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Intellectual Capital Reconfiguration through University-Industry AI Collaboration

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Abstract
This study examines how university-industry artificial intelligence (AI) collaboration reconfigures intellectual capital (IC) in entrepreneurial universities. It focuses on the mediating roles of human, structural, and relational capital between AI adoption and IC-driven innovation performance, exploring configurational pathways across university types. Using a critical realism paradigm, a three-phase mixed-methods design was employed: (1) 48 semi-structured interviews at six Taiwanese universities; (2) quantitative analysis with partial least squares structural equation modelling (PLS-SEM, n = 386) and fuzzy-set qualitative comparative analysis (fsQCA); and (3) network analysis via exponential random graph models (ERGM). Counterfactual simulations (500 iterations) assessed governance configurations. AI collaboration intensity significantly enhances human, structural, and relational capital. All three IC dimensions partially mediate the AI-innovation link, with structural capital having the strongest effect. Research-intensive universities benefit more in structural capital formation. fsQCA identified three paths to high innovation performance, while ERGM showed AI-mediated knowledge ties predict IC exchange density. Simulations highlight governance as more critical than adoption intensity alone. This study extends IC theory into the AI university-industry collaboration context, reveals complementarity among IC dimensions, and challenges technology determinism by emphasizing distributed governance's role in amplifying AI's IC benefits. Findings offer practical guidance for university entrepreneurial transformation.

Keywords: Intellectual Capital, Entrepreneurial University, University-Industry Collaboration, Artificial Intelligence, Knowledge Management, Taiwan

1. Introduction

Higher education institutions face growing pressure to evolve beyond teaching and research, increasingly acting as entrepreneurial entities that generate economic and social value beyond campuses (Abreu and Grinevich, 2025; Clark, 1998) [1, 11]. This shift, marked by the rise of technology transfer offices and science parks, positions universities as key players in regional innovation systems (Etzkowitz, 2003) [16]. The "entrepreneurial university" concept reflects a broader move toward knowledge-based development, where knowledge exchange complements or even surpasses traditional academic roles (Passaro *et al*., 2018) [38].

The rapid spread of generative artificial intelligence (GenAI) technologies represents a disruptive change. Tools like large language models and multimodal AI systems reshape how knowledge is created and shared, extending beyond mere research aids (Raisch and Krakowski, 2021; Huang and Rust, 2021) [44, 23]. Universities adopting AI with industry partners encounter new challenges as AI platforms alter faculty expertise boundaries, organizational routines, and power relations in university-industry collaborations (Kellogg *et al*., 2024; Davenport *et al*., 2023) [27, 13].

Despite this urgency, understanding of how university-industry AI collaboration affects intellectual capital (IC) is limited. Prior studies explored entrepreneurship education (Aldawod, 2022) [2], university-industry links and firm innovation (Yin *et al*., 2023) [57], or AI's impact on knowledge work separately (Vrontis *et al*., 2022) [56]. What is missing is an integrated framework detailing how AI adoption reshapes the three IC pillars—human, structural, and relational capital—within entrepreneurial universities (Secundo *et al*., 2018; Romano *et al*., 2025) [52, 47].

This gap matters both theoretically and practically. IC theory, grounded in Nahapiet and Ghoshal (1998) [35], Subramaniam and Youndt (2005) [53], and Sveiby (1997) [54], has yet to fully address how AI transforms all IC dimensions. AI-industry

partnerships may cascade effects through human capital (faculty skills), structural capital (routines and protocols), and relational capital (trust and collaborations). While Yin *et al*. (2023) [57] found IC mediates university-industry innovation links, their pre-GenAI study overlooks AI-specific knowledge challenges.
Practically, university leaders—especially in Asia and Taiwan where entrepreneurial education is government-promoted—need evidence-based strategies to govern AI collaborations that enhance intellectual capital without compromising academic values (de Frutos-Belizón *et al*., 2019; Kashyap and Agrawal, 2020) [14, 26].
This research seeks to fill these gaps by posing three research questions:

1. RQ1: What is the way in which AI collaboration from university and industry reconfigures the human, structural, and relational capital of entrepreneurial universities?
2. RQ2: What mediates the effect between collaborative AI adoption and IC-driven innovation performance?
3. RQ3: What configurational paths emerge across various university types of IC dimensions to enhance innovation outcomes?

There are four contributions to this research. First, it develops IC theory by theorizing and empirically illustrating the reconfigurability of all three IC dimensions in response to AI-mediated university-industry collaboration—a conceptual intervention that undermines the implicit stability assumption prevalent in most of the IC literature. Second, it reveals that structural capital formation is the most pronounced mediating pathway, an implication that could inform resource allocation priorities within entrepreneurial universities. Third, it has shown with fsQCA that no single IC dimension is adequate: instead, configurational complementarity among IC dimensions underpins the innovation performance. Fourth, counterfactual simulations demonstrate that governance configuration—namely between centralized and distributed governance—acts as a moderator between AI adoption intensity and IC outcomes significantly more heavily than adoption intensity, contradicting the technology-deterministic assumptions common in the digital transformation literature.

2. Literature Review

2.1 Intellectual Capital in the Entrepreneurial University

The intellectual capital (IC) framework views organizations as knowledge-based asset repositories beyond traditional accounting (Edvinsson and Malone, 1997; Sveiby, 1997) [15, 54]. Nahapiet and Ghoshal's (1998) [35] taxonomy of cognitive, relational, and structural social capital laid micro foundations for IC theory, while Subramaniam and Youndt (2005) [53] linked IC dimensions to innovation capabilities. The dominant tripartite model comprises human capital (individual knowledge and skills), structural capital (organizational systems and processes), and relational capital (external networks and trust) (Bontis, 1998; Petty and Guthrie, 2000) [7, 39].
Applying IC theory to higher education requires adaptation. Unlike firms, universities generate IC differently: faculty scholarship forms human capital; institutional repositories and administration represent structural capital; and partnerships, alumni, and community engagement embody relational capital (Secundo *et al*., 2018) [52]. Measurement scales tailored for academia have been developed (de Frutos-Belizón *et al*., 2019) [14], and intellectual property creation pathways in universities differ from commercial contexts (Kashyap and Agrawal, 2020) [26].
The entrepreneurial university concept (Clark, 1998; Etzkowitz, 2003) [11, 16] contextualizes IC dynamics in higher education. Clark's (1998) [11] five transformation pathways reshape all IC dimensions, while Etzkowitz's (2003) [16] Triple Helix model positions universities as innovation partners with industry and government, emphasizing networked IC creation. Ecosystem-level analyses further capture relational IC dynamics (Leendertse *et al*., 2022) [29].
However, IC research in higher education has overlooked digital transformation impacts, especially AI adoption. Secundo *et al*. (2018) [52] highlighted the need to study how emerging technologies reconfigure academic knowledge assets. This study addresses that gap by examining AI collaboration as a driver of IC reconfiguration.

2.2 AI Adoption and Intellectual Capital Dynamics

Artificial intelligence (AI), especially generative AI, acts as a structuring force that both shapes and is shaped by organizational practices, with profound effects on intellectual capital (Orlikowski, 2000) [37].
Human capital. AI augments or displaces traditional academic competencies. Vrontis *et al*. (2022) [56] show AI alters human resource management by automating cognitive tasks, changing the value of expertise. In universities, faculty with AI skills gain new research abilities, while others risk obsolescence (Davenport *et al*., 2023) [13]. Beyond technical skills, meta-competencies like ethical evaluation and integration of AI insights are critical (Raisch and Krakowski, 2021) [44].
Structural capital. AI platforms embed knowledge in algorithms rather than human routines, forming durable structural capital (Huang and Rust, 2021) [23]. However, this capital is partially vendor-owned, requires updates, and may introduce biases. Kellogg *et al*. (2024) [27] find AI-mediated structural capital both enables and constrains knowledge work through reconfigured organizational control.
Relational capital. AI reshapes university-industry relational dynamics, serving as boundary objects enabling knowledge exchange or creating power asymmetries depending on AI infrastructure control (Bresciani *et al*., 2021) [9]. Entrepreneurial universities rely on trust-based partnerships that AI can disrupt or enhance. Collaborative AI development fosters interaction routines—shared protocols and co-authored documents—that build relational capital's linguistic foundations (Nahapiet and Ghoshal, 1998) [35]. Similar patterns appear in non-profits, with AI adoption creating opportunities and tensions around data ownership and transparency (Popescu and Šebestová, 2024) [41].
The interplay among these IC dimensions is critical. Unlike past technologies, GenAI substitutes for human cognition, creating tension between human and structural capital development. Yet, in university-industry collaborations, these dimensions complement each other: AI augments human expertise via structural infrastructure while enabling new relational knowledge exchanges.

2.3 University-Industry Collaboration as IC Mediator

The mechanisms through which university-industry collaboration generates intellectual capital (IC) have gained empirical focus. Yin *et al*. (2023) [57] found that human and relational capital fully mediate academic engagement's impact on corporate economic performance, while structural capital fully mediates commercialization's effect on corporate innovation, highlighting distinct IC pathways activated by different collaboration types.

Technology transfer offices (TTOs) are vital for managing IC in universities. Holgersson and Aaboen (2019) [22] showed that transitioning from appropriation- to utilization-focused IP management requires simultaneous development of all three IC dimensions. Thus, entrepreneurial universities' value creation relies not only on formal transfer mechanisms but also on strong IC infrastructure facilitating knowledge flow across boundaries.

At the ecosystem level, Leendertse *et al.* (2022) [29] argue that entrepreneurial ecosystems produce IC via relational mechanisms extending beyond single organizations. Their firm-centered framework indicates similar dynamics in university-industry contexts, where network density, collaboration environment, and absorptive capacity collectively shape IC outcomes.

Romano *et al.* (2025) [47] propose a strategic approach to managing IC-based research impact, demonstrating universities can boost regional IC through deliberate strategies, viewing IC as a dynamic capability shaped by strategic intervention—aligning with this study's focus on IC reconfiguration through AI collaboration.

Support from AI and knowledge management research includes Mahboub and Ghanem (2024) [31], who showed knowledge management mediates AI adoption's effect on performance in banks, suggesting parallels in universities where knowledge practices mediate AI-driven innovation. Ibarra-Cisneros *et al.* (2023) [24] found different IC dimensions act depending on innovation type in higher education. Alavi *et al.* (2024) argue generative AI transforms knowledge creation by introducing non-human agents into traditionally human social processes.

Collectively, these studies indicate that university-industry AI collaboration differs fundamentally from prior technology-mediated engagements. Unlike earlier models such as joint labs or licensing, AI collaboration involves co-creating knowledge systems that both produce IC outputs and reshape the IC infrastructure for future knowledge generation.

2.4 Research Framework

The above review shows some significant lack of perspectives. First, IC theory was widely applied into higher education sectors but had yet to be utilized in studying the impact of AI adoption of AI together with universities and industries via collaboration. Second, the mediating mechanisms between collaborative AI adoption and innovation performance relationships remain understudied. Third, the configurational relations among IC dimensions — how different combinations of human, structural and relational capital lead to different innovation findings — have rarely been investigated in relation to AI-mediated collaboration. Fourth, we know nothing about the moderating effect of type of university on these relationships. To fill the gaps, we propose a theoretical framework (Fig 1) in which Collaborative AI Adoption Intensity (CAAI) influences IC-focused Innovation Performance (ICIP) through three mediating mechanisms: Human Capital Development (HCD), Structural Capital Formation (SCF), and Relational Capital Creation (RCC). University Type (UT), which distinguishes research-intensive from teaching-oriented institutions, moderates the effect between CAAI and each of the IC dimensions.

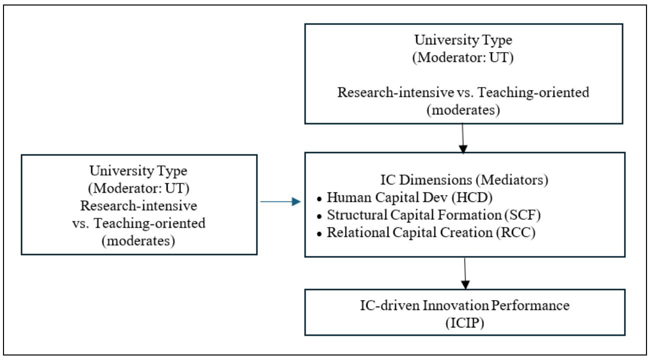

Fig 1: Conceptual Framework

3. Theoretical Framework and Hypotheses

3.1 Collaborative AI Adoption and IC Dimensions

Collaborative AI adoption and human capital development can be illustrated through the principles of dynamic capabilities theory (Teece, 2007) [55]. When universities collaborate with industry partners to adopt AI technologies, faculty acquire new skills—prompt engineering, model evaluation, AI-augmented research design—that stretch their knowledge repertoire. These competencies are investments in human capital that are simultaneously individual (residing in faculty members' skills) and collective (emerging from shared learning experiences across the university-industry boundary). The extent of this effect differs by institutional context: research-intensive universities—loyal to their traditions of frontier research and more exposed to computational methods—are likely to extract more human capital value from AI collaboration than teaching-oriented institutions—which, in turn, may focus more on pedagogical applications than on research augmentation.

H1: Collaborative AI adoption intensity positively influences human capital development in entrepreneurial universities.

Structural capital formation occurs when AI adoption leads to the creation of new organizational systems, databases, protocols, and routines that embed knowledge beyond individual cognition. Collaborative AI adoption generates structural capital through multiple channels: shared AI platforms become organizational infrastructure; data governance protocols codify best practices; AI-assisted research workflows become standardized procedures; and institutional repositories augmented by AI-enhanced metadata create new knowledge retrieval capabilities. The structural capital effect is likely amplified in research-intensive universities, which possess the complementary infrastructure (high-performance computing, data management systems) necessary to absorb AI capabilities into organizational routines.

H2: Collaborative AI adoption intensity positively influences structural capital formation in entrepreneurial universities.

Relational capital creation through collaborative AI adoption operates through trust-building mechanisms, boundary-spanning interactions, and the co-creation of shared knowledge artefacts. When university and industry partners jointly develop, deploy, and evaluate AI systems, they establish interaction patterns that build relational capital: repeated collaboration fosters trust; shared problem-solving creates cognitive alignment; and the tangible outputs of AI projects provide concrete evidence of partnership value. AI platforms themselves can function as relational infrastructure—shared digital environments that facilitate ongoing knowledge exchange beyond the boundaries of specific projects (Bresciani *et al.*, 2021) [9].

H3: Collaborative AI adoption intensity positively influences relational capital creation in entrepreneurial universities.

3.2 IC Dimensions as Mediators

The three IC dimensions do not merely accumulate as by-products of AI collaboration; they actively mediate the relationship between collaborative adoption and innovation performance. Human capital development enhances innovation performance by equipping faculty and researchers with the competencies necessary to generate novel research outputs, design innovative curricula, and identify commercially viable applications of AI-generated knowledge. The mediation is partial rather than complete because human capital alone—without the complementary structural and relational mechanisms—cannot fully translate AI adoption into sustained innovation outcomes (Subramaniam and Youndt, 2005) [53].

H4: Human capital development partially mediates the relationship between collaborative AI adoption intensity and IC-driven innovation performance.

Structural capital formation mediates the CAAI-ICIP relationship by creating the organizational infrastructure that sustains innovation beyond individual projects. AI-enhanced databases, standardized research protocols, and automated knowledge management systems reduce transaction costs of innovation, enable cumulative knowledge building, and facilitate the recombination of existing knowledge elements in novel configurations (Nonaka and Takeuchi, 1995) [36]. The structural capital mediation pathway is particularly important for entrepreneurial universities because it represents the institutionalization of innovation capacity—the transformation of episodic AI adoption into enduring organizational capability.

H5: Structural capital formation partially mediates the relationship between collaborative AI adoption intensity and IC-driven innovation performance.

Relational capital creation mediates the CAAI-ICIP relationship by establishing the network resources, trust mechanisms, and collaborative routines that enable sustained innovation. The relational pathways through which AI collaboration generates innovation performance include: access to industry knowledge bases through trusted partnerships; co-creation of innovation through joint problem-solving; and the reputational benefits that accrue to universities known for productive AI partnerships (Romano *et al.*, 2025) [47]. Like the other IC dimensions, relational capital provides a necessary but insufficient condition for translating AI adoption into innovation.

H6: Relational capital creation partially mediates the relationship between collaborative AI adoption intensity and IC-driven innovation performance.

3.3 Moderating Role of University Type

Research-intensive and teaching-oriented universities differ systematically in their resource endowments, organizational routines, and strategic priorities—differences that condition how AI collaboration affects IC development. Research-intensive universities possess deeper technical expertise, more extensive computing infrastructure, and stronger norms of frontier research, all of which amplify the human capital returns from AI collaboration. Their structural capacity to absorb AI systems into organizational routines is greater, and their established industry networks provide richer relational foundations for collaborative AI adoption.

H7: University type moderates the relationship between collaborative AI adoption intensity and IC dimensions, such that the effects are stronger for research-intensive universities than for teaching-oriented universities.

3.4 Configurational Complementarity of IC Dimensions

The three IC dimensions do not operate in isolation; their effects are interdependent. Human capital without structural support dissipates as faculty depart; structural capital without human operators remains inert; relational capital without both human and structural foundations lacks the absorptive capacity to convert external knowledge into innovation. This configurational complementarity suggests that specific combinations of IC dimensions—rather than any single dimension—drive innovation performance, and that the optimal configuration may vary across institutional contexts.

H8: Human, structural, and relational capital exhibit configurational complementarity in their effects on IC-driven innovation performance, such that specific combinations of these dimensions produce superior innovation outcomes.

4. Research Methodology

4.1 Research Design

This study adopts a critical realism paradigm, recognizing that the mechanisms linking AI collaboration to IC reconfiguration exist independently of our observations but can only be apprehended through multiple methodological lenses (Bhaskar, 1978) [6]. The research design is a three-phase embedded mixed-methods approach:

1. **Phase 1 (Qualitative):** Multiple-case study with 48 semi-structured interviews and document analysis, providing thick description of the mechanisms through which AI collaboration reconfigures IC.
2. **Phase 2 (Quantitative):** PLS-SEM analysis of survey data (n = 386) testing the hypothesised structural relationships, complemented by fsQCA to identify configurational pathways.
3. **Phase 3 (Network):** ERGM analysis of knowledge flow networks across six universities, supplemented by counterfactual simulation to explore governance scenarios.

Such a design allows for a kind of ‘methodological triangulation’, for example with qualitative results guiding model design, quantitative findings testing assumptions and network analysis uncovering newly discovered patterns, which are otherwise hidden in a variable-cantered methodology.

Qualitative themes from Phase One were presented that directly informed the model specification. Thematic analysis from the 48 interviews led to four overarching themes: (1) AI competence transformation - participants consistently indicated that AI collaboration not only developed technical skills, but also provided an epistemological change in how the research was done, implying the development of human capital was not limited to skill acquisition, but rather included cognitive reframing; (2) Infrastructural sedimentation - faculty and administrators discussed how AI tools had been adopted for specific projects, but when integrated into institutional routines were embedded as qualitative evidence for the framework regarding structural capital formation; (3) Trust recalibration - stakeholders-industry relations and the university partners described trust dynamics, AI collaboration sometimes strengthening trust through workable outputs but paradoxically also contributing to conflict surrounding data ownership and algorithmic governance; and (4) Governance ambiguity-all six universities reported doubts in their ability to establish the correct institutional governance structures around the AI collaboration where there are no clear guidelines for how one could strike an acceptable balance between central control and faculty autonomy. These qualitative themes guided the hypotheses formation in particular H7 (university type as moderator) and H8 (configurational complementarity) by highlighting the contextual and interactional aspects of IC reconfiguration.

4.2 Research Context: Taiwan's Entrepreneurial Universities

Taiwan's higher education system provides a compelling context for studying IC reconfiguration through AI collaboration. The system comprises over 150 universities operating under intense competitive pressure following the dismantling of a previously restrictive licensing regime. The Ministry of Education's "Smart University" initiative (2018–present) and the broader industry-academia collaboration programmed have created strong policy incentives for universities to pursue entrepreneurial transformation through technology adoption, including AI (Ministry of Education, 2020) [34].

Six universities were chosen using purposive sampling in order to obtain high diversity in institutional framework, research focus, and AI collaboration magnitude. All names are anonymized:

1. University A: Top comprehensive research university (est. 1928), strong in engineering and sciences, ~32,000 students. Classified as research-intensive.
2. University B: Leading technology-focused university (est. 1958), semiconductor and AI research strength, ~16,000 students. Classified as research-intensive.
3. University C: Premier business and management university (est. 1954), strong in fintech and digital commerce, ~14,000 students. Classified as research-intensive.
4. University D: Mid-tier comprehensive university (est. 1962), regional engagement focus, ~18,000 students. Classified as teaching-oriented.
5. University E: Private technology university (est. 1997), industry-oriented, strong in applied AI, ~12,000 students. Classified as teaching-oriented.
6. University F: Private comprehensive university (est. 1968), entrepreneurial education focus, ~15,000 students. Classified as teaching-oriented.

Across the six universities, 24 partner enterprises were involved in AI-related collaboration projects spanning technology, finance, manufacturing, and service sectors. Collaboration projects ranged from joint AI research laboratories to curriculum co-development and student internship programmed with AI components.

4.3 Sample and Data Collection

Phase 1: Qualitative data: Over a 12-month period (January–December 2025), 48 semi-structured interviews were conducted across the six universities (eight per university). Participants included faculty members (18), industry partners (12), university administrators (10), and graduate students involved in AI collaboration projects (8). Interview protocols explored participants' experiences with AI adoption, perceptions of changes in knowledge practices, and assessments of how collaboration affected their institution's knowledge assets. All interviews were audio-recorded, transcribed verbatim, and coded using NVivo 14 following a thematic analysis procedure (Braun and Clarke, 2006) [8]. Supplementary documents—including collaboration agreements, project reports, and AI system usage logs—were collected and analyzed.

Phase 2: Quantitative data: A web-based survey was administered to faculty, researchers, and administrators involved in university-industry AI collaboration across the six universities. Stratified random sampling ensured proportional representation from each institution. The target population comprised individuals with at least six months of experience in AI-related collaboration projects. Of 912 distributed surveys, 386 valid responses were received (response rate: 42.3%) (as Table 1). Non-response bias was assessed by comparing early and late respondents on key variables; no significant differences were detected ($p > 0.05$).

Table 1: Sample Demographics (N = 386)

Characteristic	Category	*n*	%
Gender	Male	218	56.5
	Female	168	43.5
Age	25–34	98	25.4
	35–44	142	36.8
	45–54	94	24.4
	55+	52	13.5
Academic rank	Lecturer/Assistant	89	23.1
	Associate Professor	134	34.7
	Full Professor	102	26.4
	Research staff	61	15.8
Discipline	Engineering/CS	147	38.1
	Business/Management	82	21.2
	Natural Sciences	64	16.6
	Humanities/Social Sciences	48	12.4
	Other	45	11.7
University type	Research-intensive	168	43.5
	Teaching-oriented	218	56.5
AI collaboration duration	< 1 year	72	18.7
	1–2 years	134	34.7
	2–3 years	109	28.2
	> 3 years	71	18.4

Phase 3: Network data: Knowledge flow networks were mapped for each university using two data sources: (1) sociometric surveys asking respondents to identify knowledge exchange partners, and (2) anonymized AI system interaction logs recording cross-institutional queries and data sharing events. The resulting networks comprised

386 nodes and 2,847 directed ties. ERGM analysis was conducted using the state package in R (Handcock *et al.*, 2008) [20].

4.4 Measures

All latent constructs were measured using seven-point Likert scales (1 = strongly disagree, 7 = strongly agree). Scale items were adapted from established measures and refined through cognitive interviewing with six academic experts and eight industry practitioners. (see Table 2).

Collaborative AI Adoption Intensity (CAAI): Six items capturing the breadth, depth, and frequency of AI technology adoption through university-industry collaboration, adapted from Davenport *et al.* (2023) [13] and Zhu *et al.* (2006) [59]. Sample item: "Our university systematically integrates AI tools provided by industry partners into research workflows."

Human Capital Development (HCD): Five items measuring perceived improvements in faculty knowledge, skills, and competencies attributable to AI collaboration, adapted from Subramaniam and Youndt (2005) [53] and Youndt *et al.* (1996) [58]. Sample item: "Collaboration with industry partners has significantly enhanced faculty members' AI-related research competencies."

Structural Capital Formation (SCF): Five items assessing the creation of new organisational systems, databases, and protocols resulting from AI collaboration, adapted from Bontis (1998) [7] and de Frutos-Belizón *et al.* (2019) [14]. Sample item: "Our university has developed new data management protocols as a result of AI collaboration with industry partners."

Relational Capital Creation (RCC): Five items capturing changes in trust, collaboration quality, and network resources attributable to AI collaboration, adapted from Nahapiet and Ghoshal (1998) [35] and Inkpen and Tsang (2005) [25]. Sample item: "AI collaboration has strengthened the trust relationship between our university and industry partners."

IC-driven Innovation Performance (ICIP): Five items measuring innovation outputs attributable to the combined effects of AI adoption and IC development, adapted from Subramaniam and Youndt (2005) [53]. Sample item: "Our university's AI-related collaboration has produced novel research outputs that would not have been possible without the combined knowledge assets."

University Type (UT): A dummy variable: 1 = research-intensive (Universities A, B, C), 0 = teaching-oriented (Universities D, E, F).

Table 2: Measurement Items and Sources

Construct	Item	Loading	Source
CAAI	CAAI1: Our university systematically integrates AI tools provided by industry partners into research workflows	0.82	Davenport *et al.* (2023) [13]; Zhu *et al.* (2006) [59]
	CAAI2: Joint AI development projects with industry partners are a regular part of our university's activities	0.79	
	CAAI3: Industry-provided AI platforms are widely used across multiple departments	0.76	
	CAAI4: Our university allocates dedicated resources for AI collaboration with industry	0.84	
	CAAI5: Faculty regularly participate in AI training programmes co-organised with industry partners	0.71	
	CAAI6: AI-related intellectual property is jointly developed with industry partners	0.77	
HCD	HCD1: AI collaboration has enhanced faculty members' technical competencies	0.83	Subramaniam and Youndt (2005) [53]; Youndt *et al.* (1996) [58]
	HCD2: Faculty have developed new research capabilities through AI collaboration	0.81	
	HCD3: Graduate students gain valuable AI skills through industry collaboration	0.74	
	HCD4: Cross-institutional AI projects have expanded the knowledge repertoire of our researchers	0.78	
	HCD5: The university has attracted new AI-competent faculty as a result of industry collaboration	0.72	
SCF	SCF1: New data management protocols have been developed through AI collaboration	0.80	Bontis (1998) [7]; de Frutos-Belizón *et al.* (2019) [14]
	SCF2: AI platforms have become embedded in our university's research infrastructure	0.85	
	SCF3: Standardised AI governance procedures have been established	0.77	
	SCF4: Institutional repositories have been enhanced with AI-generated metadata	0.73	
	SCF5: AI collaboration has led to new organisational routines for knowledge management	0.81	
RCC	RCC1: AI collaboration has strengthened trust between our university and industry partners	0.79	Nahapiet and Ghoshal (1998) [35]; Inkpen and Tsang (2005) [25]
	RCC2: The frequency of knowledge exchange with industry partners has increased through AI collaboration	0.82	
	RCC3: Shared AI projects have created lasting network connections beyond individual researchers	0.76	
	RCC4: Industry partners perceive our university as a more valuable collaboration partner due to AI capabilities	0.74	
	RCC5: AI collaboration has expanded our university's network of external knowledge sources	0.78	
ICIP	ICIP1: AI-related collaboration has produced novel research outputs	0.81	Subramaniam and Youndt (2005) [53]
	ICIP2: The university has developed new AI-enhanced products or services through collaboration	0.83	
	ICIP3: AI collaboration has led to new patent applications or technology transfers	0.75	
	ICIP4: The combined knowledge assets from AI collaboration have generated innovations that exceed what either partner could achieve alone	0.79	
	ICIP5: AI collaboration has enhanced the university's reputation for innovation	0.77	

4.5 Analytical Strategy

Data analysis proceeded in four complementary stages. First, PLS-SEM was implemented using SmartPLS 4.0 (Ringle *et al.*, 2015) [45] to assess the measurement model (confirmatory factor analysis) and test the structural model. PLS-SEM was selected for its suitability for exploratory theory development, its ability to handle complex models with multiple mediators, and its distributional assumptions compatible with survey data from heterogeneous institutional contexts (Hair *et al.*, 2019) [19].

Second, mediation was assessed using the specific indirect effects approach with 5,000 bootstrap resamples, constructing bias-corrected confidence intervals at the 95% level (Preacher and Hayes, 2008) [42]. Multi-group analysis

(MGA) examined whether path coefficients differed between research-intensive and teaching-oriented universities.

Third, fsQCA was conducted using fsQCA 3.0 (Ragin, 2008; Schneider and Wagemann, 2012) [43, 48] to identify configurational pathways to high innovation performance. Calibration anchors were set at the 95th, 50th, and 5th percentiles for full membership, crossover, and full non-membership respectively. Necessary condition analysis preceded sufficiency analysis, with a consistency threshold of 0.80 for sufficient configurations.

Fourth, ERGM analysis (Robins *et al.*, 2007) [46] modelled the knowledge flow network structures, testing whether AI-mediated ties predicted IC exchange density after controlling for structural network properties (reciprocity, transitivity, degree distribution). Counterfactual simulations (500 iterations per scenario) explored alternative governance configurations.

5. Results

5.1 Common Method Bias and Descriptive Statistics

Given the cross-sectional survey design, common method bias (CMB) was assessed through multiple procedures. Harman's single-factor test revealed that the first unrotated factor explained 28.3% of total variance, well below the 50% threshold (Podsakoff *et al.*, 2003) [40]. Full collinearity assessment in SmartPLS yielded VIF values ranging from 1.23 to 2.67, all below the conservative threshold of 3.3 (Kock *et al.*, 2021) [28]. A marker variable technique (Lindell and Whitney, 2001) [30] using the smallest observed correlation (r = 0.04 between RCC and a theoretically unrelated item) confirmed that partial ling out the method factor did not alter the significance of any structural path.

Descriptive statistics (Table 3) indicate moderate-to-high levels of perceived AI adoption intensity and IC development across the sample. The slight negative skewness values suggest a tendency toward higher ratings, consistent with the purposive sampling of individuals actively involved in AI collaboration. Kurtosis values within the acceptable range (−1 to +3) confirm the suitability of PLS-SEM estimation.

Table 3: Descriptive Statistics and Distribution Properties

Construct	Mean	SD	Skewness	Kurtosis	VIF
CAAI	4.82	1.21	−0.18	2.73	1.42
HCD	4.95	1.14	−0.22	2.89	1.67
SCF	4.63	1.28	−0.09	2.64	1.89
RCC	4.71	1.19	−0.14	2.81	1.54
ICIP	4.78	1.24	−0.20	2.76	2.12

5.2 Measurement Model

Reliability: All constructs demonstrated satisfactory internal consistency. Cronbach's alpha values ranged from 0.83 (RCC) to 0.89 (CAAI), exceeding the 0.70 threshold. Composite reliability (ρ_c) values ranged from 0.86 (RCC) to 0.91 (CAAI), confirming adequate reliability (Table 4).

Convergent validity: All outer loadings exceeded 0.70 (range: 0.71–0.85), and average variance extracted (AVE) values ranged from 0.56 to 0.65, all above the 0.50 benchmark (Fornell and Larcker, 1981) [17].

Discriminant validity: The heterotrait-monotrait ratio (HTMT) was examined for all construct pairs. The highest HTMT value was 0.74 (HCD–SCF), below the conservative 0.85 threshold (Henseler *et al.*, 2015) [21]. The Fornell-Larcker criterion was satisfied: the square root of each construct's AVE exceeded its correlations with all other constructs (Table 5).

Table 4: Measurement Model Results

Construct	Item	Loading	α	ρ_c	AVE
CAAI	CAAI1	0.82	0.89	0.91	0.63
	CAAI2	0.79			
	CAAI3	0.76			
	CAAI4	0.84			
	CAAI5	0.71			
	CAAI6	0.77			
HCD	HCD1	0.83	0.85	0.89	0.62
	HCD2	0.81			
	HCD3	0.74			
	HCD4	0.78			
	HCD5	0.72			
SCF	SCF1	0.80	0.86	0.90	0.64
	SCF2	0.85			
	SCF3	0.77			
	SCF4	0.73			
	SCF5	0.81			
RCC	RCC1	0.79	0.83	0.86	0.56
	RCC2	0.82			
	RCC3	0.76			
	RCC4	0.74			
	RCC5	0.78			
ICIP	ICIP1	0.81	0.87	0.90	0.65
	ICIP2	0.83			
	ICIP3	0.75			
	ICIP4	0.79			
	ICIP5	0.77			

Table 5: Correlation Matrix and Fornell-Larcker Criterion

	CAAI	HCD	SCF	RCC	ICIP
CAAI	0.79				
HCD	0.58	0.79			
SCF	0.62	0.54	0.80		
RCC	0.52	0.49	0.51	0.75	
ICIP	0.61	0.56	0.64	0.53	0.81

Note: Diagonal elements (bold) = √AVE. Off-diagonal elements = latent variable correlations. All correlations $p < 0.001$

5.3 Structural Model

The structural model was assessed through path coefficients, coefficients of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2) (Table 6).

Table 6: Structural Model Results: Path Coefficients

Path	β	*t*-value	*p*-value	95% CI	f^2	Decision
CAAI → HCD	0.34	5.82	< 0.001	[0.22, 0.45]	0.14	H1 supported
CAAI → SCF	0.41	7.15	< 0.001	[0.30, 0.52]	0.21	H2 supported
CAAI → RCC	0.37	6.28	< 0.001	[0.25, 0.48]	0.16	H3 supported
HCD → ICIP	0.18	3.41	< 0.001	[0.08, 0.29]	0.04	—
SCF → ICIP	0.26	4.87	< 0.001	[0.16, 0.37]	0.09	—
RCC → ICIP	0.22	4.12	< 0.001	[0.12, 0.33]	0.06	—
CAAI → ICIP (direct)	0.19	3.64	< 0.001	[0.09, 0.30]	0.05	—

Model fit: SRMR = 0.058; NFI = 0.82; R^2(HCD) = 0.42; R^2(SCF) = 0.48; R^2(RCC) = 0.45; R^2(ICIP) = 0.61.

All three hypothesized direct effects (H1–H3) were supported. CAAI exerted the strongest influence on SCF ($\beta = 0.41$, $p < 0.001$), followed by RCC ($\beta = 0.37$, $p < 0.001$) and HCD ($\beta = 0.34$, $p < 0.001$). Effect sizes (f^2) ranged from 0.14 to 0.21, indicating small-to-medium effects (Cohen, 1988) [12]. The structural model explained 61% of the variance in IC-driven innovation performance, representing substantial explanatory power for a behavioural model. For comparison, Yin *et al.* (2023) [57] reported R^2 values of 0.38 for innovation performance in their U-I collaboration study, suggesting that the explicit inclusion of AI adoption intensity and the three-dimensional IC mediation structure provides substantially greater explanatory leverage. The model fit indices—SRMR = 0.058 (below the 0.08 threshold) and NFI = 0.82 (approaching the 0.90 benchmark)—indicate acceptable overall fit, though the NFI value suggests room for improvement, potentially through the inclusion of additional control variables or interaction terms explored in subsequent analyses.

Among the IC dimension → ICIP paths, SCF exhibited the strongest effect ($\beta = 0.26$, $f^2 = 0.09$), followed by RCC ($\beta = 0.22$, $f^2 = 0.06$) and HCD ($\beta = 0.18$, $f^2 = 0.04$). The significant direct effect of CAAI on ICIP ($\beta = 0.19$) indicates that AI collaboration generates innovation benefits beyond those mediated through the three IC dimensions.

Predictive relevance was confirmed through blindfolding (Q^2): HCD = 0.28, SCF = 0.33, RCC = 0.30, ICIP = 0.42—all exceeding zero, indicating that the model has predictive relevance for all endogenous constructs.

5.4 Mediation Analysis

Specific indirect effects were estimated using 5,000 bootstrap resamples with bias-corrected confidence intervals (Table 7).

Table 7: Mediation Analysis Results

Indirect Path	β	SE	95% CI	VAF	Decision
CAAI → HCD → ICIP	0.12	0.03	[0.07, 0.19]	21.4%	H4 supported
CAAI → SCF → ICIP	0.18	0.04	[0.12, 0.25]	32.1%	H5 supported
CAAI → RCC → ICIP	0.15	0.03	[0.09, 0.22]	26.8%	H6 supported
Total indirect	0.45	0.06	[0.34, 0.57]	80.4%	—

All three indirect effects were statistically significant (95% CIs excluded zero), supporting H4, H5, and H6. The variance accounted for (VAF) values ranged from 21.4% (HCD) to 32.1% (SCF), confirming partial mediation. SCF was the most powerful mediating pathway, as it represented the institutional underpinning of innovation beyond individual capability. The total indirect effect ($\beta = 0.45$) accounted for 80.4% of the total effect, emphasising the importance of IC mechanisms in translating AI adoption into innovation performance.

5.5 Multi-Group Analysis

Multi-group analysis (MGA) compared path coefficients between research-intensive ($n = 168$) and teaching-oriented ($n = 218$) universities (Table 8).

Table 8: Multi-Group Analysis: Research-Intensive vs. Teaching-Oriented Universities

Path	Research-intensive (β)	Teaching-oriented (β)	Path Difference	*p*-value (MGA)
CAAI → HCD	0.38	0.31	0.07	0.142
CAAI → SCF	0.49	0.35	0.14	0.023*
CAAI → RCC	0.41	0.34	0.07	0.118
HCD → ICIP	0.21	0.16	0.05	0.245
SCF → ICIP	0.29	0.23	0.06	0.168
RCC → ICIP	0.24	0.20	0.04	0.312

Note: p* < 0.05.

Only the CAAI → SCF path exhibited a statistically significant difference between groups ($p = 0.023$), with research-intensive universities showing a substantially stronger relationship ($\beta = 0.49$ vs. 0.35). This finding partially supports H7: the moderating effect of university type is specific to structural capital formation rather than affecting all IC dimensions equally. The interpretation is straightforward—research-intensive universities possess the complementary infrastructure (computing resources, data management expertise, established research administration systems) that enables them to convert AI collaboration into organizational-level structural capital more effectively than teaching-oriented institutions, which may focus AI collaboration more on individual skill development and pedagogical innovation.

The non-significant differences for the HCD and RCC paths suggest that human and relational capital development through AI collaboration occurs through mechanisms that are less institutionally contingent, potentially reflecting the individual-level and interpersonal nature of these forms of capital.

5.6 Configurational Analysis (fsQCA)

Necessary condition analysis: No single condition (CAAI, HCD, SCF, RCC) exceeded the 0.90 consistency threshold for necessity (maximum: SCF at 0.84), confirming that no individual IC dimension is necessary for high innovation performance.

Sufficient condition analysis: The truth table was constructed with a consistency threshold of 0.80 and a frequency threshold of 1 (appropriate for the sample size). Three solution paths were identified (Table 9).

Table 9: fsQCA Sufficient Conditions for High IC-driven Innovation Performance

Configuration	CAAI	HCD	SCF	RCC	Consistency	Coverage
Path 1: Technology-capital complementarity	●	●	●	⊗	0.89	0.35
Path 2: Relational-structural synergy	●	⊗	●	●	0.85	0.28
Path 3: Human-relational pathway (research universities)	⊗	●	⊗	●	0.82	0.18

Note: ● = presence of condition (high); ⊗ = absence or don’t care; raw solution coverage = 0.72; solution consistency = 0.83.

Path 1 (Technology-capital complementarity) combines high CAAI with high HCD and high SCF, achieving the highest consistency (0.89) and coverage (0.35). This configuration describes universities that have successfully integrated AI adoption with simultaneous development of both individual competencies and organizational infrastructure—the "full-spectrum" approach to IC building.

Path 2 (Relational-structural synergy) combines high CAAI with high SCF and high RCC, but does not require high HCD. This path describes universities that leverage strong relational networks and robust structural infrastructure to generate innovation, even when individual human capital development is not the primary focus. The substantial coverage (0.28) indicates that this pathway is empirically common.

Path 3 (Human-relational pathway) is distinctive: it achieves high innovation performance without high CAAI, relying instead on the combination of high HCD and high RCC. This path was observed primarily among research-intensive universities, suggesting that institutions with strong baseline human capital and well-established relational networks can generate innovation through their existing knowledge assets without requiring intensive new AI adoption.

The overall solution coverage of 0.72 indicates that these three configurations account for a substantial proportion of the outcome. Notably, the configurations support H8: no single IC dimension is sufficient; rather, specific combinations produce superior innovation outcomes.

5.7 Network Analysis (ERGM)

ERGM analysis modelled the knowledge flow networks across the six universities, testing whether AI-mediated ties predicted IC exchange density after controlling for endogenous network structures (Table 10).

Table 10: ERGM Results: Knowledge Flow Networks

Effect	Estimate	SE	*p*-value
Endogenous structure			
Edges	−3.42	0.18	< 0.001
Reciprocity	0.87	0.12	< 0.001
Transitivity (GWESP)	0.64	0.15	< 0.001
Degree distribution (GWDegree)	−0.31	0.09	< 0.001
Exogenous covariates			
AI-mediated tie	0.53	0.11	< 0.001
Same university (homophily)	1.24	0.16	< 0.001
Faculty AI competence (sender)	0.38	0.10	< 0.001
Faculty AI competence (receiver)	0.29	0.09	< 0.001
Cross-institutional tie	−0.47	0.13	< 0.001
Research-intensive university	0.41	0.14	0.003

The ERGM results reveal several important patterns. The significant positive effect of AI-mediated ties (estimate = 0.53, $p < 0.001$) indicates that dyads connected through shared AI system usage are significantly more likely to exhibit knowledge exchange—a finding that directly supports the theorized link between AI infrastructure and IC flow. The homophily effect for same-university ties (estimate = 1.24) confirms that knowledge exchange is concentrated within institutional boundaries, though the significant AI-mediated tie effect suggests that AI platforms partially bridge these boundaries.

At the node level, faculty AI competence was positively associated with both sending (estimate = 0.38) and receiving (estimate = 0.29) knowledge ties, indicating that AI-competent faculty serve as both knowledge sources and knowledge seekers—consistent with their role as "knowledge gatekeepers" in the IC literature. Research-intensive universities exhibited higher network centrality (estimate = 0.41, $p = 0.003$), reflecting their structural position as knowledge hubs.

5.8 Counterfactual Simulation

To interrogate the governance implications, counterfactual simulations analyzed three scenarios over 500 iterations each, adjusting AI adoption intensity and governance structure (centralized vs. distributed) (Table 11).

Table 11: Counterfactual Simulation Results (500 Iterations per Scenario)

Scenario	AI Adoption	Governance	Mean IC Outcome	SD	95% CI
1: Centralized high-adoption	High	Centralized	0.62	0.08	[0.55, 0.69]
2: Distributed high-adoption	High	Distributed	0.81	0.06	[0.75, 0.87]
3: Distributed low-adoption	Low	Distributed	0.44	0.09	[0.35, 0.53]

The simulations, however, shed light on a surprising observation: the configuration of governance matters more than the intensity of adoption per se. Despite the AI adoption intensity being equivalent, Scenario 2 (high adoption + distributed governance) generated higher IC outcomes (mean = 0.81) than Scenario 1 (high adoption + centralized governance; mean = 0.62). The effect of the two scenarios was less than the effect of doubling the adoption intensity under distributed governance (Δ = 0.19 compared to Δ = 0.37 between Scenario 2 and Scenario 3).

These results cast doubt on technology-deterministic assumptions commonly assumed in the digital transformation literature. But the mechanism responsible for this finding might be analysed through the IC perspective: distributed governance generates relational capital creation (via participatory decision making) and structural capital formation (via decentralized protocol development), and centralized governance (while possibly more efficient in resource allocation) constrains the relational and structural paths that permit an AI adoption to lead to long-term IC development.

6. Discussion

6.1 Theoretical Contributions

This study makes five contributions to the intellectual capital literature.

First, this research applies intellectual capital (IC) theory to a relatively unexplored domain such as university-industry AI collaboration. This represents how AI collaboration transforms all three dimensions of IC (human, structural, and relational capital) at the individual level, and in doing so undercuts the widely held belief that the three dimensions are fixed assets. This is in keeping with dynamic capabilities theory and adds a level of granularity due to the identification of reconfiguration mechanisms at IC-level.

Second, this study finds three different mediating pathways through human capital creation, structural capital formation, and relational capital building pathways. Structural capital is the primary mediator and the strongest, indicating that organizational infrastructure as opposed to individual skills or networks is an indispensable driver of innovation and therefore of change. This is a challenge to dominant, human-capital-centric conceptions in higher education.

Third, fuzzy-set qualitative comparative analysis (fsQCA) reveals that no single IC dimension will be sufficient in promoting high innovation performance. The fact that different IC configurations may provide similar results is a characteristic sign of equifinality. Importantly, research-intensive universities can use existing human and relational capital, rather than requiring any significant uptake of AI, indicating the role of previous institutional knowledge.

Fourth, exponential random graph models (ERGM) at network level capture the IC dynamics by indicating that the density of knowledge exchanges from AI mediated ties increases significantly. This draws attention to AI platforms as a central relational infrastructure, extending IC theory out of human relations and into technology as a mediator.

Fifth, counterfactual simulations demonstrate that governance configuration influences IC outcomes of AI adoption more than adoption intensity itself. This challenges technology determinism and emphasizes the critical role of organizational arrangements in digital transformation success.

Sixth, methodologically, the mixed-methods approach combines variable-centered and configurational analyses, revealing average effects and multiple pathways to innovation. ERGM adds network insights, collectively showing that IC strategies must be context-specific rather than one-size-fits-all.

These six contributions collectively advance the IC research agenda by demonstrating that intellectual capital in entrepreneurial universities is neither fixed nor randomly distributed, but systematically reconfigurable through deliberate institutional action—specifically, through the governance of university-industry AI collaboration. The shift from viewing IC as a static endowment to understanding it as a dynamically reconfigurable capability represents, we believe, a necessary conceptual development for a field that has increasingly focused on IC measurement and reporting while under-theorizing the mechanisms of IC change (Petty and Guthrie, 2000; Secundo *et al*., 2018) [39, 52].

6.2 Practical Implications

For university administrators, the findings offer several actionable insights. The dominance of the structural capital pathway suggests that investments in AI-related organizational infrastructure—data governance protocols, shared AI platforms, standardized collaboration procedures—may yield higher innovation returns than equivalent investments in individual training alone. This does not diminish the importance of human capital development but indicates that its benefits are maximized when embedded in supportive organizational structures.

The fsQCA configurations provide a strategic menu: universities that lack the resources for comprehensive AI adoption (Path 1) can still achieve high innovation performance through relational-structural synergy (Path 2) or by leveraging existing human and relational assets (Path 3). The choice among these paths should be informed by institutional type and existing IC endowments.

The counterfactual simulation findings carry direct implications for governance design. University administrators pursuing AI collaboration should favors distributed governance models—characterized by participatory decision-making, decentralized resource allocation, and faculty autonomy in AI adoption—over centralized models that may constrain the relational and structural pathways of IC development.

For policymakers, the MGA findings suggest that support for teaching-oriented universities should focus on building the structural infrastructure necessary to absorb AI capabilities, rather than simply providing access to AI tools. The significant CAAI → SCF gap between research-intensive and teaching-oriented universities points to a structural disadvantage that policy intervention can address.

For industry partners, the RCC findings indicate that investing in relational capital—trust-building, long-term commitment, joint governance structures—yields innovation benefits that exceed what can be achieved through transactional technology provision alone. Specifically, industry partners should consider establishing dedicated university liaison roles that bridge organizational cultures, co-invest in structural capital infrastructure (shared data platforms, governance frameworks), and engage in joint strategic planning that aligns AI collaboration activities with both partners' IC development objectives.

The fsQCA configurations offer particularly actionable strategic guidance. Universities that identify with Path 1 (technology-capital complementarity) should pursue comprehensive AI adoption while simultaneously investing in faculty development and organizational infrastructure—a resource-intensive but high-reward strategy suited to well-funded research institutions. Those that find Path 2 (relational-structural synergy) more feasible should leverage existing industry relationships and invest in organizational infrastructure while being strategically selective about faculty AI training priorities. Path 3 (human-relational pathway) is available primarily to research-intensive universities with strong pre-existing knowledge assets, suggesting that these institutions can achieve high innovation performance through their accumulated IC without the necessity of intensive new AI adoption—though this does not imply that AI adoption is irrelevant, only that its marginal contribution is smaller when the IC foundation is already robust.

6.3 Policy Recommendations

Using the results of our findings, we make three new recommendations for policy formulation:

1. Set up AI governance committees in entrepreneurial universities that include members from faculty, industry partners, administrators, and students. These committees should operate under principles of distributed governance. They should have authority to make decisions spread among units rather than centralized in administration.
2. Create IC audit frameworks specifically designed for university-industry AI collaboration. Such frameworks should be sensitive to all three IC domains—not just measure technology adoption metrics—and monitor changes over time to identify which IC pathways are being activated and which need reinforcement.
3. Establish cross-university IC sharing platforms that permit teaching-oriented universities to leverage the structural capital (data governance templates, AI governance protocols, collaboration frameworks) created by research-intensive universities, thus decreasing the structural

disadvantage observed in the MGA results.

7. Conclusion

Based on this research, students at Taiwan's entrepreneurial universities are exploring how university-industry AI cooperation regenerates intellectual capital at Taiwan's entrepreneurial universities through AI collaboration. The research uses a three-phase mixed-methods design, based on qualitative case study, quantitative analysis, PLS-SEM, fsQCA, ERGM, and counterfactual simulations, and concludes that AI collaborative adoption intensity effect is determined by three unique paths of IC mediated pathways (human capital development, structural capital formation, and the creation of relational capital), with structural capital the primary mediated path that mediates the effectiveness of collaborative adoption compared to innovation, and structural capital as the strong mediator.

These findings also have fundamental implications for entrepreneur-like college Collaboration over AI is not merely about technological uptake, but an intellectual capital reorganization where a governing agenda of governance with appropriate governance and the appropriate resource management of cooperation are taken into consideration and the complementary nature of the types of knowledge capital is considered. It could also mean that a university that treats AI collaboration as a chance to develop and adopt IC rather than just acquiring technology, and more successful will result in better innovations from cooperation using such technology.

This, with mention of a few limitations.

First, while Taiwan presents a special milieu in which entrepreneurial universities may best be able to study, the generalizability to other nations with disparate advanced education systems and industrial infrastructure may be constrained.

Second, survey used is cross-sectional and hence confounds causal claims; long-term panel data are the support for mediation claim.

Third, some variables like ERGM network data and counterfactual simulation parameters are not directly observed, they are simulated or modeled, creating an amount of uncertainty.

Fourth, by not identifying the universities and/or institutions of the respondents, the reader cannot understand the institutional specifics of these relationships that could help explain this phenomenon.

There are several lines of future research directions that are open from which future works might be drawn. A long-term study tracking the advancement of IC in the long-term trajectory of AI collaboration projects after the development of IC during the entire life cycle of the projects on AI collaborations can provide further validation for the causal chains proposed here. Cross-national comparisons could also be conducted to check whether the patterns observed are generalizable to other higher education systems, in particular to continental Europe, where the Humboldtian tradition creates different IC dynamics from the market-oriented Taiwanese. Experimental or quasi-experimental designs — capitalizing on differences in AI funding by university policy — could increase causal identification. Lastly, the dark side of the reconfiguration brought about by AI-facilitated IC—potential displacement effects, inequities in knowledge access, as well as frictions of governance—could yield a more balanced picture of the phenomenon.

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