports integration; innovation represents application/reconfiguration.
Empirical status	Cross-sectional survey analysis	Suitable for associational inference; causal and institution-level claims are not supported.

Note. Because the design is cross-sectional, “impact” is interpreted as a predictive association rather than a causal effect.

3. METHOD

3.1 Research design and analytical positioning

The study uses a quantitative, cross-sectional explanatory mediation design. The analytical objective is to evaluate whether the proposed measurement architecture produces the theorized direct and indirect associations while testing whether those associations can be interpreted as relations among distinct constructs. The design is explanatory in model structure but not causal in identification. No temporal separation, randomized allocation, instrumental variable, natural experiment, or panel structure is available.

The selected analytical approach combines composite-score measurement diagnostics with robust regression mediation. Partial least squares structural equation modelling was considered because the questionnaire contains multidimensional constructs and the requested study is prediction oriented. However, the decisive limitation in the supplied matrix is not algorithm choice. CI and knowledge-sharing composites are so highly correlated that either PLS-SEM or covariance-based SEM would confront the same construct-distinctiveness problem. Composite-score regression was used for transparent coefficient estimation, while internal consistency, item discrimination, construct correlations, HTMT, collinearity, and common-factor dominance were evaluated before the structural paths were interpreted (Henseler et al., 2015; Hair et al., 2022).

3.2 Study setting, data source, and sample

The analytical dataset contained 240 complete responses. The analysis used the prespecified survey variables, comprising consent and eligibility indicators, gender, age category, qualification, 24 competitive-intelligence items, eight knowledge-sharing items, and 12 institutional-innovation items. All substantive responses were recorded on seven-point Likert scales. No missing or out-of-range values were identified in the measurement items.

All 240 records indicate consent and positive responses to the three eligibility fields. The labelled scale items contain no missing values and no values outside the intended 1–7 range. No duplicate



respondent identifier was found, all 240 item-response patterns were unique, and no record selected the same response for all 44 items. Two cases had a within-person standard deviation below .30 and were retained because no prespecified field-quality criterion, completion-time variable, or factual inconsistency justified deletion. The analysis therefore uses all 240 cases.

The study was conducted across ten geographically proximate universities in Wuhan, Hubei Province: Wuhan University; Huazhong University of Science and Technology; Central China Normal University; Wuhan University of Technology; China University of Geosciences (Wuhan); Zhongnan University of Economics and Law; Huazhong Agricultural University; Hubei University; Hubei University of Technology; and Wuhan Institute of Technology. A balanced institutional quota was applied, with 24 usable responses retained from each university, producing a final sample of 240 respondents.

Participants were academic and administrative personnel whose roles provided knowledge of institutional planning, academic affairs, quality assurance, research management, admissions, external relations, digital transformation, or university-level innovation. Eligibility was confirmed before questionnaire completion. Printed questionnaires and an equivalent online survey form were used to improve access across participating institutions. University identifiers were used only for monitoring institutional quotas and were removed from the final analytical file to protect institutional confidentiality. Data collection was completed before the dataset was finalized on 3 August 2026.

3.3 Instrument Development and Survey Administration

The questionnaire was initially prepared in English and translated into Simplified Chinese. DeepL was used to support the initial translation, after which the Chinese wording was reviewed by bilingual academic personnel to ensure conceptual consistency, clarity, and suitability for the higher-education context. Differences in terminology were resolved before distribution.

The same item wording, item order, and seven-point response scale were maintained in both printed and online versions. Printed questionnaires were distributed through relevant university administrative units, while the online version was circulated through an electronic survey link. Both formats included the same participant information, eligibility questions, consent statement, and measurement items.

3.4 Measures and variable operationalization

All substantive items use a seven-point response format from 1 (strongly disagree) to 7 (strongly agree). Scale scores were computed as equal-weight arithmetic means, preserving the metric of the original items. All 44 documented measurement items were retained; no item was removed after inspecting the structural coefficients.

Competitive intelligence comprises 24 items. Intelligence planning (CI1–CI3) addresses information priorities and responsibilities. Environmental scanning (CI4–CI6) addresses policy, stakeholder, labor-market, technology, and comparable-institution monitoring. Collection (CI7–CI9) concerns multiple sources, credibility, and timeliness. Analysis (CI10–CI12) concerns systematic

interpretation, opportunity/threat evaluation, and actionable insight. Dissemination (CI13–CI15) concerns timely delivery and formal cross-departmental channels. Utilization (CI16–CI18) concerns programme, planning, resource, risk, and opportunity decisions. Governance (CI19–CI21) concerns procedures, legality, ethics, confidentiality, and quality. Feedback (CI22–CI24) concerns decision-maker feedback, outcome review, and process improvement.

Knowledge sharing comprises eight items. KS1–KS4 measure knowledge donation, including the sharing of strategic information, project lessons, effective practices, and documented insights. KS5–KS8 measure knowledge collection, including seeking cross-departmental knowledge, knowing relevant experts, requesting advice, and accessing shared platforms or repositories.

Institutional innovation comprises 12 items. II1–II3 measure academic and programme innovation; II4–II6 administrative and process innovation; II7–II9 digital-service innovation; and II10–II12 research, partnership, and external-engagement innovation. The outcome therefore represents perceived breadth of implemented institutional improvement rather than individual creativity.

Gender, age category, and highest qualification were included as controls because they are the only respondent characteristics contained in the analytical file. Categorical dummy variables were created with the first observed category as the reference group. These controls improve descriptive comparability but do not remove omitted-variable bias. Organizational tenure, role, university type, size, research intensity, digital maturity, and institutional fixed effects could not be estimated.

Table 2 records the measurement structure and scoring rules used in the analysis.

Table 2. Construct operationalization

Construct/domain	Codes	Items	Score	Interpretation
Competitive Intelligence	CI1–CI24	24	Mean	Perceived strength of the governed intelligence cycle.
Planning	CI1–CI3	3	Mean	Decision needs and assigned responsibility.
Environmental scanning	CI4–CI6	3	Mean	Monitoring of policy, demand, technology, and peer institutions.
Collection	CI7–CI9	3	Mean	Breadth, credibility, and timeliness of information.
Analysis	CI10–CI12	3	Mean	Conversion of information into implications and action.
Dissemination	CI13–CI15	3	Mean	Timely delivery through appropriate channels.
Utilization	CI16–CI18	3	Mean	Use in programmes, planning, resources, risks, and opportunities.
Governance	CI19–CI21	3	Mean	Ethics, legality, confidentiality, and quality controls.
Feedback	CI22–CI24	3	Mean	Review of usefulness, outcomes, and process improvement.
Knowledge Sharing	KS1–KS8	8	Mean	Donation and collection of institutionally useful knowledge.
Institutional Innovation	II1–II12	12	Mean	Academic, process, digital-service, and partnership innovation.

Note. All items were scored from 1 to 7. No reverse-coded items were present.

3.5 Statistical analysis

The analysis proceeded in five stages. First, the workbook was audited for duplicate identifiers, missing and out-of-range values, straight-line patterns. Second, frequencies and percentages were calculated for the recorded demographic variables, and means, standard deviations, ranges, skewness,

and excess kurtosis were calculated for the three construct composites. Third, internal consistency was evaluated using Cronbach's alpha and corrected item–total correlations. Alpha values of .70 or above and corrected item–total correlations above .30 were considered acceptable. Fourth, construct overlap was examined using Pearson correlations, the heterotrait–monotrait ratio, predictor variance-inflation factors, and the proportion of standardized item variance explained by the first unrotated component.

Fourth, discriminant validity and common-factor dominance were assessed. Pearson correlations described construct-level association. The heterotrait–monotrait ratio (HTMT) compared average cross-construct item correlations with average within-construct item correlations. Values below .85 or .90 are commonly used as evidence of discriminant validity, whereas confidence intervals that include 1 indicate non-distinct constructs (Henseler et al., 2015). Predictor VIF was calculated for CI and knowledge sharing in the innovation equation. A principal-components diagnostic recorded the proportion of standardized item variance explained by the first unrotated component. This is not a complete common-method test, but a value above 50% is a warning signal when combined with extremely high correlations and single-source measurement (Podsakoff et al., 2003). Although the Fornell–Larcker criterion is widely used in latent-variable analysis, it was not applied because the present analysis did not estimate latent-variable AVE values (Fornell & Larcker, 1981).

Fifth, the mediation model was estimated with standardized composites and HC3 heteroskedasticity-robust standard errors. The mediator equation was:

$$KS_i = \alpha_0 + a(CI_i) + \gamma'Z_i + \epsilon_{1i} \quad (1)$$

where KS is knowledge sharing, CI is competitive intelligence, and Z is the vector of gender, age-category, and qualification controls.

The outcome equation was:

$$II_i = \beta_0 + c'(CI_i) + b(KS_i) + \delta'Z_i + \epsilon_{2i} \quad (2)$$

where II is institutional innovation, c-prime is the direct association after the mediator is included, and b is the association between knowledge sharing and innovation conditional on CI and the controls.

The indirect association was computed as:

$$\text{Indirect association} = a \times b \quad (3)$$

A nonparametric case-resampling bootstrap with 10,000 draws and a fixed random seed of 20260803 was used to estimate percentile 95% confidence intervals for a, b, c-prime, the total association c, and a x b. A confidence interval excluding zero was treated as statistical support for the indirect component, following the resampling logic described by Hayes (2022). Because the records are cross-sectional, the product is described as an indirect association rather than a causal mediated effect.

Effect sizes were reported through R-squared for each endogenous composite and f-squared changes associated with CI and knowledge sharing. The structural results were interpreted only after the measurement diagnostics. All computations were performed in Python with NumPy, SciPy, statsmodels, scikit-learn, and Matplotlib. The complete analysis script accompanies the manuscript.

3.6 Missing-data handling, robustness, and ethical considerations

Robustness in this study refers to analytical stability rather than causal identification. HC3 standard errors reduce sensitivity to heteroskedasticity. Bootstrap resampling evaluates sampling variation within the analytical dataset. Control-adjusted and unadjusted patterns were compared during code development and produced substantively similar estimates. These procedures do not solve common-method bias, construct overlap, or omitted institutional conditions. The most important robustness check is therefore the discriminant-validity audit itself.

Permission to distribute the questionnaire was obtained from the relevant administrative authorities of the participating universities. Participation was voluntary, and informed consent was obtained before respondents began the questionnaire. No names, contact details, identification numbers, or other direct identifiers were collected. Responses were analyzed anonymously and stored under restricted access. No separate ethics approval number is reported because no formal approval identifier was issued for the anonymous, minimal-risk survey.

4. RESULTS AND DISCUSSION

4.1 Data audit and response profile

The data-screening process retained all 240 cases. Respondent codes were unique, all scale responses fell within the intended 1–7 range, and no exact straight-line response pattern was observed. Two responses showed limited within-person variation but were retained because they contained no missing values, out-of-range responses, or factual inconsistencies.

The demographic profile was balanced by gender: 121 respondents were recorded as female (50.4%) and 119 as male (49.6%). Age categories were distributed across 20–29 years (67; 27.9%), 30–39 (61; 25.4%), 40–49 (57; 23.8%), and 50–59 (55; 22.9%). Qualifications were bachelor's degree (48; 20.0%), master's degree (106; 44.2%), and doctoral degree (86; 35.8%). Table 3 reports these characteristics. The profile describes the analytical sample and should not be generalized to the wider Chinese higher-education workforce without a documented probability-sampling frame.

Table 3. Recorded response profile (N = 240)

Variable	Category	n	%
Gender	Female	121	50.4
	Male	119	49.6
Age	20–29	67	27.9
	30–39	61	25.4
	40–49	57	23.8
	50–59	55	22.9
Qualification	Bachelor	48	20.0
	Master	106	44.2
	Doctoral	86	35.8

Note. Institutional quotas were monitored during data collection, but university identifiers were removed from the analytical file to preserve confidentiality.

4.2 Descriptive Statistics and Internal Consistency

All three composite means were high and almost identical. Competitive intelligence averaged 5.630 (SD = .794), knowledge sharing 5.617 (SD = .812), and institutional innovation 5.630 (SD = .817). Scores occupied a reasonably broad part of the seven-point scale, although the negative skewness values indicate more favorable than unfavorable responses. Figure 2 displays the construct means and 95% confidence intervals. The near equality of the means is not problematic by itself, but it foreshadows the common-variance pattern observed in the correlations.

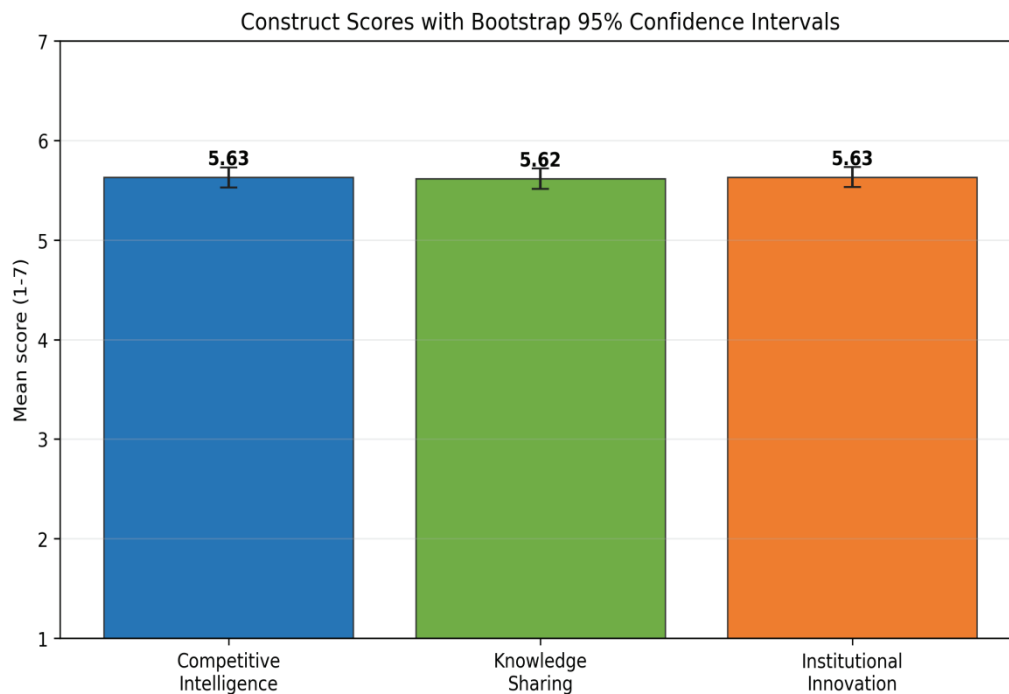


Figure 2. Construct means with 95% confidence intervals on the seven-point response scale.

Internal consistency was high across all three measures. Cronbach's alpha was .977 for competitive intelligence, .931 for knowledge sharing, and .954 for institutional innovation. Corrected item-total correlations ranged from .735 to .825 for competitive intelligence, .703 to .803 for knowledge sharing, and .749 to .805 for institutional innovation. These values indicate that the items were internally consistent within their assigned scales. Internal consistency, however, does not establish that neighbouring constructs are empirically distinct.

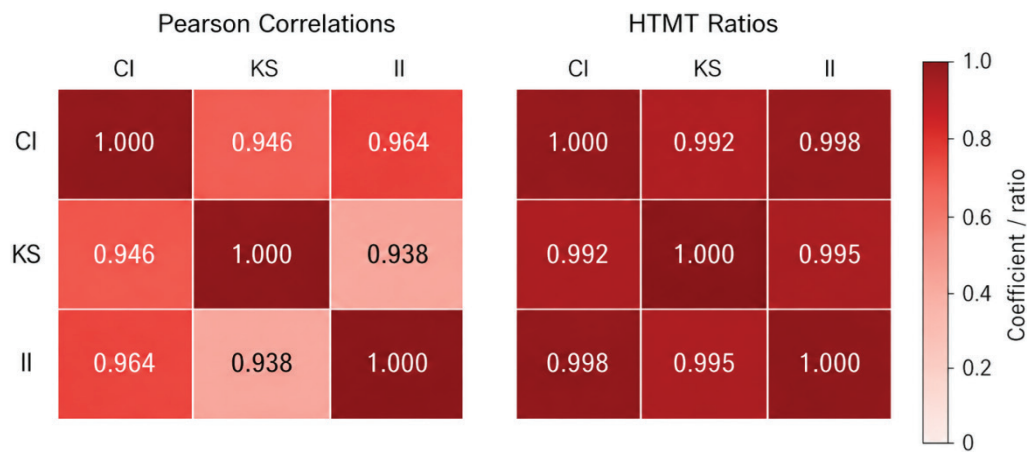
These values require a cautious reading. An alpha near .98 for a 24-item scale can reflect broad coverage of a coherent capability, but it can also indicate item redundancy or a dominant response factor. High CR and AVE do not establish that neighboring constructs are different. Reliability answers whether items move together; it does not answer whether CI, knowledge sharing, and innovation represent separate empirical objects.

Table 4. Descriptive statistics and internal-consistency diagnostics

Construct	Mean	SD	Cronbach's α	Corrected item–total correlation range
Competitive Intelligence	5.630	.794	.977	.735–.825
Knowledge Sharing	5.617	.812	.931	.703–.803
Institutional Innovation	5.630	.817	.954	.749–.805

Note. Corrected item–total correlations were calculated between each item and the remaining items in its assigned scale.

Figure 3 visualizes the correlations and HTMT ratios that determine whether the nominally reliable scales are empirically distinct.



HTMT values above .90 indicate insufficient discriminant validity.

Figure 3. Construct correlations and HTMT ratios. HTMT values above .90 indicate insufficient discriminant validity.

Discriminant validity was not established. Competitive intelligence correlated .946 with knowledge sharing and .964 with institutional innovation; knowledge sharing correlated .938 with institutional innovation. Each correlation exceeded the square root of the relevant AVE. HTMT was .992 for CI–knowledge sharing, .998 for CI–innovation, and .995 for knowledge sharing–innovation. These values are not marginal exceedances. They are close to 1 and indicate that the three scales produce almost the same rank ordering of respondents.

The same problem appears in the structural diagnostics. CI and knowledge sharing had a predictor VIF of 9.54 in the innovation equation. The first unrotated component explained 64.1% of the variance across all 44 standardized items. Podsakoff et al. (2003) caution that no single statistical test can diagnose common-method bias, but the combination of one source, one time point, uniformly positive wording, correlations above .93, HTMT near 1, and a dominant first factor is compelling evidence of common evaluative variance. Table 5 summarizes the matrices.

Table 5. Construct correlations and HTMT ratios

Construct	1	2	3
1. Competitive Intelligence	1.000	.946	.964
2. Knowledge Sharing	.992	1.000	.938
3. Institutional Innovation	.998	.995	1.000

Note. Pearson correlations appear above the diagonal, and HTMT ratios appear below the diagonal. HTMT values above .90 indicate insufficient discriminant validity.

4.3 Structural associations and bootstrap mediation

In the control-adjusted mediator model, competitive intelligence was strongly associated with knowledge sharing ($a = .944$, HC3 SE = .020, 95% bootstrap CI [.903, .982], $p < .001$). The equation explained 89.7% of the variance in knowledge sharing. Such an R-squared is unusually high for distinct organizational constructs and should be read together with the HTMT result.

In the institutional-innovation equation, knowledge sharing remained positively associated with innovation after CI and the categorical controls were included ($b = .255$, HC3 SE = .058, 95% bootstrap CI [.143, .363], $p < .001$). Competitive intelligence also retained a positive direct association (c -prime = .723, HC3 SE = .059, 95% bootstrap CI [.612, .836], $p < .001$). The model explained 93.7% of the variance in institutional innovation. The total CI–innovation association was .964 (95% bootstrap CI [.934, .992]).

The non-zero bootstrap interval provides coefficient-level support for a positive indirect association. Because the direct and indirect associations were both positive, the pattern is consistent with complementary partial mediation; however, this interpretation remains provisional because the three measures did not demonstrate adequate discriminant validity. Figure 4 presents the path model, while Figure 5 shows the bootstrap distribution of the indirect association.

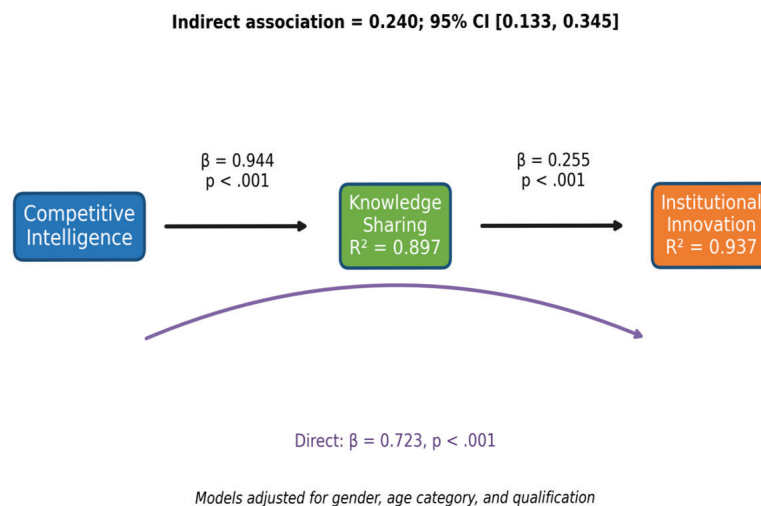


Figure 4. Control-adjusted standardized structural associations and explained variance.

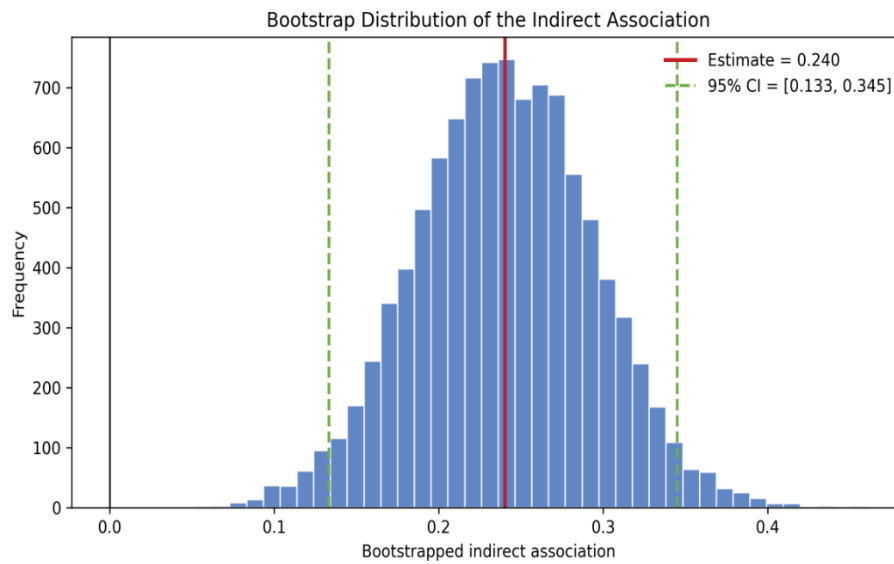


Figure 5. Distribution of the 10,000 bootstrap estimates for the indirect association $a \times b$.

Table 6. Control-adjusted robust mediation estimates

Path	Beta	HC3 SE	t	p	Bootstrap 95% CI	R-squared
CI → Knowledge Sharing (a)	.944	.020	46.68	< .001	[.903, .982]	.897
Knowledge Sharing → Innovation (b)	.255	.058	4.42	< .001	[.143, .363]	.937
CI → Innovation, direct (c-prime)	.723	.059	12.34	< .001	[.612, .836]	.937
CI → Innovation, total ©	.964	.015	63.76	< .001	[.934, .992]	.930
Indirect association ($a \times b$)	.240	—	—	—	[.133, .345]	—

Note. Models use standardized composites and adjust for gender, age category, and qualification. Confidence intervals are based on 10,000 case-resampling bootstrap draws.

The hypothesis decisions therefore need two columns: statistical path support and measurement-secure substantive support. H1–H4 satisfy the first criterion. None satisfies the second because the predictor, mediator, and outcome do not demonstrate acceptable discriminant validity. Table 7 preserves that distinction. This is not a semantic qualification. Mediation requires that a, b, and c-prime refer to separable variables. When HTMT is approximately 1, the decomposition may be mathematically precise while substantively ambiguous.

Table 7. Hypothesis decisions with measurement qualification

Hypothesis	Statistical result	Decision	Interpretation
H1	$c = .964$; $c' = .723$; $p < .001$	Supported	Provisional support due to CI–II measurement overlap
H2	$a = .944$; $p < .001$	Supported	Provisional support due to CI–KS measurement overlap
H3	$b = .255$; $p < .001$	Supported	Positive conditional association; interpret with collinearity caution
H4	$a \times b = .240$; 95% CI [.133, .345]	Supported	Positive indirect association; not evidence of causal mediation

Note. Hypothesis support refers to the prespecified coefficient and bootstrap criteria. The results should be interpreted as composite-score associations because discriminant validity was insufficient.

4.4 Interpretation in relation to competitive-intelligence theory

The structural pattern is consistent with the proposed theoretical sequence. Stronger competitive-intelligence practices were associated with stronger knowledge sharing, and both were associated with institutional innovation. This pattern aligns with the knowledge-based view, in which dispersed knowledge creates organizational value through integration, and with dynamic-capabilities theory, in which sensing is followed by interpretation, coordinated action, and reconfiguration (Grant, 1996; Teece, 2007).

The measurement diagnostics nevertheless indicate that respondents did not sharply differentiate the three institutional capabilities. A broad favourable evaluation of the university may therefore account for part of the observed covariance. The results should consequently be understood as preliminary evidence for the proposed mechanism rather than as definitive proof of three independent organizational processes. Future research should sharpen the distinction between formal intelligence dissemination and employee knowledge-sharing behaviour and should measure the constructs at different times or through different respondent sources.

Relative to international higher-education research, the findings converge with evidence that competitive intelligence supports managerial information needs, recruitment strategy, and institutional responsiveness (Oraee et al., 2021; Oraee, 2023; Mgweba et al., 2024; Mogale et al., 2025). The present study extends that literature by modelling knowledge sharing as a possible link between the full intelligence cycle and a broader institutional-innovation outcome rather than examining a single function such as recruitment. Nevertheless, the present correlations above .93 and HTMT values near 1 mean that cross-national similarity in the proposed mechanism cannot yet be claimed. The contribution is therefore a testable university-level framework, not evidence that the competitive-intelligence-innovation process is stronger in China than elsewhere. Replication across countries, institution types, and independent data sources is required.

4.5 Theoretical and methodological contributions

The first theoretical contribution is that of placing knowledge sharing in a specific stage of the intelligence-to-innovation process. Competitive intelligence is not a culture of information, but a governed sensing and interpretation capability. The treatment of knowledge sharing is not dissemination, but about cross boundary integration. Institutional innovation is not personal creativity but rather is considered as implemented change in several University functions. This separation helps to elucidate the mechanism that future field studies ought to be able to test.

The second contribution is the blending of knowledge-based and dynamic-capabilities explanations without reference to either of them. The knowledge-based view is why dispersed knowledge needs to be synthesized; dynamic capabilities are why integration is important when change occurs and how integration relates to the sensing and reconfiguration process. Every theory corresponds to a measurable aspect in the model. Organized sensing and analysis items are CI items; integration items are knowledge-sharing items and applied change items are innovation items.

The third contribution is methodological. The analysis shows that coefficient reproducibility and construct validity answer different questions. The indirect association is stable across 10,000 bootstrap draws, yet HTMT values near 1, severe predictor collinearity, and common-factor dominance prevent the same result from being interpreted as secure evidence of mediation among distinct capabilities. By reporting the complete analytical specification, fixed random seed, control coding, and measurement diagnostics, the study treats discriminant validity as a condition for substantive inference rather than as a secondary reporting exercise. This distinction is especially important in competitive-intelligence research, where respondents may evaluate intelligence, collaboration, and innovation through a single favourable assessment of their institution.

The fourth contribution is with regard to the level of analysis. The survey is based on institutional referents (our university) but no individual identifier for the university, only individual answers to the survey are available. The analysis thus estimates the perceptions of institutional practices. It does not measure the average grade of a university, compare universities or make claims about the ability of universities. The discipline is being able to avoid a common mistake in ecological survey research in organizations.

Taken together, these contributions reposition competitive intelligence in higher education from an episodic information activity to a governed, multi-level organizational capability. The study's contribution to Sustainable Competitive Intelligence lies in explaining how universities can reduce information asymmetry, coordinate intelligence across operational, managerial, and executive levels, and sustain innovation without subordinating academic and public-value objectives to short-term competitive pressure. Sustainable advantage in this context is therefore the capacity to learn, adapt, and renew institutional practices responsibly over time through permanent governance, accountability, and feedback mechanisms.

4.6 Practical, policy, and competitive-intelligence implications

Despite the structural coefficients needing to be interpreted with care, the framework is still valuable for institutional design. The eight CI domains can be used as an audit cycle for university leaders. Planning questions: Do key decisions start with clear intelligence needs? Scanning and collection questions: Does the institution consider external performance reports? Analysis asks the question, "Are options and implications created from information? Dissemination and knowledge sharing questions: Are there people with relevant needs to access and contest those interpretations? Utilization: Does evidence inform partnership, programme, service and resource decisions? Governance and feedback question the moral, traceable and learnable nature of the process.

The policy relevance of higher education in China is the issue of institutional response and not imitation. Both national and provincial reforms and developments in regional labor markets, as well as student expectations, technological change and partnership opportunities, must be read in the context of each university's mission. A governed intelligence system can help to diminish reactive decision making and ensure that institutions record the reasons for launching a programme, restructuring a service, or focusing on a partnership. It can also help to safeguard academic autonomy by bringing to the forefront of what is being done and why, rather than abdicating decision making to passing external pressures.

Deliberate infrastructure is needed for knowledge sharing. External signals can be linked to local expertise through cross-functional intelligence forums, short decision briefs, searchable repositories, after action reviews, and communities of practice. Rewards should be given for contributions to knowledge, not for information volume. Governance should establish confidentiality, source evaluation, and access rights and accountability. The goal of the practical is to enhance the relevance, reliability and use of shared knowledge, not to maximize sharing.

The study outlines a boundary problem for competitive-intelligence practitioners. When it comes to disseminating, if it's defined as collegial interaction, it can be tricky to distinguish between CI and knowledge sharing. The intelligence products and decision processes themselves should, therefore, be separated from the broader knowledge context in which employees interpret and act on them. This separation can enhance practice audits and also scholarly measurement.

For institutional intelligence systems, the managerial implication is to avoid locating competitive intelligence solely within a central analytics or planning office. Operational units should capture local signals and implementation feedback; cross-functional and middle-management forums should compare evidence and resolve conflicting interpretations; and senior leaders should establish priorities, risk tolerances, resource commitments, and accountability. A sustainable intelligence system should assess not only immediate recruitment, ranking, or efficiency gains but also academic quality, equity, stakeholder trust, resource resilience, and alignment with the university's public mission. In this form, competitive intelligence can support sustainable institutional innovation by reducing information asymmetry, preserving an auditable link between evidence and action, and preventing short-term competitive pressure from displacing long-term institutional value.

Table 8 translates the model into practical actions while preserving the evidence boundary.

Table 8. Institution-level actions and validation indicators

Capability area	Practical action	Observable validation indicator
Planning	Define key intelligence questions for major programme, partnership, and technology decisions.	Documented intelligence requirement linked to a named decision and review date.
Scanning/collection	Use multiple lawful sources covering policy, demand, employment, technology, and comparable institutions.	Source register with credibility, timeliness, and relevance checks.
Analysis	Require alternatives, assumptions, uncertainty, and recommended actions in intelligence briefs.	Decision brief with traceable evidence and analytical reasoning.
Dissemination	Route intelligence to responsible users before the decision window closes.	Timestamped delivery and acknowledgement by intended decision users.
Knowledge sharing	Create cross-unit forums, repositories, and after-action reviews.	Participation, knowledge reuse, and documented changes arising from exchange.
Utilization	Record how intelligence influenced a programme, process, digital service, or partnership decision.	Decision log linking intelligence to action or justified non-action.
Governance/feedback	Apply privacy, ethics, quality, and outcome-review rules.	Audit trail; comparison of expected and observed decision outcomes.
Research validation	Collect CI, knowledge sharing, and innovation from different sources or waves.	HTMT < .90, acceptable VIF, and stable indirect association in new field data.

Note. These actions are theory- and instrument-derived recommendations; they should not be interpreted as causal treatment effects.



4.7 Robustness, alternative explanations, and limitations

The indirect association was positive for all 10,000 bootstrap draws and the hypothesis decisions were the same using HC3 standard errors. This stability does not establish knowledge sharing as a causal mechanism. Common-method variance, reverse ordering, and omitted institutional conditions remain plausible explanations. The most likely scenarios are common method evaluation, reverse ordering, and missing institutional conditions.

The reverse ordering is plausible since visible innovation could spur knowledge transfer and investments in intelligence practices. A new programme or digital service that has been introduced at an institution may encourage staff to share lessons and formalize environmental scanning. This is not discernable from the hypothesized order with a cross-sectional design. Likewise, variables that are not included are equally important. Leadership support, innovation culture, resource slack, digital infrastructure, institutional autonomy, and university type could produce high scores on all three constructs.

The cross-sectional, single-source design is the largest external-validity limitation. The dataset contains no institution code, role, tenure, collection timestamp, response-rate denominator, or objective innovation indicator. Consequently, the analysis cannot estimate institutional clustering, compare universities, establish temporal order, or determine whether the sample represents the wider population of Chinese higher-education employees. These limitations restrict causal and population-level interpretation even though the computational results are stable.

The exclusive reliance on self-reported perceptions further limits external organizational validation. Respondents may overestimate the consistency of intelligence routines or institutional innovation because all three constructs were measured in the same questionnaire, at the same time, and through uniformly positive wording. Without independent evidence—such as decision records, innovation portfolios, programme approvals, digital-service adoption logs, or evaluations obtained from separate respondent groups—the composite scores cannot be treated as verified measures of organizational performance. External validity is also constrained by the geographically concentrated Wuhan sample and the use of balanced institutional quotas rather than a documented probability-sampling frame. The estimates may therefore not generalize to universities in other Chinese regions, institution types, or governance environments. Finally, the ordering of competitive intelligence, knowledge sharing, and innovation is theoretical rather than temporal, so reverse causation and omitted common causes remain plausible. The findings support associations within the present sample, not causal effects or population-wide estimates.

A second limitation is constructing design. CI includes dissemination, which is conceptually close to knowledge donation. The solution is not to delete inconvenient items after seeing the results. Future instrument development should use expert content-validity assessment, cognitive interviews, a pilot study, exploratory factor analysis in one sample, confirmatory analysis in another, and behavioral or event-referenced wording. A three-wave design would measure CI first, knowledge sharing several weeks later, and institutional innovation later still. Independent informants or archival innovation indicators would further reduce same-source inflation.



A third limitation concerns clustering. Intended respondents may be nested within universities, but the workbook lacks university identifiers. Standard errors cannot be clustered, within-university agreement cannot be estimated, and institutional aggregation cannot be justified. Future research should sample enough universities and respondents per university to estimate ICC(1), ICC(2), and within-group agreement before using institution-level language.

5. FINAL CONSIDERATIONS

This study examined whether knowledge sharing accounts for an indirect component of the association between competitive intelligence and institutional innovation in Chinese higher education. Competitive intelligence was operationalized across the intelligence cycle, knowledge sharing through donation and collection, and institutional innovation across academic, administrative, digital-service, and partnership activities.

The structural results supported the proposed relationships. Competitive intelligence was positively associated with knowledge sharing and institutional innovation, while knowledge sharing remained positively associated with innovation after competitive intelligence was considered. The bootstrapped indirect association was .240, with a 95% confidence interval of [.133, .345]. At the coefficient level, this pattern is consistent with complementary partial mediation.

The interpretation remains cautious because construct correlations ranged from .938 to .964, HTMT values ranged from .992 to .998, the predictor VIF was 9.54, and the first component accounted for 64.1% of item variance. These findings indicate substantial measurement overlap. The study therefore provides preliminary support for the proposed intelligence–sharing–innovation sequence but does not establish a causal or fully measurement-distinct mediation mechanism.

Future research should use time-lagged or multi-source data, retain anonymized university and respondent-role codes, distinguish formal intelligence dissemination from general knowledge-sharing behaviour, and validate the measurement model before testing the structural relationships.

Declaration of AI-assisted tools: DeepL was used to support the initial translation of the questionnaire from English into Simplified Chinese, after which bilingual academic personnel reviewed and finalized all wording. OpenAI's ChatGPT was used for English-language editing, text organization, and drafting support based on the authors' original analyses and results. Neither tool was used for data collection, Python-based statistical computation, model estimation, or generation of numerical findings. The authors independently reviewed and verified all AI-assisted output and assume full responsibility for the final manuscript.

Author contributions: Conceptualization: Yuanshuang Ma and Gulmira Karabalaeva; data source identification and curation: Yuanshuang Ma and Gulmira Karabalaeva; formal analysis and interpretation: Yuanshuang Ma; writing—original draft: Yuanshuang Ma; writing—review and editing: Gulmira Karabalaeva; supervision: Gulmira Karabalaeva. All authors have read and agreed to the final version of the manuscript.

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Data availability statement: The respondent-level data are confidential and are not publicly available. They may be obtained from the corresponding author upon reasonable academic request, subject to institutional permission and appropriate confidentiality safeguards.

Ethics statement: Permission was obtained from the relevant university administrations. Participation was voluntary, informed consent was obtained before survey completion, and all responses were anonymous and confidential. No separate ethics approval number was issued for the minimal-risk anonymous survey.



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