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International Cooperation Models for Economics and Management Talent Development in the AI Era: Evidence from Beijing Applied Universities

Liyan Liu

School of Economics and Management, Beijing Institute of Petrochemical Technology, Beijing, China
Email: lucyliuliyan@bipt.edu.cn

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Abstract

The rapid advancement of artificial intelligence poses unprecedented challenges for international cooperation in developing economics and management talent. This study employs a mixed-methods design—combining interviews, questionnaires, and policy document analysis—to identify core competency demands and key elements of innovative international cooperation models. The analysis yields four principal findings. First, knowledge structure, practical competencies, and international perspective constitute the core demand dimensions, with AI literacy penetration—defined as the diffusion of AI-related knowledge, skills, and competencies among individuals—and cross-cultural empathy emerging as potential differentiators between applied and research-oriented universities. This differentiation, however, is based on respondents' subjective comparative judgments and awaits validation through direct institutional sampling. Second, AI literacy penetration exerts the strongest effect on cooperation effectiveness, with the three competencies accounting for the majority of explained variance. Third, a competency-to-resources-to-institutions-to-effectiveness transmission chain is detected, with indirect effects accounting for nearly half of the total effect. Fourth, the competency-origin model demonstrates superior fit over resource-origin alternatives. Policy document analysis shows AI-related keywords growing at roughly four to five times the rate of international cooperation keywords over the past decade, corroborating the policy urgency of this research. This study challenges the implicit resource-dominant logic in international cooperation research and offers empirical evidence to inform strategic adjustments in municipal applied universities.

Keywords

Artificial Intelligence, Economics and Management Talent Development, International Cooperation, Demand Diagnosis, Element Deconstruction

1. Introduction

1.1. Research Background

Education worldwide is undergoing rapid digital transformation. Artificial intelligence is reshaping industrial structures and labor markets while systematically transforming higher education—its talent development objectives, pedagogical approaches, and paradigms of international engagement. According to the Beijing Municipal Education Commission, since general AI literacy courses were launched in fall 2024, 52 higher education institutions in Beijing have offered such courses. All 22 municipal public undergraduate institutions now offer them, with more than 100,000 students enrolled. AI literacy has thus transitioned from frontier exploration to general education, becoming a fundamental requirement of contemporary higher education.

As applied disciplines closely tied to economic and social development, economics and management face unprecedented opportunities and challenges in international cooperation for talent development. Digital technologies have dissolved traditional spatial and temporal boundaries in education, spawning new collaborative forms such as virtual teaching and research centers, online dual-degree programs, and cross-border data sharing. At the same time, the restructuring of global value chains and the "Dual Circulation" development paradigm impose greater demands on cross-cultural communication, digital decision-making, and AI application competencies (Liu & Mo, 2022). As China's national political, cultural, international exchange, and science and technology innovation center, Beijing's higher education institutions directly shape the global competitiveness of the capital's education through the internationalization of their economics and management talent development.

The Chinese higher education system features a distinctive binary structure comprising research-oriented universities and applied universities. Research-oriented institutions—typically national key universities under the central government—emphasize theoretical inquiry and academic publication. Applied universities, by contrast, are predominantly municipal institutions that prioritize practical skill development and regional economic service. This structural distinction carries important implications for international cooperation strategies, yet existing research has rarely examined how these institutional differences shape talent development priorities in the AI era. Understanding this institutional context is essential for interpreting the findings of this study and assessing their generalizability.

1.2. Problem Statement

Despite Beijing's higher education institutions having accumulated substantial experience in international cooperation, economics and management disciplines continue to exhibit significant structural deficiencies in their international engagement in the AI context. These deficiencies manifest as two interrelated challenges.

One critical issue is the absence of precise demand profiling. Systematic and precise identification of the core competency demands for internationally oriented economics and management talent in the AI context remains lacking. Existing research largely remains at the level of macro-level policy advocacy, failing to substantively address what new and rigorous demands AI imposes on the knowledge structure of economics and management professionals, what specific AI-related competencies employers expect of economics and management graduates, and whether structural differences exist in talent demand between municipal applied universities and national research-oriented institutions.

A further obstacle lies in fragmented resource allocation. International cooperation models remain predominantly project-driven, lacking systematic analysis and organic integration of the core elements—competency restructuring, resource integration, and institutional innovation—enabled by AI technologies. The weighting relationships and coupling mechanisms among these elements remain unexplored, resulting in international cooperation practices that lack a scientific basis for resource allocation.

The essence of these dual challenges is the absence of an empirically grounded demand diagnostic framework and element analysis model—precisely the core question this study seeks to address.

1.3. Research Significance

This study constructs a Competency-Resources-Institutions three-dimensional analytical framework, employs Structural Equation Modeling to estimate the driving weights of each element on international cooperation effectiveness, and utilizes nested model comparisons to test the relative merits of different resource allocation logics. In doing so, it fills a theoretical gap in demand diagnosis and element deconstruction for economics and management international cooperation in the AI context. Through systematic empirical investigation, this study provides a precise competency demand profile for internationally oriented economics and management talent to support Beijing's "Four Centers" strategic development and offers data-driven evidence to inform the strategic adjustment of international cooperation in municipal applied universities.

1.4. Research Methodology and Innovation

We employ a mixed-methods design integrating qualitative interviews, quantitative questionnaires, and policy document analysis to achieve the dual objectives of demand diagnosis and element deconstruction. The innovations are threefold.

Methodologically, this is the first study to introduce Structural Equation Modeling with nested model comparisons to test resource allocation logics in economics and management international cooperation. Perspectivally, it distinguishes the differentiated demands between applied and research-oriented universities. Theoretically, it proposes and provides preliminary empirical evidence for a competency-driven resource allocation paradigm.

2. Literature Review and Theoretical Framework

2.1. Review of Domestic and International Research

2.1.1. International Research: Technology-Driven and Ecosystem-Oriented

International research on AI and international cooperation in higher education falls into three main streams. One line of inquiry concerns the intelligent reconstruction of curriculum systems (Spires et al., 2019). Top business schools such as Harvard Business School and MIT Sloan School of Management have developed immersive courses using AI-enhanced case libraries, including financial trading simulations and multinational enterprise management training, which deeply integrate teaching content with technological applications (Wang et al., 2020). A second strand addresses the digital upgrading of accreditation systems. International accreditation bodies including AACSB and EQUIS have incorporated data governance capability and digital competence into their evaluation standards, compelling global business schools to establish technology-empowered training systems (Akhmadieva et al., 2024). Currently, approximately 6 percent of business schools globally hold AACSB accreditation, with 49 Chinese mainland business schools accredited—second only to the United States. A third stream concerns the innovation of university-industry collaborative ecosystems. Multinational corporations including Microsoft and Google have co-established "Digital Economy Industry Academies" with more than 50 business schools, driving industry-education integration in international cooperation through authentic business projects (Naltchadjian & Alami, 2024).

However, Western research predominantly bases its findings on the institutional environments and resource endowments of developed countries, with insufficient attention to technological adaptability and cultural differences in Belt and Road countries. There is also a notable lack of dedicated discussion of the applicability of these findings to applied universities as opposed to elite research-oriented business schools.

2.1.2. Domestic Research: Policy-Driven and Regionally Focused

Domestic research is organized around policy drivers and regional practices. One strand involves policy-led model exploration. Beijing's 14th Five-Year Plan for Education Reform promotes the establishment of "digital hubs" between Tsinghua University, Peking University, and overseas institutions, facilitating new cooperative forms such as online dual-degree programs and virtual teaching and research centers (Lin, 2024). A second strand addresses curriculum and faculty technological empowerment. Scholars have focused on the development of cross-curricular course clusters integrating intelligent technology with economics and management and digital teaching materials, as well as enhancing faculty cross-border digital teaching capacities (Zhong, 2023; Wang & Liu, 2023). A third strand comprises regional collaborative practices. The Beijing-Tianjin-Hebei Digital Economy Education Alliance promotes credit recognition and resource sharing (Wang, 2024), while the Guangdong-Hong Kong-Macao Greater Bay Area pilots cross-border education data interoperability.

2.1.3. Identification of Research Gaps

Synthesizing domestic and international research, three significant limitations persist. There is a lack of precise identification of internationalization demands for economics and management talent across knowledge structure, practical competency, and international perspective dimensions—most research remains at the level of general advocacy. Analyses of international cooperation innovation elements are predominantly parallel listings, lacking empirical testing of weighting relationships and coupling mechanisms among elements. Existing studies also fail to effectively distinguish structural differences in talent demands and resource allocation between research-oriented and applied universities.

2.2. Core Concept Definitions

Economics and management disciplinary international cooperation refers to cross-border collaborative activities conducted by higher education institutions centered on economics, management, and finance disciplines through joint training, cross-border campus establishment, and research collaboration, with the core objective of cultivating globally oriented applied talent with digital literacy.

International cooperation innovation elements are the key driving factors that facilitate the transformation of economics and management international cooperation models from traditional forms to AI-empowered new forms. We operationalize these into three dimensions: internationalization competency elements, resource integration elements, and institutional safeguard elements.

2.3. Theoretical Framework: Differentiating Two Resource Allocation Logics

The core theoretical premise of this study is that, in the context of rapid AI iteration, two distinct resource allocation logics exist in international cooperation model innovation.

The resource-dominant logic takes existing resources—including funding, projects, and partner networks—as the decision-making starting point, with talent development objectives adjusted according to resource availability. Its implicit assumption is that more resources lead to more successful cooperation. This logic predominates in traditional international cooperation research but may lead to the passive stance of "doing what resources permit" rather than "allocating resources according to what competencies are needed".

The competency-driven logic takes clearly defined competency development objectives as the decision-making starting point, with resources and institutional arrangements aligned around competency objectives. Its implicit assumption is that clearer objectives lead to more effective allocation. This logic advocates first determining what kind of talent to cultivate, then designing resource integration plans and institutional safeguard mechanisms accordingly.

These two logics are not diametrically opposed but represent different prioritization orders in resource allocation. We seek to empirically test which logic better fits the empirical pathways of element action in the AI context. Specifically, if the data support a competency-to-resources-to-institutions-to-effectiveness transmission chain, they provide evidence for the competency-driven logic; if the data better support a resources-to-effectiveness pathway, they provide support for the resource-dominant logic.

The competency-driven logic proposed in this study fundamentally differs from the Resource-Based View prevalent in existing literature. The Resource-Based View emphasizes that resource scarcity determines competitive advantage, implicitly adopting a resources-first decision logic. In contrast, we argue that in the context of rapid AI technological change, the clarity and appropriateness of competency objectives should take priority over static resource inventories—because the value of resources can only be accurately assessed in terms of their contribution to specific competency objectives. This distinction constitutes the foundation of this study's theoretical contribution.

3. Research Design

3.1. Mixed-Methods Research Design

To overcome the limitations inherent in any single methodological approach, we adopted a mixed-methods design that triangulates qualitative interviews, quantitative surveys, and policy document analysis.

Qualitative Research. In-depth interviews were conducted with fifty-nine respondents across four stakeholder groups: twenty-two faculty members from the economics and management schools of five Beijing municipal applied universities; five administrators, including international cooperation directors and associate deans in charge of international cooperation, from the same five institutions; twenty-two enterprise representatives, comprising seven from technology innovation firms, eight from international trade firms, and seven from financial services firms; and ten students and graduates, including six current third- or fourth-year students and four recent graduates within three years of graduation. Each interview lasted between sixty and ninety minutes and covered three thematic areas: the perceived impact of AI on international cooperation, observed changes in talent competency demands, and perceived constraints of existing cooperation models. The qualitative analysis in Section 6.1 draws on all thirty-five interview transcripts from faculty and enterprise representatives—the two groups most directly involved in competency demand articulation—while the full set of fifty-nine interviews informs the broader case findings reported in Section 5. The twenty-two faculty interviews serve as the primary evidence base for loop hypothesis testing, as explained in Section 5.3.

Interview transcripts were independently coded by two researchers following a three-stage procedure comprising open coding, axial coding, and selective coding. Initial inter-coder agreement stood at 84.6 percent, rising to 96.2 percent after discussion, yielding a Kappa coefficient of 0.89 that signals excellent reliability. Points of disagreement arose primarily over the boundary between digital innovativeness and AI literacy penetration and were settled through arbitration by a third researcher.

Quantitative Research. Structured questionnaires were distributed to five respondent groups: enterprise executives and human resources directors from partner enterprises; university international cooperation administrators from the five sampled institutions; full-time faculty members from the economics and management schools of these institutions; third- and fourth-year economics and management students; and recent graduates who had completed their degrees within the preceding three years. This five-group sampling frame ensured coverage of both the demand side of talent development, represented by enterprises and graduates, and the supply side, represented by faculty and administrators. The questionnaire instrument was developed on the basis of both the interview findings and a comprehensive literature review. In total, 380 questionnaires were distributed and 312 valid responses were obtained, corresponding to an effective response rate of 82.1 percent. The distribution of respondents across the five groups is reported in Table 1.

After the initial draft was completed, three experts in economics and management education research were invited to evaluate each item for relevance and representativeness. Based on their feedback, two ambiguous items were removed and five items were reworded. A pilot test was subsequently conducted with thirty economics and management students, which prompted further refinements to item order and anchor descriptions. The respondent pools for the interviews and the questionnaires partially overlapped: 61.5 percent of enterprise respondents participated in both data collection phases. Consequently, the independence between the dimensions identified through grounded theory and the constructs measured by the questionnaire is limited—a limitation we revisit in Section 8.4.

Policy Document Analysis. Twenty-one Beijing municipal policy documents related to education internationalization and AI in education, covering the period from 2015 to 2025, were subjected to quantitative coding. Documents were included if they met three criteria: they were issued by the Beijing Municipal Committee, the Municipal Government, or the Municipal Education Commission; their content addressed higher education internationalization or AI applications in education; and their publication date fell between January 2015 and June 2025. A complete list of the documents is provided in **Appendix A**.

Keyword retrieval was performed using exact matching supplemented by synonym aggregation. For example, the concept of data literacy was coded through a combined search term that encompassed "data literacy", "data thinking", and "data analysis capability", with all mentions counted together. Coding was independently performed by two researchers, and inter-coder reliability was established with a Kappa coefficient of 0.87. To compare keyword frequencies across periods, we employed Mann-Whitney U tests, contrasting the pre-period spanning 2015 to 2019 with the post-period from 2020 to 2025.

3.2. Sample Selection and Data Sources

Institutional Sample. To ensure representativeness and heterogeneity, we selected five municipal universities that cover three institutional types: engineering-focused institutions, represented by Beijing University of Technology and Beijing Institute of Petrochemical Technology; economics and finance-focused institutions, represented by Capital University of Economics and Business and Beijing Technology and Business University; and a comprehensive institution, Beijing Union University. Among these, Beijing University of Technology hosts the Beijing-Dublin International College, a notable early example of systematic Sino-foreign cooperative education among municipal universities. Capital University of Economics and Business has partnered with the University of Arizona to establish the School of Data Science, offering Sino-American dual degrees through a four-year, fully in-China model.

Enterprise Sample. In alignment with Beijing's functional positioning as a national center for politics, culture, international exchange, and science and technology innovation, we sampled enterprises from three sectors: science and technology innovation, comprising AI and big data firms; international trade, covering cross-border e-commerce and international trading companies; and financial services, including the international business divisions of banks, securities firms, and insurance institutions. While the sample provides strong coverage of enterprises associated with the Science and Technology Innovation Center and the International Exchange Center, it offers more limited representation of organizations linked to the Cultural Center and the Political Center. We acknowledge this as a limitation of the study. The distribution of interview respondents across institutions and enterprise types was as follows. Among the twenty-two faculty interviewees, five came from Beijing University of Technology, five from Beijing Institute of Petrochemical Technology, and four from each of the remaining three institutions. The five administrators were distributed one per institution, each serving as the primary international cooperation officer of their respective school. Among the twenty-two enterprise representatives, seven were from technology innovation firms, eight from international trade firms, and seven from financial services firms. Within each sector, we further stratified the sample by enterprise size, with approximately half of the respondents coming from large firms and half from medium or small enterprises. This stratified sampling approach ensured coverage across both industry sectors and enterprise size categories. The six current students were drawn from all five universities, with at least one student from each institution, and the four graduates had completed their degrees from three of the five institutions within the preceding three years.

3.3. Variable Design and Measurement

To operationalize the key constructs in our conceptual framework, we developed a comprehensive measurement instrument. The full questionnaire is provided in **Appendix B**. Unless otherwise noted, all multi-item scales employed a 5-point Likert response format, with higher scores indicating greater endorsement of the construct in question.

3.3.1. Dependent Variables

The dependent variable, internationalization competency demands, was operationalized across three theoretically derived dimensions: knowledge structure, practical competencies, and international perspective.

Knowledge structure demands were measured using an eight-item scale comprising three sub-domains. The first sub-domain, AI foundational literacy, consisted of three items assessing respondents' perceptions of the importance of understanding AI's basic principles, evaluating the reliability of AI outputs, and possessing basic data literacy. The second sub-domain, data-driven decision-making capabilities, comprised four items measuring proficiency with business intelligence tools, data visualization and storytelling, data-based prediction and optimization, and foundational statistical analysis. A single final item captured the perceived importance of interdisciplinary knowledge integration across economics, management, and data science. This scale demonstrated strong internal consistency, yielding a Cronbach's α of 0.87.

Practical competency demands were assessed with an eleven-item scale encompassing four distinct competency clusters. The first cluster, cross-border business operation capabilities, comprised four items measuring international settlement, supply chain compliance, business negotiation, and full-process cross-border operations. The second cluster, digital tool practical capabilities, consisted of four items addressing AI-driven business forecasting, ERP system operation, RPA design and deployment, and cross-border data compliance. Two additional items measured project management and teamwork capabilities, and a final single item captured digital innovativeness, specifically the ability to use AI tools to identify and develop new business opportunities. The scale yielded a Cronbach's α of 0.89.

International perspective demands were operationalized through a six-item scale split evenly between two sub-dimensions. Three items measured cross-cultural communication capabilities, including understanding diverse business cultural logics, communicating effectively across cultures, and adapting to multicultural team environments. The remaining three items tapped international regulatory adaptation capabilities, covering knowledge of international trade rules, ESG standards, and international organizational mechanisms. The Cronbach's α for this scale was 0.84.

Across all twenty-five items measuring competency demands, the overall scale exhibited excellent internal consistency, with a Cronbach's α of 0.92.

3.3.2. Independent Variables

Two conceptually distinct constructs are employed in this study. AI literacy penetration refers to the individual-level diffusion of AI-related knowledge, skills, and competencies, measured through competency perceptions and self-assessments. AI technology penetration, by contrast, refers to the organizational-level diffusion of AI tools and infrastructure, measured through the number of AI tool types deployed by enterprises. The former serves as the focal independent variable in the structural equation modeling analysis; the latter functions as a contextual predictor in the ordinal logistic regression. AI technology penetration was measured using a dual-approach strategy. Objective indicators captured the number of AI tool types deployed by enterprises, ranging from zero to five categories: natural language processing, machine learning prediction, RPA automation, intelligent customer service, and AI-assisted decision-making. Complementing this objective measure, we employed a three-item perceptual scale assessing respondents' subjective evaluation of AI integration in their organizations, with items such as "AI technology has been deeply applied in our organization's operations". The perceptual scale demonstrated good internal consistency, with a Cronbach's α of 0.83, and its correlation with the objective indicator was substantial at 0.76, $p < 0.01$, confirming measurement validity. We used the perceptual scale scores in our main analysis, reserving the objective indicators for robustness checks.

International cooperation model types were classified based on interview coding and literature review. We identified three distinct types of economics and management international cooperation in municipal universities: the academic alliance type, characterized by institutional memoranda of understanding and academic exchanges; the project-driven type, involving stage-based cooperation through specific projects; and the platform-mediated type, which relies on third-party education service providers or online platforms for resource matching. Two researchers independently classified each institution based on interview materials, achieving perfect agreement.

Policy driving intensity was derived from quantitative scoring of twenty-one policy documents. The scoring rubric incorporated three dimensions. The first dimension, policy level, assigned three points to Municipal Committee or Government documents, two points to Municipal Education Commission documents, and one point to others. The second dimension, policy objective clarity, awarded three points for explicit mention of AI-empowered international cooperation, two points for relevance without focus, and one point for no mention. The third dimension, supporting measure completeness, gave two points for dedicated funding or implementation guidelines and one point for principle-level statements alone. Total scores ranged from one to eight points. Two researchers independently completed the scoring, achieving excellent inter-rater reliability with an ICC of 0.92.

3.3.3. Mediating Variables and Outcome Variable

Resource integration degree was assessed using a four-item composite scale. Items captured the frequency of university-industry collaboration, the extent of enterprise participation in curriculum development, partner institutions' resource commitment, and the adequacy of government resource support. The scale demonstrated acceptable internal consistency with a Cronbach's α of 0.79.

Institutional completeness degree was measured with another four-item scale covering clarity of rights and responsibilities, comprehensiveness of procedural regulations, the presence of evaluation systems, and the adequacy of risk prevention mechanisms. The Cronbach's α for this scale was 0.81.

International cooperation effectiveness served as our core outcome variable. This construct was operationalized across three sub-dimensions, each measured with three items. The cooperation scale effectiveness sub-dimension assessed growth in student participation, expansion of partner networks, and diversification of project types. The cooperation quality effectiveness sub-dimension measured stakeholder satisfaction, project sustainability, and contributions to teaching and research quality. The talent development effectiveness sub-dimension evaluated improvements in student international competence, graduate competitiveness in the international job market, and overall talent development quality. The overall scale demonstrated strong internal consistency with a Cronbach's α of 0.88, while the sub-dimension alphas were 0.82, 0.85, and 0.80, respectively. Confirmatory factor analysis confirmed the suitability of a second-order factor structure, with a CFI of 0.936 and an RMSEA of 0.062, supporting the integration of the three sub-dimensions into a single higher-order construct.

3.3.4. Control Variables

To address potential confounding effects, we included several control variables in our ordinal logistic regression analyses. University type was coded as engineering-focused, economics-finance-focused, or comprehensive. Respondent identity was classified into four categories: enterprise executive, university administrator, faculty, and student. Enterprise size was categorized as large with five hundred or more employees, medium with between fifty and four hundred ninety-nine employees, or small with fewer than fifty employees.

In the structural equation modeling analyses, we did not include additional control variables. This decision reflects our primary focus on the theoretical path relationships among latent constructs and the fact that our latent variable measurement models already account for measurement error through multiple indicators. This approach is consistent with established practice in comparable studies (Hair et al., 2010). Future research could extend our model by incorporating additional control variables to further test the robustness of our findings.

4. Descriptive Statistics

4.1. Basic Characteristics

Table 1 presents the demographic and organizational characteristics of the survey respondents. Among the 312 valid respondents, enterprise executives and human resources directors constituted the largest professional group, accounting for 27.9 percent of the sample. Current students represented 32.7 percent, while recent graduates who had completed their degrees within the preceding three years made up 17.3 percent. Full-time faculty and university international cooperation administrators accounted for 15.1 percent and 7.1 percent, respectively. This distribution ensures that the sample captures perspectives from both the "demand side" of talent development—enterprise executives and recent graduates—and the "supply side" represented by university faculty and administrators.

At the institutional level, the five sampled universities were evenly distributed across three types: engineering-focused institutions represented 40 percent, economics and finance-focused institutions another 40 percent, and comprehensive institutions the remaining 20 percent. This institutional heterogeneity enhances the generalizability of the findings across different categories of municipal applied universities. Within the enterprise subsample of 87 respondents, large firms with 500 or more employees constituted 47.1 percent, medium-sized firms with 50 to 499 employees accounted for 33.3 percent, and small firms with fewer than 50 employees represented 19.5 percent. The industry distribution was relatively balanced: technology innovation firms comprised 32.2 percent, international trade firm's 35.6 percent, and financial services firms' 32.2 percent. This balanced sectoral coverage allows for meaningful comparisons of competency demands across different industry contexts, a key analytical objective of this study. Overall, the sample demonstrates sufficient variation across respondent identity, university type, enterprise size, and industry sector to support the multivariate analyses undertaken in subsequent sections.

Table 1. Sample basic characteristic distribution (N = 312).

Variable	Category	Frequency (n)	Percentage (%)
Respondent Identity	Enterprise Executives/HR Directors	87	27.9
	University International Cooperation Administrators	22	7.1
	Full-time Faculty	47	15.1
	Current Students (3rd/4th Year)	102	32.7
	Recent Graduates (within 3 years)	54	17.3
University Type (Institutional Sample)	Engineering-focused	2 institutions	40.0
	Economics/Finance-focused	2 institutions	40.0
	Comprehensive	1 institution	20.0
Enterprise Size (Enterprise Sample, n = 87)	Large (≥500 employees)	41	47.1
	Medium (50 - 499 employees)	29	33.3
	Small (<50 employees)	17	19.5
Industry Type (Enterprise Sample, n = 87)	Technology Innovation	28	32.2
	International Trade	31	35.6
	Financial Services	28	32.2

Note: Percentages for university type are based on the 5 sampled institutions; percentages for other categories are based on total respondents (N = 312) or the enterprise subsample (n = 87).

4.2. Descriptive Statistics of Major Variables

Table 2 presents descriptive statistics for all key constructs examined in this study. All variables were measured on a 5-point scale except policy driving intensity, which employed an 8-point composite scoring system. Among the three competency demand dimensions, all scored above the midpoint, with means ranging from 4.21 to 4.39. Practical competency demands recorded the highest mean at 4.39 (SD = 0.61), closely followed by knowledge structure demands at 4.31 (SD = 0.58). International perspective demands yielded the lowest mean among the dependent variables at 4.21 (SD = 0.55). This pattern suggests that respondents across all stakeholder groups consistently rated practical and knowledge-based competencies as highly important, while international perspective—though still valued—was perceived as somewhat less critical.

International cooperation effectiveness, our core outcome variable, showed a mean of 3.82 (SD = 0.73). This score is considerably lower than the competency demand dimensions, indicating that while respondents attach high importance to these competencies, their perception of current cooperation effectiveness is more moderate and exhibits greater variation across respondents. This gap between demand importance and perceived effectiveness underscores the practical urgency of reforming international cooperation models.

Table 2. Descriptive statistics of major variables.

Variable Dimension	Items	Mean (M)	SD	Min	Max	Cronbach's α
Dependent Variables						
Knowledge Structure Demands	8	4.31	0.58	2.13	5.00	0.87
Practical Competency Demands	11	4.39	0.61	2.10	5.00	0.89
International Perspective Demands	6	4.21	0.55	2.33	5.00	0.84
International Cooperation Effectiveness	9	3.82	0.73	1.89	5.00	0.88
Independent Variables						
AI Technology Penetration	3 + objective indicators	3.84	0.72	1.67	5.00	0.83
Policy Driving Intensity	Composite score (1 - 8)	5.21	1.85	1.00	8.00	—
Mediating Variables						
Resource Integration Degree	4	3.76	0.69	1.75	5.00	0.79
Institutional Completeness Degree	4	3.58	0.73	1.50	5.00	0.81

Note: All scales employ 5-point Likert ratings. The overall scale exhibits excellent internal consistency with a Cronbach's α of 0.92. Policy driving intensity is based on textual quantitative scoring rather than scale data. AI technology penetration was measured using 3 perceptual scale items combined with objective indicators.

For the independent and mediating variables, AI technology penetration registered a mean of 3.84 (SD = 0.72), suggesting moderate AI adoption across sampled institutions. Resource integration degree yielded a mean of 3.76 (SD = 0.69), while institutional completeness degree produced the lowest mean among all variables at 3.58 (SD = 0.73). The finding that institutional completeness received the lowest rating is noteworthy: it suggests that institutional safeguards and procedural mechanisms are perceived as the weakest link in the current international cooperation ecosystem. Policy driving intensity averaged 5.21 on an 8-point scale (SD = 1.85), reflecting considerable variation in policy support for international cooperation across the documents reviewed.

Internal consistency reliability was uniformly high across all multi-item scales. Cronbach's alpha coefficients ranged from 0.79 to 0.92, with the overall competency demands scale achieving the highest value. All coefficients comfortably exceeded the commonly accepted threshold of 0.70, confirming the reliability of our measurement instruments. The knowledge structure, practical competency, and international perspective demand scales demonstrated alphas of 0.87, 0.89, and 0.84, respectively. The mediating variables showed acceptable reliability with alphas of 0.79 and 0.81, while international cooperation effectiveness exhibited strong reliability at 0.88.

The observed score ranges indicate that the full spectrum of responses was captured across each construct, with minimum and maximum values spanning from near the floor to the ceiling of each scale. This variation suggests adequate differentiation among respondents and supports the appropriateness of the scales for subsequent multivariate analyses. Taken together, these descriptive statistics provide a solid empirical foundation for the structural equation modeling and regression analyses reported in the following sections.

5. Empirical Analysis I: Core Competency Demand Profiling

5.1. Knowledge Structure Dimension Demand Analysis

5.1.1. Integration Demand for AI Foundational Literacy and Economics and Management Domain Knowledge

Interview results indicate that a substantial majority of enterprise executive respondents explicitly stated that economics and management graduates who possess only finance or marketing knowledge are far from sufficient. Specifically, 92.3 percent of these respondents emphasized that graduates need the ability to "converse with AI", which entails understanding the basic principles of machine learning, knowing the analytical frameworks of data science, and effectively communicating with technical teams. A financial services human resources director noted that their organization now asks every fresh graduate during interviews how they think AI will change the way their role works; those who respond with a vague statement that AI is important are effectively eliminated from consideration.

Questionnaire data further substantiated this qualitative finding. Within the AI foundational literacy dimension, respondents rated three competencies as most important: understanding AI's basic principles and application boundaries, with a mean score of 4.52 and a standard deviation of 0.61; being able to evaluate the reliability and bias of AI output results, with a mean of 4.38 and a standard deviation of 0.67; and possessing data literacy and basic programming comprehension, with a mean of 4.21 and a standard deviation of 0.72. Enterprise respondents, comprising eighty-seven individuals with a mean rating of 4.61 and a standard deviation of 0.55, rated AI literacy as significantly more important than did all student respondents, who numbered one hundred fifty-six with a mean of 4.15 and a standard deviation of 0.68. This combined student group includes the one hundred two current students and fifty-four recent graduates reported in **Table 1**. The independent samples t-test yielded a value of 5.83 with 241 degrees of freedom and a *p*-value below 0.001, and Cohen's d was 0.75. This indicates that enterprises perceive considerably greater urgency regarding AI literacy compared to students' self-perceptions, with a moderate-to-large effect size.

5.1.2. Prioritization of Data-Driven Decision-Making Capabilities

Within the data-driven decision-making capability sub-dimension, item means were ordered as follows. Business intelligence tool application capabilities, exemplified by tools such as Tableau and Power BI, recorded the highest mean of 4.55 with a standard deviation of 0.62. Data visualization and storytelling capabilities followed with a mean of 4.43 and a standard deviation of 0.65, while data-based prediction and optimization decision-making capabilities yielded a mean of 4.39 and a standard deviation of 0.68. Foundational statistical analysis capabilities registered the lowest mean among the four items at 4.12 with a standard deviation of 0.71. A one-way repeated-measures ANOVA revealed significant differences among these items, with an F-value of 12.84 for degrees of freedom 3 and 933, a *p*-value below 0.001, and an effect size eta-squared of 0.040. Post-hoc pairwise comparisons employing Bonferroni correction with an alpha level of 0.0083 indicated that business intelligence tool application capabilities were rated significantly higher than foundational statistical analysis capabilities, with a *p*-value below 0.001, and data visualization was rated significantly higher than foundational statistical analysis, with a *p*-value of 0.002. Other pairwise differences did not reach statistical significance after correction. This ordering reveals an important pattern: enterprise expectations for data capabilities have evolved from being able to run statistics to being able to tell stories and make decisions with data.

Policy document analysis corroborates this trend, as presented in **Table 3**. Across the 21 policy documents spanning 2015 to 2025, the frequency of keywords such as "data literacy", "data analysis", and "data-driven" increased from an annual average of 2.3 occurrences with a standard deviation of 1.4 in the 2015-2019 period to 11.7 occurrences with a standard deviation of 3.2 in the 2020-2025 period. The Mann-Whitney U test indicated a significant pre-post difference with a U-value of 0.00 and a *p*-value of 0.004, representing a more than fourfold increase. The Beijing Education Sector AI Application Guidelines for 2025 explicitly states that higher education should focus on developing "golden courses, golden faculty, golden majors, and golden teaching materials", and should explore intelligent applications of AI in AI-integrated courses and faculty-student AI literacy enhancement.

Table 3. Quantitative policy document coding framework.

Coding Dimension	Operational Definition	Scoring Rules
Policy Level	Administrative level of the issuing authority	Municipal Committee or Municipal Government: 3 points; Municipal Education Commission: 2 points; Other: 1 point
Policy Objective Clarity	Explicit mention of AI-empowered international cooperation	Explicitly mentioned: 3 points; Relevant but not focused: 2 points; Not mentioned: 1 point
Supporting Measure Completeness	Presence of dedicated funding or implementation guidelines	Present: 2 points; Principle-only statements: 1 point

5.2. Practical Competency Dimension Demand Analysis

5.2.1. Cross-Border Business Full-Process Operational Capabilities

Interview findings reveal that as Chinese enterprises increasingly expand globally, the question for economics and management professionals is no longer whether to internationalize but how to efficiently execute international business with AI assistance. Questionnaire data show that the three most valued cross-border business capabilities are as follows. International settlement and cross-border payment operation capabilities were rated as extremely important by 87.6 percent of enterprise respondents, with a 95 percent confidence interval ranging from 82.1 to 92.8 percent. Cross-border supply chain coordination and compliance management capabilities followed, with 81.2 percent of respondents rating them as extremely important and a 95 percent confidence interval from 74.8 to 87.6 percent. International business negotiation and cross-cultural communication capabilities were rated as extremely important by 78.5 percent of respondents, with a 95 percent confidence interval from 71.9 to 85.1 percent.

A vice president of an international trade enterprise commented that their business covers more than 50 countries, each with different regulations, taxes, and logistics. In the past, they had to check everything manually; now AI can assist with compliance screening and risk assessment. The prerequisite, however, is that employees know what to ask and how to verify—and that is precisely what most economics and management graduates lack.

5.2.2. Enterprise Demand Intensity for Digital Tool Practical Competencies

Questionnaire data indicate that enterprises' most valued digital tool competencies are AI-driven business forecasting and intelligent decision-making tool practical capabilities, which had a mean of 4.48 and a standard deviation of 0.58. ERP system operation capabilities followed with a mean of 4.41 and a standard deviation of 0.63, while RPA process design and deployment capabilities had a mean of 4.35 and a standard deviation of 0.66. Notably, 82.4 percent of enterprise respondents, with a 95 percent confidence interval from 76.1 to 88.7 percent, indicated that current economics and management graduates' digital tool practical capabilities fall far short of job requirements. This proportion was significantly higher than students' self-assessment: only 38.6 percent of students, with a 95 percent confidence interval from 32.3 to 44.9 percent, perceived their own digital tool capabilities as insufficient. The chi-square test yielded a value of 45.23 with one degree of freedom and a p-value below 0.001, and the phi coefficient was 0.43.

The largest gaps are concentrated in practical operation of AI-assisted analytical tools and cross-border data compliance processing. This finding suggests that applied universities' curriculum and practical training urgently require upgrading beyond the level of teaching concepts to practicing tools.

5.3. International Perspective Dimension Demand Analysis

5.3.1. Cross-Cultural Communication and Global Governance Participation Capabilities

Cross-cultural communication competence was rated by 95.7 percent of enterprise respondents, with a 95 percent confidence interval from 92.5 to 98.9 percent, as an essential quality for internationally oriented economics and management professionals. However, further inquiry revealed that enterprises' understanding of cross-cultural competence has evolved from good foreign language skills to understanding different business cultural logics and collaborating effectively with AI assistance. A technology enterprise international business director noted that AI can translate in real time, but it cannot translate Indian clients' sensitivity to pricing, German clients' strictness about processes, or Southeast Asian clients' emphasis on relationships. These cultural insights are the core of cross-cultural competence.

For global governance participation capability, item means were as follows. Understanding international economic and trade rules and agreements, such as WTO rules and RCEP, had a mean of 4.33 and a standard deviation of 0.58. ESG standards and international compliance requirements yielded a mean of 4.28 and a standard deviation of 0.61, while international organizational mechanisms and participation pathways had a mean of 3.95 and a standard deviation of 0.72. A repeated-measures ANOVA showed significant differences, with an F-value of 34.54 for degrees of freedom 2 and 622, a p-value below 0.001, and an effect size eta-squared of 0.100. Post-hoc pairwise comparisons indicated that international economic and trade rules were rated significantly higher than international organizational mechanisms, with a p-value below 0.001, and ESG standards were rated significantly higher than international organizational mechanisms, also with a p-value below 0.001. The former two did not differ significantly from each other, with a *p*-value of 0.234. This ordering reflects enterprise demand for rule-oriented international talent: graduates need to know not just how to do business but also under what regulatory frameworks to do business.

5.3.2. Industry Variations in International Certification and Standard Adaptation Capabilities

Significant industry variations exist in the emphasis on international certifications and standards. As shown in Table 4, the financial services sector most highly values IFRS and anti-money laundering compliance standards, with a mean of 4.72 and a standard deviation of 0.45. The international trade sector, with thirty-one respondents, most highly values INCOTERMS and letter of credit operational standards, with a mean of 4.58 and a standard deviation of 0.50. The technology sector most highly values cross-border data flow regulations, such as the EU GDPR, and international intellectual property protection, with a mean of 4.49 and a standard deviation of 0.55. A one-way ANOVA revealed significant between-group differences, with an F-value of 4.89 for degrees of freedom 2 and 84, a *p*-value of 0.010, and an effect size eta-squared of 0.104.

This industry variation suggests that applied universities should avoid a one-size-fits-all international perspective development approach. Instead, they should design differentiated international regulatory content based on specialization and target employment industries.

Table 4. Industry variations in international certification and standard adaptation capabilities.

Industry Sector	n	Most Valued Standards/Certifications	Mean	SD
Financial Services	28	IFRS, Anti-Money Laundering Compliance Standards	4.72	0.45
International Trade	31	INCOTERMS, Letter of Credit Operational Standards	4.58	0.50
Technology	28	Cross-Border Data Flow Regulations (e.g., GDPR), Intellectual Property Protection	4.49	0.55

Note: One-way ANOVA results: $F(2, 84) = 4.89$, $p = 0.010$, $\eta^2 = 0.104$.

5.4. Demand Stratification and Typological Conclusions

5.4.1. Differentiated Demand Profiles: Municipal Applied versus Research-Oriented Universities

Through interviewees' comparative judgments regarding differences between research-oriented and applied universities, this study identifies structural differences in talent demands. Research-oriented universities demonstrate demand emphasis biased toward frontier theoretical exploration capability and academic research capability, with greater expectations for students to track international academic frontiers and possess independent research capabilities. Applied universities display demand emphasis significantly biased toward practical tool competencies and cross-border business execution capabilities, with enterprises more concerned about whether students can directly perform on the job and can quickly adapt to workplace requirements.

This comparison is based on interview respondents' subjective comparative judgments rather than direct questionnaire sampling of research-oriented universities. Specifically, 68.6 percent of respondents had cooperative experience with both types of institutions and were asked to evaluate, based on their direct experience, the competency demand differences between the two types. Consequently, the following data should be interpreted as exploratory comparisons rather than rigorous statistical tests, and conclusions drawn from them require cautious interpretation.

In respondents' comparative judgments, research-oriented universities' demand for deep understanding of AI algorithm principles, with a mean rating of 4.23 and a standard deviation of 0.58, exceeded that of applied universities, which received a mean rating of 3.67 and a standard deviation of 0.71, representing a mean difference of 0.56. Conversely, applied universities' demand for practical operation of AI business tools, with a mean of 4.58 and a standard deviation of 0.56, exceeded that of research-oriented universities, which yielded a mean of 3.94 and a standard deviation of 0.65, representing a mean difference of 0.64. The effect sizes for these differences, calculated as Cohen's d based on paired comparisons, were 0.87 and 1.07, respectively, reaching moderate-to-large magnitudes. These data derive from respondents' overall impression ratings rather than independent responses from the two types of institutions, and thus formal t-tests were not conducted.

A significant limitation warrants explicit acknowledgment: we did not directly include an independent sample of research-oriented universities. The comparative conclusions regarding applied versus research-oriented universities are primarily based on respondents' comparative judgments and should therefore be considered exploratory findings. Future research should validate these findings through direct sampling of research-oriented universities.

5.4.2. Technological Application and Cross-Cultural Execution Dual-Core Competency Model

Based on the above findings, we propose a Technological Application and Cross-Cultural Execution Dual-Core Competency Model for economics and management talent in municipal applied universities.

The first core is the technological application layer, which refers to the practical ability to integrate AI technologies with economics and management domain knowledge, including AI business tool operation, data-driven business decision-making, and cross-border digital platform operation. This layer addresses the question of what tools to use and how to use them.

The second core is the cross-cultural execution layer, which refers to the ability to effectively execute international business operations across diverse business cultural contexts, including cross-cultural business insight, international rule understanding and adaptation, and multicultural team collaboration. This layer addresses the question of in what context and how to execute.

The Dual-Core Competency Model differs fundamentally from the "digital literacy plus cross-cultural competence" framework prevalent in existing literature. The latter typically treats the two competencies as parallel independent modules to be developed separately, advocating teaching both technical tools and cross-cultural knowledge. In contrast, the Dual-Core Model emphasizes the interactive coupling between technological application and cross-cultural execution. AI tool application scenarios are inherently cross-cultural, and cross-cultural execution must leverage AI tools for efficiency enhancement. Their integration rather than simple addition constitutes the distinctive feature of economics and management international talent development in applied universities.

Consider a Cross-Border E-commerce AI Operations course. Students must not only master AI product selection tool operation and data interpretation at the technological application layer but also understand the cultural preferences of target market consumers, the influence of religious beliefs on consumer behavior, and local e-commerce regulatory compliance requirements at the cross-cultural execution layer. These two dimensions are inextricably linked within any given business task and should be developed together in an integrated manner. This exemplifies the interactive coupling logic rather than parallel addition. This model provides clear competency targeting for the subsequent element deconstruction and model design.

6. Empirical Analysis II: Deconstruction of International Cooperation Innovation Elements and Pathway Testing

6.1. Internationalization Competency Element Reconstruction: Grounded Theory Coding

Through three-level grounded theory coding of 35 interview transcripts, we identified three core competency sub-dimensions of internationally oriented economics and management talent. As presented in Table 5, AI Literacy Penetration was mentioned by 91.4 percent of respondents, with 32 out of 35 respondents referencing it. Cross-Cultural Empathy was cited by 82.9 percent, with 29 out of 35 respondents referencing it. Digital Innovativeness was noted by 57.1 percent, with only 20 out of 35 respondents referencing it. The substantially lower coverage of Digital Innovativeness suggests that this competency may be more relevant to mid-level or senior professional roles rather than constituting a universal requirement for all economics and management talent.

These interview-derived dimensions subsequently informed the operationalization of the questionnaire scales used in the SEM analysis, with items developed to capture each dimension's core characteristics. The three interview-derived dimensions were operationalized using specific subsets of the twenty-five competency demand items described in Section 3.3.1. AI Literacy Penetration was measured with four items drawn from both the knowledge structure and practical competency scales, assessing understanding of AI's basic principles, evaluation of AI output reliability, data literacy, and the ability to use AI tools for compliance judgment. Cross-Cultural Empathy was measured with four items from the international perspective and practical competency scales, capturing understanding of different business cultural logics, effective communication in multicultural contexts, adaptation to multicultural team environments, and cross-cultural team collaboration and conflict resolution. Digital Innovativeness was measured with three items from the practical competency scale, capturing AI-driven business forecasting capabilities, the ability to use AI tools to identify new business opportunities, and RPA process design capabilities. Thus, while the demand framework in Section 5 organizes competency demands into knowledge structure, practical competencies, and international perspective—reflecting how respondents perceive the importance of different competency domains—the SEM constructs reorganize these items into theoretically coherent latent variables that correspond directly to the grounded theory dimensions identified in the interviews. The former answers the question of what competencies are considered important, while the latter addresses how these competencies cluster and operate as drivers of cooperation effectiveness. The qualitative findings thus provided the conceptual foundation for the quantitative measurement model that follows (Table 5).

Table 5. Coverage rates of core competency sub-dimensions from grounded theory coding.

Competency Sub-Dimension	Respondents Mentioning	Percentage	Interpretation
AI Literacy Penetration	32 out of 35	91.4%	Universal/core competency
Cross-Cultural Empathy	29 out of 35	82.9%	Universal/core competency
Digital Innovativeness	20 out of 35	57.1%	Mid- to senior-level competency

6.2. Ordinal Logistic Regression Model: Identification of Key Predictors

The purpose of this section is to identify which candidate predictor variables exert significant independent effects on the perceived level of internationalization competency demand. This screening process serves as a basis for selecting variables to be included in the subsequent SEM pathway analysis. The two analytical stages thus form a sequential logic of screening followed by explanation.

The dependent variable captures respondents' overall assessment of internationalization competency demand. The dependent variable was constructed as the mean score across all twenty-five items measuring the three competency demand dimensions: knowledge structure demands with eight items, practical competency demands with eleven items, and international perspective demands with six items.

This continuous mean score was then recoded into an ordered categorical variable with five levels. The cut-points were as follows: mean scores from 1.00 to 1.80 were classified as low demand; scores from 1.81 to 2.60 as moderately low demand; scores from 2.61 to 3.40 as moderate demand; scores from 3.41 to 4.20 as moderately high demand; and scores from 4.21 to 5.00 as high demand. These thresholds were selected to ensure approximately balanced distribution across categories. The full twenty-five-item scale achieved a Cronbach's α of 0.92, confirming that aggregation of the three sub-dimensions is statistically justified. It is an ordered categorical variable ranging from 1 (low demand) to 5 (high demand), with intermediate values representing moderately low, moderate, and moderately high levels.

The model specification is as follows:

$$\log\left(\frac{P(Y \le j)}{1-P(Y \le j)}\right) = \alpha_j - (\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k), j = 1,2,3,4 \tag{1}$$

The regression results (Table 6) indicate that for every one-point increase in AI technology penetration, the demand level increases by approximately 1.84 times (OR = 1.844, $p < 0.001$), making it the strongest predictor. Enterprise executives and graduates rated demand significantly higher than students, reflecting a perception gap between workplace and campus stakeholders. Financial services and international trade industries showed significantly higher demand than technology innovation, suggesting industry variations in emphasis on internationalization competencies. Enterprise size and university type did not reach significance.

Table 6. Ordinal logistic regression model results.

Variable	Coefficient (β)	S.E.	Wald χ^2	p-value	OR	95% CI
AI Technology Penetration	0.612	0.142	18.56	<0.001	1.844	[1.396, 2.436]
Identity: Enterprise Executive (vs. Student)	0.483	0.165	8.57	0.003	1.621	[1.174, 2.238]
Identity: University Administrator (vs. Student)	0.351	0.198	3.14	0.076	1.421	[0.964, 2.095]
Identity: Faculty (vs. Student)	0.287	0.184	2.43	0.119	1.332	[0.929, 1.911]
Identity: Graduate (vs. Student)	0.412	0.176	5.48	0.019	1.510	[1.070, 2.132]
Enterprise Size: Large (vs. Small)	0.294	0.174	2.86	0.091	1.342	[0.954, 1.888]
Enterprise Size: Medium (vs. Small)	0.182	0.191	0.91	0.340	1.200	[0.825, 1.746]
Industry: Financial Services (vs. Technology)	0.412	0.181	5.18	0.023	1.510	[1.059, 2.153]
Industry: International Trade (vs. Technology)	0.356	0.178	4.00	0.046	1.428	[1.007, 2.026]
University Type: Engineering-focused (vs. Comprehensive)	−0.154	0.169	0.83	0.362	0.857	[0.615, 1.194]
University Type: Economics/Finance-focused (vs. Comprehensive)	0.096	0.173	0.31	0.578	1.101	[0.784, 1.545]

Note: Model fit: −2 Log Likelihood = 687.34, Cox & Snell R^2 = 0.243, Nagelkerke R^2 = 0.289, n = 312.

The Nagelkerke R^2 value of 0.289 indicates that the model has moderate explanatory power for competency demand levels, with the included predictors explaining approximately 29 percent of the variance in demand levels. The remaining 71 percent of variance is attributable to factors not included in this study, such as individual characteristics, institutional resource endowments, and regional economic environments, providing scope for future research to explore additional predictor variables. To assess potential institutional clustering, we fitted a mixed-effects ordinal logistic model with university as a random intercept. The intraclass correlation coefficient was 0.031, indicating that less than four percent of the variance in competency demand ratings was attributable to between-university differences. Given this negligible clustering effect, we proceeded with the fixed-effects ordinal logistic model reported above.

6.3. Structural Equation Modeling: Competency Pathway Weights and Mediation Testing

6.3.1. Measurement Model

The three latent constructs—AI Literacy Penetration, Cross-Cultural Empathy, and Digital Innovativeness—were each measured by three or four items. Confirmatory factor analysis produced standardized factor loadings ranging from 0.62 to 0.84, all statistically significant at the $p < 0.001$ level. Composite reliability values for the three constructs were 0.86, 0.83, and 0.81, respectively, while the average variance extracted estimates were 0.61, 0.58, and 0.55. All of these values exceeded the recommended thresholds (CR > 0.7, AVE > 0.5; Hair et al., 2010). Discriminant validity was also established: the square root of the average variance extracted for each latent variable—0.78, 0.76, and 0.74, respectively—exceeded the correlations between that variable and the other latent constructs, which ranged from 0.41 to 0.53, thereby satisfying the Fornell-Larcker criterion (Fornell & Larcker, 1981).

6.3.2. Structural Model and Pathway Analysis

The structural model was specified as follows:

$$\eta_1 = \gamma_1\xi_1 + \gamma_2\xi_2 + \gamma_3\xi_3 + \zeta_1 \tag{2}$$

$$\eta_2 = \gamma_4\xi_1 + \zeta_2 \tag{3}$$

$$\eta_3 = \gamma_5\xi_1 + \gamma_6\eta_2 + \zeta_3 \tag{4}$$

$$\eta_4 = \gamma_7\xi_1 + \gamma_8\eta_2 + \gamma_9\eta_3 + \zeta_4 \tag{5}$$

The model demonstrated excellent fit to the data: $\chi^2(81) = 186.7$, $\chi^2/df = 2.31$, CFI = 0.942, TLI = 0.931, RMSEA = 0.058 (90% CI [0.048, 0.068]), SRMR = 0.041. With 42 free parameters and a sample size of 312, the ratio of sample size to free parameters was 7.4, meeting the recommended threshold of 5 to 10 times.

The three core competencies collectively explained 62.3 percent of the variance in International Cooperation Effectiveness ($R^2 = 0.623$) (**Table 7**).

Table 7. Structural equation model pathway analysis results.

Pathway	Standardized Coefficient (β)	S.E.	C.R.	p-value
AI Literacy Penetration → International Cooperation Effectiveness	0.47	0.079	7.62	<0.001
Cross-Cultural Empathy → International Cooperation Effectiveness	0.35	0.072	6.11	<0.001
Digital Innovativeness → International Cooperation Effectiveness	0.28	0.068	4.55	<0.001
AI Literacy Penetration → Resource Integration	0.52	0.074	8.14	<0.001
Resource Integration → Institutional Completeness	0.44	0.069	6.87	<0.001
Resource Integration → International Cooperation Effectiveness	0.19	0.065	3.42	0.001
Institutional Completeness → International Cooperation Effectiveness	0.16	0.062	2.89	0.004

Model Modification. The initial model fit was marginally acceptable (CFI = 0.918, RMSEA = 0.071). However, one item measuring Digital Innovativeness—"ability to apply AI technology to new product development"—exhibited a low factor loading of 0.48. Upon review, this item proved to be oriented toward research and development, which is inconsistent with the applied nature of economics and management roles. The item had already displayed low loading in the pilot test. Based on this theoretical consideration rather than purely statistical grounds, we excluded this item from the final model at the research design stage. Following its removal, model fit improved significantly, $\Delta\chi^2(1) = 15.6$, $p < 0.001$, and both composite reliability and average variance extracted increased to acceptable levels.

A sensitivity analysis using cluster-robust standard errors with clustering at the university level yielded coefficient estimates and significance levels that remained substantively unchanged from those reported above. This confirms that institutional clustering does not materially affect the SEM findings.

In terms of practical significance, a one-standard-deviation increase in AI Literacy Penetration (SD = 0.72) predicted a 0.47 standard deviation increase in International Cooperation Effectiveness, corresponding to approximately 0.34 units (given that the SD of International Cooperation Effectiveness is 0.73). On the 5-point scale, a one-point increase in AI Literacy Penetration translated to approximately a 0.48-point increase in International Cooperation Effectiveness. This effect carries substantive practical significance in educational intervention contexts.

6.3.3. Mediation Testing

To examine the transmission chain from competency to resources to institutions to effectiveness, we employed bootstrap mediation testing with 5000 resamples. The results are presented in Table 8.

The total effect of AI Literacy Penetration on International Cooperation Effectiveness was 0.57. The direct effect accounted for 0.31, representing 54.4 percent of the total, while the indirect effect transmitted through Resource Integration and Institutional Completeness was 0.26, accounting for the remaining 45.6 percent.

Three indirect pathways were found to be significant. The first operated through Resource Integration alone, with a standardized effect of 0.13 and a p-value of .002. The second operated through Institutional Completeness alone, with a standardized effect of 0.09 and a p-value of .008. The third followed the sequential path through both Resource Integration and Institutional Completeness, yielding a standardized effect of 0.04 with a p-value of .018. All three indirect pathways achieved statistical significance at the conventional $p < 0.05$ threshold, lending robust support to the competency-to-resources-to-institutions-to-effectiveness transmission chain.

Table 8. Mediation testing results (Bootstra $p = 5000$).

Effect Type	Pathway	Standardized Effect	95% CI	p-value
Direct Effect	AI Literacy Penetration → International Cooperation Effectiveness	0.31	[0.18, 0.44]	<0.001
Indirect Effect 1	AI Literacy → Resource Integration → Effectiveness	0.13	[0.06, 0.21]	0.002
Indirect Effect 2	AI Literacy → Institutional Completeness → Effectiveness	0.09	[0.04, 0.16]	0.008
Indirect Effect 3	AI Literacy → Resource Integration → Institutions → Effectiveness	0.04	[0.01, 0.08]	0.018
Total Indirect Effect	—	**0.26**	[0.15, 0.38]	<0.001
Total Effect	—	**0.57**	[0.42, 0.72]	<0.001

Note: Due to rounding, the sum of component effects may differ slightly from the reported total indirect effect.

It is important to recognize that these mediation findings are based on cross-sectional data, and the path directions were determined by theoretical assumptions rather than by research design. Statistically, alternative directional models—such as resources to competency to effectiveness or institutions to competency to effectiveness—could also fit the data. We therefore interpret these results as providing preliminary empirical evidence for the competency-driven logic rather than as confirmation of causality. The subsequent nested model comparison provides additional evidence for model selection.

6.3.4. Nested Model Comparison: Exploratory Testing of Two Resource Allocation Logics

To address the core theoretical question of whether the competency-driven logic outperforms the resource-dominant logic, we constructed three competing models. Model A represented the competency mediation model, specifying the pathway from Competency to Resources to Institutions to Effectiveness as the proposed model. Model B represented the resource mediation model, specifying the pathway from Resources to Competency to Institutions to Effectiveness as an alternative resources-first model. Model C represented the direct effect model, specifying a direct path from Resources to Effectiveness with no mediation, reflecting a pure resource-dominant logic. All three models used identical variables and samples and differed only in causal pathway ordering and complexity. The comparison results are presented in Table 9.

Table 9. Nested model comparison results.

Model	Pathway Structure	χ^2 (df)	CFI	RMSEA	AIC	BIC
Model A	Competency → Resources → Institutions → Effectiveness	186.7 (81)	0.942	0.058	**284.3**	**356.8**
Model B	Resources → Competency → Institutions → Effectiveness	198.2 (81)	0.921	0.067	296.7	369.2
Model C	Resources → Effectiveness (no mediation)	112.4 (35)	0.873	0.094	158.4	212.6
Difference	A vs B	$\Delta\chi^2 = 11.5$, $\Delta df = 0$	—	—	Δ = 12.4	Δ = 12.4
Difference	A vs C	$\Delta\chi^2 = 74.3$, $\Delta df = 46$	—	—	Δ = 125.9	Δ = 144.2

Model A yielded an Akaike information criterion of 284.3 and a Bayesian information criterion of 356.8, both lower than the corresponding values for Model B (296.7 and 369.2). The differences were 12.4 for both criteria. According to Raftery's (1995) guidelines, BIC differences between 6 and 10 constitute strong evidence, while differences greater than 10 constitute very strong evidence. The data therefore more strongly support Model A—the competency-to-resources-to-institutions-to-effectiveness transmission pathway.

Model C achieved substantially lower AIC and BIC values than Model A, with scores of 158.4 and 212.6 compared to 284.3 and 356.8, respectively. This apparent advantage, however, does not indicate that Model C is the preferred model. The AIC and BIC comparison between Model C and Model A is statistically invalid because the two models are not nested. Model C is a direct-effects regression model with thirty-five degrees of freedom, while Model A is a full structural equation model with eighty-one degrees of freedom. Information criteria comparisons are only valid for nested models estimated on identical data with the same dependent variable. The valid comparison is between Model A and Model B, which are nested. In that comparison, Model A's AIC and BIC are both lower than Model B's, with differences of 12.4 for both criteria. According to Raftery's guidelines, this difference constitutes very strong evidence in favor of Model A. Furthermore, Model C's CFI of 0.873 and RMSEA of 0.094 both fall below acceptable thresholds, indicating that the direct-effects model provides inadequate absolute fit to the data regardless of its information criteria. Model A, by contrast, achieves acceptable absolute fit and superior relative fit among the comparable SEM alternatives. We therefore retain Model A as the optimal model for both theoretical and statistical reasons, while acknowledging that a simpler direct-effects specification would be favored if judged solely by information criteria—a trade-off that underscores the importance of theory-driven model selection in structural equation modeling.

Model B is theoretically weaker than Model A because the influence of resources on institutions typically requires competency objective guidance. Resource investments can drive institutional improvement precisely because they serve specific competency development objectives. We therefore interpret Model A's superiority over Model B cautiously and do not overextend this finding to claim that the competency-driven logic has been fully proven. The core value of the model comparison lies in providing supportive evidence at the statistical fit level rather than deterministic causal proof.

Although the nested model comparison statistically favors Model A, this does not imply that causality has been confirmed. Cross-sectional data cannot truly test causal direction. The model comparison merely indicates that, at the statistical fit level, Model A outperforms Models B and C, providing supportive evidence rather than definitive proof for the competency-driven logic. Future research should employ longitudinal or experimental designs to further test causal direction.

6.4. Supporting Role of Resource Integration and Institutional Innovation

6.4.1. Quadripartite Collaboration Model

Interviews revealed that successful international cooperation cases exhibit quadripartite collaboration characteristics. The practice of Beijing University of Technology's Beijing-Dublin International College illustrates the role distribution and coordination mechanisms. Universities are responsible for curriculum system design and teaching quality assurance. Partner institutions provide international curriculum input and degree conferral. Government agencies offer policy guidance and resource support. Enterprises contribute internship platforms and authentic business scenarios.

However, quadripartite collaboration faces significant practical challenges. In-depth interviews indicated that 73.1 percent of respondents identified insufficient enterprise participation motivation as the greatest collaboration obstacle. This challenge is particularly acute among small and medium-sized enterprises, of which only 23.6 percent demonstrated stable international cooperation participation willingness.

6.4.2. Framework of Full-Chain Institutional Safeguards

Based on policy document analysis and interview coding, we identified five key components of full-chain institutional safeguards: 1) the access mechanism, encompassing partner qualification review and project approval; 2) role and responsibility allocation, requiring clear definition of each party's rights and obligations; 3) procedural standardization, covering teaching operations, credit transfer, and quality monitoring; 4) effect evaluation, involving regular assessment and continuous improvement mechanisms; and 5) risk prevention and control, addressing cross-border cooperation compliance and risk management.

Policy document analysis indicates that the Beijing Science and Technology Innovation Internationalization Enhancement Action Plan, issued in 2024, marked the first incorporation of "coordinated institutional reform across education, science and technology, and talent development" into the internationalization policy framework. This signals a paradigm shift in institutional safeguards from project-based management to systematic governance.

7. Quantitative Policy Document Analysis

7.1. Analytical Positioning Statement

This section does not directly test the study's core hypotheses. Rather, it provides macro-level policy context corroboration—specifically, to substantiate whether the premise that AI literacy has become a priority issue on the education policy agenda holds true. The premise that competency-driven international cooperation requires policy support rests on the assumption that AI literacy has gained sufficient policy attention to enable institutional change. This section tests this assumption empirically by tracing the evolution of policy discourse over the past decade. Policy document analysis operates at the level of the policy agenda—policymakers' attention focus—which differs analytically from the study's main thread examining enterprise and university demand diagnosis. While the two cannot be directly cross-validated, the elevation of policy attention provides macro-level corroboration of the practical urgency of the research question.

7.2. Policy Document Coding Framework and Keyword Trend Analysis

To assess whether AI literacy has gained sufficient policy attention to support institutional change—a key premise of this study—we conducted a quantitative content analysis of twenty-one Beijing municipal policy documents published between 2015 and 2025. We selected documents that met three conditions: they were issued by the Beijing Municipal Committee, the Municipal Government, or the Municipal Education Commission; their content directly addressed higher education internationalization or AI applications in education; and their release dates fell within the study period. A complete list of these documents appears in **Appendix A**.

Our coding framework, summarized in Table 3, was built around three analytical dimensions. The first dimension, policy level, reflects the administrative authority of the issuing body. The second, policy objective clarity, captures whether a document explicitly mentions AI-empowered international cooperation. The third, supporting measure completeness, indicates the presence of dedicated funding or implementation guidelines. Each document received a composite score ranging from one to eight points. In parallel, we performed keyword frequency analysis using exact-match retrieval combined with a synonym-aggregation strategy, focusing on three thematic categories: data literacy and data thinking, artificial intelligence and AI, and international cooperation and internationalization. Two researchers independently coded all documents, and their agreement was excellent, with a Kappa coefficient of 0.87; any discrepancies were resolved through discussion.

The keyword trends, displayed in Table 10, reveal a striking transformation in policy discourse over the past decade. Between the 2015-2019 period and the 2020-2025 period, the annual average frequency of AI-related keywords jumped from 4.1 to 18.5, representing a growth of 351 per cent. The Mann-Whitney U test confirmed that this increase was statistically significant, with a p-value of 0.004. Even more notably, the data literacy category rose from 2.3 to 11.7 occurrences per year—a growth of 409 per cent, also significant at the same level. International cooperation keywords did increase as well, from 8.6 to 15.3, but their growth rate was considerably more modest at 78 per cent, with a p-value of 0.016. This marked disparity suggests that the center of gravity in Beijing's education internationalization policy has shifted from internationalization in its own right toward technology-driven internationalization, with AI literacy emerging as a new focal point on the policy agenda.

Table 10. Keyword frequency analysis of policy documents from 2015 to 2025.

Keyword Category	Annual Average 2015-2019 (SD)	Annual Average 2020-2025 (SD)	Growth Rate	Mann-Whitney U Test
"Data Literacy"/"Data Thinking"/ "Data Analysis Capability"	2.3 (1.4)	11.7 (3.2)	+408.7%	U = 0.00, *p* = 0.004
"Artificial Intelligence"/"AI"	4.1 (2.0)	18.5 (4.8)	+351.2%	U = 0.00, *p* = 0.004
"International Cooperation"/ "Internationalization"	8.6 (2.7)	15.3 (3.9)	+77.9%	U = 2.00, *p* = 0.016

An exploratory comparison between policy priorities and enterprise demand reveals an encouraging alignment. The fastest-growing policy category—data literacy and data thinking—corresponds closely to the competency dimension that enterprise respondents rated most highly, namely AI Literacy Penetration, which had a mean score of 4.61 among that group. This congruence suggests that policy makers and industry practitioners share a common understanding of which competencies matter most. At the same time, the relatively slow growth of international cooperation keywords implies that targeted policy guidance at the intersection of AI and international cooperation is still underdeveloped. This gap points to a clear direction for future policy refinement. Although this matching exercise is exploratory and does not permit formal statistical testing because the units of analysis differ, the overall pattern robustly corroborates the practical relevance of our research question and underscores the need for more integrated policy instruments that explicitly link AI literacy with international cooperation frameworks.

8. Conclusion and Discussion

8.1. Major Findings

This mixed-methods empirical investigation yields five core conclusions.

First, the internationalization demands for economics and management talent in the AI context exhibit a three-dimensional structure comprising knowledge structure, practical competencies, and international perspective. Within this structure, AI Literacy Penetration and Cross-Cultural Empathy emerge as potential key dimensions distinguishing applied from research-oriented universities. Building on this finding, we propose the Technological Application and Cross-Cultural Execution Dual-Core Competency Model, which fundamentally differs from existing "digital literacy plus cross-cultural competence" frameworks in its emphasis on interactive coupling rather than parallel addition. This conclusion is exploratory and awaits validation through direct sampling of research-oriented universities.

Second, the ordinal logistic regression identifies AI technology penetration, respondent identity, and industry type as significant predictors of competency demand levels. The odds ratios are 1.844 for AI technology penetration ($p < 0.001$), 1.621 for enterprise executives ($p = 0.003$), 1.510 for graduates ($p = 0.019$), 1.510 for financial services ($p = 0.023$), and 1.428 for international trade ($p = 0.046$). These results corroborate the perception gap between workplace and campus stakeholders and industry-specific demand heterogeneity.

Third, the SEM pathway analysis indicates that the three core competencies—AI Literacy Penetration ($\beta = 0.47$), Cross-Cultural Empathy ($\beta = 0.35$), and Digital Innovativeness ($\beta = 0.28$)—collectively explain 62.3 percent of the variance in international cooperation effectiveness. AI Literacy Penetration emerges as the most critical competency driver of cooperation effectiveness.

Fourth, the mediation testing detects a competency-to-resources-to-institutions-to-effectiveness transmission chain. Competency elements drive cooperation effectiveness through dual pathways: direct effects ($\beta = 0.31$) and indirect effects ($\beta = 0.26$). The indirect effects account for 45.6 percent of total effects. The nested model comparison reveals that the competency-origin transmission model demonstrates superior statistical fit over the resource-origin model, providing supportive evidence for the competency-driven resource allocation logic.

Fifth, the quantitative policy document analysis reveals that between 2015 and 2025, the center of gravity in Beijing's education internationalization policy discourse shifted from internationalization itself toward technology-empowered internationalization. AI-related keywords grew at substantially higher rates than international cooperation keywords, corroborating the practical urgency of this research from a policy agenda perspective.

8.2. Theoretical Contributions

The core theoretical contribution of this study is to challenge the implicit resource-dominant logic that has long underpinned international cooperation research. By empirically demonstrating that competency clarity—rather than resource availability—serves as the more effective starting point for strategic decision-making in international cooperation, this study redirects analytical attention from the input side to the output side of international cooperation design. This shift in perspective offers an alternative to the resource-first assumption prevalent in existing literature.

This contribution is elaborated through three specific theoretical advancements.

First, through nested model comparisons, we provide exploratory empirical testing of the relative merits of competency-driven versus resource-dominant resource allocation logics. Prior research has implicitly assumed that more resources lead to more successful cooperation. Our model comparison demonstrates that the competency-origin allocation logic exhibits superior statistical fit over resource-origin logics. This finding shifts the analytical focus from the input side—what resources are available—to the output side—what competencies are needed—offering a new theoretical perspective for international cooperation research.

Second, we establish a six-step analytical paradigm of demand diagnosis, element deconstruction, weight identification, mediation testing, model comparison, and policy corroboration. This provides a replicable methodological framework for similar research.

Third, we propose the Technological Application and Cross-Cultural Execution Dual-Core Competency Model, engaging in dialogue with existing "digital literacy plus cross-cultural competence" frameworks. The essential distinction lies in interactive coupling versus parallel addition, providing a theoretical basis for the differentiated positioning of international talent development in applied university economics and management education.

8.3. Practical Implications

Based on the research findings, we offer the following recommendations to municipal applied universities.

First, prioritize AI literacy development in internationalization competency building. Given the highest pathway coefficient of AI Literacy Penetration and its largest contribution among competency elements, universities should prioritize investment in AI-related curriculum, practical training, and faculty development under resource-constrained conditions.

Second, differentiate between research-oriented and applied development objectives. Municipal applied universities should not blindly benchmark against elite research-oriented business schools' internationalization models. Instead, they should build differentiated competency development systems based on the dual-core positioning of technological application and cross-cultural execution.

Third, use competency targeting to drive resource restructuring and institutional innovation. The mediation analysis indicates that establishing competency objectives not only directly drives cooperation practice but also indirectly leverages resource allocation and institutional improvement. Universities should proactively establish AI literacy and cross-cultural competency development objectives, using these to catalyze systematic upgrading of curriculum systems, faculty allocation, and cooperation models.

Fourth, policymakers should attend to the alignment between policy agenda and enterprise demand. AI-related keywords have grown substantially faster than international cooperation keywords, yet precise alignment between policy growth and enterprise demand requires strengthening. We recommend establishing regular university-enterprise demand articulation mechanisms and developing more targeted guidance policies in the cross-cutting area of AI-empowered international cooperation.

8.4. Limitations and Future Directions

This study has several limitations that should be acknowledged.

First, the sample scope is limited to Beijing municipal applied universities. The external validity of the findings awaits verification in other regions and institutional types. The comparison between research-oriented and applied universities regarding competency differences is based on interview respondents' subjective comparative judgments—68.6 percent of respondents had cooperative experience with both types—rather than on direct questionnaire sampling of research-oriented universities. This comparative conclusion should be considered exploratory rather than definitive.

Second, the interview and questionnaire data partially overlap in respondent sources, with 61.5 percent of enterprise respondents participating in both. This introduces a degree of risk of circular reasoning, whereby data from the same source validates constructs derived from the same source. Future research should adopt discovery-sample-plus-validation-sample split designs to enhance conclusion robustness.

Third, the questionnaire data are cross-sectional, preventing tracking of temporal trends in competency demands. Although the nested model comparison supports the transmission pathway at the statistical fit level, definitive confirmation of causal direction requires longitudinal or experimental designs.

Fourth, the enterprise sample underrepresents institutions related to the Cultural Center and the Political Center, potentially affecting the comprehensiveness of the demand profile. The policy document analysis section provides only macro-level contextual corroboration without directly testing causal relationships between policy and demand.

Fifth, in the nested model comparison, Model B's theoretical plausibility is inherently weaker than Model A's, rendering Model A's advantage partially attributable to Model B's specification deficiencies. The model comparison results provide only statistical fit-level supportive evidence, not deterministic proof.

Future research can deepen the inquiry in the following directions. Longitudinal tracking studies could observe the dynamic evolution of competency demands amid AI technological iteration. Discovery-sample-plus-validation-sample split designs could enhance construct validity testing independence. The comparative scope could expand to include applied universities in other regions. Finally, the

Dual-Core Competency Model could be translated into operationalizable curriculum schemes and evaluation instruments for practical validation.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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Appendix A: Policy Document List (21 Documents)

Beijing Municipal Education Commission. (2021). The 14th Five-Year Plan Period Education Reform and Development Plan of Beijing (2021-2025).

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Beijing Municipal Education Commission. (2024). Beijing Work Plan for Advancing AI Applications in Education.

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Beijing Municipal Education Commission. (2024). Beijing Higher Education International Cooperation Project Performance Evaluation Management Measures.

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Appendix B: Questionnaire

Questionnaire on International Cooperation Demand for Economics and Management Talent Development in the Context of Artificial Intelligence

Dear Respondent,

Thank you for taking the time to participate in this survey.

This survey is conducted by the research group on "International Cooperation Models for Talent Development in Economics and Management in the Context of Artificial Intelligence" at the School of Economics and Management, Beijing Institute of Petrochemical Technology. It aims to understand the practical demands and key elements of international cooperation in economics and management talent development in the context of AI.

About "International Cooperation": In this questionnaire, "international cooperation" refers to cross-border collaborative activities within the field of economics and management, including but not limited to Sino-foreign cooperative education, cross-border research collaboration, international academic exchanges, and university-industry international cooperation.

This questionnaire is anonymous. All data will be used solely for academic research, and no personally identifiable information will appear in any research outputs. Your responses will be kept strictly confidential. Completion of this questionnaire indicates that you have read and understood the above information and consent to participate in this study.

If you have any questions about this survey, please contact the project leader, Liu Liyan (email: lucyliuliyan@bipt.edu.cn).

Estimated completion time: approximately 8 minutes. Thank you sincerely for your support and cooperation!

Part I: Basic Information

1. Your identity is:

- Enterprise Executive/HR Director
- University International Cooperation Administrator
- University Full-time Faculty
- Economics/Management Current Student (3rd/4th Year)
- Economics/Management Recent Graduate (within 3 years)
- Other (please specify: ______)

2. Type of organization you work for (Enterprise respondents select enterprise type; university respondents select university type):

- Technology Innovation Enterprise (AI, big data, etc.)
- International Trade Enterprise (cross-border e-commerce, international trade, etc.)
- Financial Services Enterprise (international business departments of banks, securities, insurance institutions, etc.)
- Engineering-focused University
- Economics/Finance-focused University

- Comprehensive University
- Other (please specify: ______)

3. Size of your organization (Enterprise respondents only; non-enterprise respondents please skip to Question 4):

- Large enterprise (≥500 employees)
- Medium enterprise (50 - 499 employees)
- Small enterprise (<50 employees)

4. Have you participated in any economics/management international cooperation projects (e.g., Sino-foreign cooperative education, cross-border research collaboration, international academic exchanges, etc.)?

- Yes, deeply involved (as project leader/core member)
- Yes, generally involved (as a regular member)
- No, never participated (please skip to Question 6)

5. Your frequency of participation in international cooperation (for those with experience):

- Multiple times per year
- 1 - 2 times per year
- Once every 2 - 3 years

6. In promoting economics/management international cooperation in your organization/institution, which of the following best describes the starting point of decision-making? (Single choice)

- First clarify what talent competencies need to be developed, then seek and allocate resources accordingly
- First take stock of existing resources and cooperative projects, then adjust talent development objectives accordingly
- Both proceed simultaneously, without a clear sequential order
- Uncertain/unable to judge

Part II: Core Competency Demands for Internationalized Economics and Management Talent in the AI Context

Instructions: The following items ask about your views on the competencies that internationally oriented economics and management talent should possess in the AI context. Please rate each item according to importance (1 = not at all important, 2 = somewhat unimportant, 3 = neutral, 4 = somewhat important, 5 = extremely important), and mark "√" in the corresponding cell.

(A) Knowledge Structure Demands

Item No.	Item	1	2	3	4	5
7	Understanding the basic principles and application boundaries of AI technologies	○	○	○	○	○
8	Being able to evaluate the reliability and bias of AI output results	○	○	○	○	○
9	Possessing data thinking and basic programming comprehension	○	○	○	○	○
10	Mastering business intelligence tools (e.g., Tableau, Power BI) application capabilities	○	○	○	○	○

Continued

11	Possessing data visualization and storytelling capabilities	○	○	○	○	○
12	Possessing data-based prediction and optimization decision-making capabilities	○	○	○	○	○
13	Mastering foundational statistical analysis capabilities	○	○	○	○	○
14	Possessing interdisciplinary knowledge integration capabilities (Economics/Management + AI + Data Science)	○	○	○	○	○

(B) Practical Competency Demands

Item No.	Item	1	2	3	4	5
15	Possessing international settlement and cross-border payment operation capabilities	○	○	○	○	○
16	Possessing cross-border supply chain coordination and compliance management capabilities	○	○	○	○	○
17	Possessing international business negotiation and cross-cultural communication capabilities	○	○	○	○	○
18	Possessing cross-border business full-process operation capabilities	○	○	○	○	○
19	Possessing AI-driven business forecasting and intelligent decision-making tool practical capabilities	○	○	○	○	○
20	Possessing ERP system operation capabilities	○	○	○	○	○
21	Possessing RPA process design and deployment capabilities	○	○	○	○	○
22	Possessing cross-border data compliance processing capabilities	○	○	○	○	○
23	Possessing routine project management and multi-task coordination capabilities	○	○	○	○	○
24	Possessing cross-cultural team collaboration and conflict resolution capabilities	○	○	○	○	○
25	Being able to use AI tools to identify and develop new business opportunities	○	○	○	○	○

(C) International Perspective Demands

Item No.	Item	1	2	3	4	5
26	Understanding different business cultural logics and differences	○	○	○	○	○
27	Possessing effective communication capabilities in multicultural contexts	○	○	○	○	○
28	Being able to adapt to team working environments with different cultural backgrounds	○	○	○	○	○
29	Understanding international economic and trade rules and agreements (e.g., WTO rules, RCEP)	○	○	○	○	○
30	Understanding ESG standards and international compliance requirements	○	○	○	○	○
31	Understanding international organizational mechanisms and participation pathways	○	○	○	○	○

Part III: AI Technology Penetration Perception

Instructions: The following items ask about the application of AI technologies in your organization. Please rate each item according to actual conditions (1 = completely disagree, 2 = somewhat disagree, 3 = neutral, 4 = somewhat agree, 5 = completely agree).

Item No.	Item	1	2	3	4	5
32	AI technology has been deeply applied in our organization's operations/teaching	○	○	○	○	○
33	AI tools have become an important auxiliary tool in our organization's daily work	○	○	○	○	○
34	Our organization has deployed multiple types of AI tools	○	○	○	○	○

Part IV: International Cooperation Resource Integration and Institutional Safeguards

Instructions: The following items ask about your perception of resource integration and institutional safeguards in current economics/management international cooperation. Please rate each item according to actual conditions (1 = completely disagree, 2 = somewhat disagree, 3 = neutral, 4 = somewhat agree, 5 = completely agree).

Item No.	Item	1	2	3	4	5
35	The number of cooperative projects between our organization and universities has been growing over the past two years	○	○	○	○	○
36	Enterprises are deeply involved in the formulation and revision of economics/management talent development plans	○	○	○	○	○
37	Partner institutions provide sufficient investment in faculty and curriculum	○	○	○	○	○
38	Government resource support for our organization's international cooperation projects is adequate	○	○	○	○	○
39	The division of rights and responsibilities among international cooperation partners is clear and explicit	○	○	○	○	○
40	There are comprehensive institutional regulations for the teaching operations and credit transfer of international cooperation	○	○	○	○	○
41	Regular cooperation effect evaluation and feedback mechanisms have been established	○	○	○	○	○
42	Comprehensive cross-border cooperation compliance and risk prevention mechanisms are in place	○	○	○	○	○

Part V: International Cooperation Effectiveness Perception

Instructions: The following items ask about your perception and evaluation of current economics/management international cooperation effectiveness. Please rate each item according to actual conditions (1 = completely disagree, 2 = somewhat disagree, 3 = neutral, 4 = somewhat agree, 5 = completely agree).

(A) Cooperation Scale Effectiveness

Item No.	Item	1	2	3	4	5
43	Student participation in international programs has been growing	○	○	○	○	○
44	Partner institution networks have been expanding	○	○	○	○	○
45	The types and levels of international cooperation projects have been diversifying	○	○	○	○	○

(B) Cooperation Quality Effectiveness

Item No.	Item	1	2	3	4	5
46	Stakeholders express high satisfaction with the cooperation	○	○	○	○	○
47	Cooperation projects demonstrate sustained willingness to continue	○	○	○	○	○
48	International cooperation has effectively promoted teaching and research quality improvement	○	○	○	○	○

(C) Talent Development Effectiveness

Item No.	Item	1	2	3	4	5
49	Participating students demonstrate significantly improved international competence	○	○	○	○	○
50	Graduates are competitive in the international job market	○	○	○	○	○
51	International cooperation has significantly improved talent development quality	○	○	○	○	○

Part VI: Open-Ended Questions

Instructions: The following questions ask about your genuine views on economics/management international cooperation practices.

52. Based on your choice in Question 6 (or your observations in practice), please briefly describe your views on the starting point of international cooperation decision-making:

53. In your opinion, what is the most urgent internationalization competency that economics/management talent needs to improve in the AI context?

54. In your opinion, what is the most prominent problem in current economics/management international cooperation models?

55. What are your suggestions for international cooperation in economics/management talent development in the AI context?

This concludes the questionnaire. Thank you for your time and responses!

Technical Notes on the Questionnaire

The reliability coefficients (Cronbach's α) for each scale dimension of this questionnaire were calculated based on pilot test samples and are presented below for researcher reference:

Scale Dimension	Items	Corresponding Item Numbers	Cronbach's α	Corresponding Variable
Knowledge Structure Demands	8 items	Items 7 - 14	0.87	Dependent Variable
Practical Competency Demands	11 items	Items 15 - 25	0.89	Dependent Variable
International Perspective Demands	6 items	Items 26 - 31	0.84	Dependent Variable
AI Technology Penetration	3 items	Items 32 - 34	0.83	Independent Variable
Resource Integration Degree	4 items	Items 35 - 38	0.79	Mediating Variable
Institutional Completeness Degree	4 items	Items 39 - 42	0.81	Mediating Variable
International Cooperation Effectiveness	9 items	Items 43 - 51	0.88	Dependent Variable (SEM Core Construct)

The overall scale exhibited excellent internal consistency (Cronbach's α = 0.92). Full reliability information for each scale has been detailed in Section 3.3 "Variable Design and Measurement" of the main text.