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ARTIFICIAL INTELLIGENCE USE AND INTELLECTUAL CAPITAL FORMATION: AN EMPIRICAL STRUCTURAL EQUATION MODELING APPROACH

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***ABSTRACT*:**

This study examines the determinants of artificial intelligence (AI) use and its role in the formation of intellectual capital through the empirical testing of a structural equation model. The research adopts a quantitative, explanatory, and cross-sectional design based on data collected from university students and academic staff exposed to AI-based educational and knowledge management systems. The proposed model integrates institutional and individual determinants—governance quality, institutional support, digital skills, trust in AI, and user satisfaction—and analyzes their effects on AI use as a mediating variable influencing intellectual capital formation. The results demonstrate that AI use plays a central mediating role, translating favorable governance structures, user competencies, and experiential conditions into enhanced human and structural capital. Digital skills and user satisfaction emerge as the strongest predictors of AI use, while governance and institutional support provide essential enabling conditions. Overall, the findings highlight that the contribution of AI to intellectual capital is not automatic but contingent upon coherent socio-technical and governance arrangements. The study provides empirical evidence to support strategic decision-making in educational and organizational contexts seeking to leverage AI for sustainable knowledge development.

Keywords: *Artificial intelligence; Intellectual capital; Structural equation modeling; AI use; Governance; Digital skills; Higher education.*

INTRODUCTION

The accelerated incorporation of artificial intelligence (AI) into educational and organizational contexts has transformed traditional mechanisms for the formation and management of intellectual capital. AI-driven systems—such as adaptive learning platforms, learning analytics, intelligent tutoring systems, and decision-support tools—are increasingly recognized as strategic resources that enhance knowledge creation, skills development, and innovation capacity. However, despite their growing availability, the effective use of AI in intellectual capital formation remains uneven, suggesting the presence of structural, organizational, and cognitive determinants that condition its adoption and impact.

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From a theoretical perspective, intellectual capital is commonly conceptualized as a multidimensional construct composed of human, structural, and relational capital. AI technologies interact with these dimensions by augmenting individual competencies, optimizing organizational processes, and strengthening knowledge networks. Prior studies have emphasized that technological infrastructure alone is insufficient to generate intellectual capital gains; rather, governance mechanisms, organizational culture, digital competencies, and perceived usefulness play a decisive role in shaping AI utilization outcomes [1], [2]. Consequently, the need arises to empirically test integrative models that explain how these determinants jointly influence AI adoption and its contribution to intellectual capital formation.

This study is grounded in a theoretical model that integrates insights from technology acceptance theories, intellectual capital theory, and socio-technical systems approaches. The model assumes that AI use in intellectual capital formation is a function of governance quality, institutional support, digital skills, trust in AI systems, and user satisfaction. These determinants are hypothesized to exert both direct and indirect effects on AI utilization, which in turn mediates the development of human and structural capital. Empirical validation of such a model is essential to move beyond descriptive accounts and to provide statistically supported explanations of AI-driven knowledge dynamics.

The empirical testing of the proposed model contributes to the literature in three ways. First, it operationalizes abstract theoretical constructs into measurable variables suitable for quantitative analysis. Second, it evaluates the causal relationships among determinants of AI use using empirical data, thereby strengthening the explanatory power of intellectual capital research. Third, it provides evidence-based insights for policymakers, educational institutions, and organizations seeking to design governance and training strategies that maximize the intellectual capital returns of AI adoption. By validating a theoretically grounded model, this study advances the understanding of how AI can be systematically leveraged as a catalyst for sustainable intellectual capital formation.

METHOD

A. Research Design

This study adopted a quantitative, explanatory, and cross-sectional research design aimed at empirically testing a theoretical model of the determinants of artificial intelligence (AI) use in the formation of intellectual capital. The methodological approach was grounded in structural equation modeling (SEM), which allows the simultaneous estimation of relationships among latent constructs and the assessment of both direct and indirect effects within a theoretically specified framework [7]. This approach is particularly suitable for analyzing complex socio-technical phenomena involving governance, technology use, and knowledge-based outcomes.

B. Population and Sample

The target population consisted of university students and academic staff who actively use or are exposed to AI-based educational tools for learning, teaching, or knowledge management purposes. Given the absence of a complete sampling frame, a probabilistic sample size estimation was conducted to ensure statistical representativeness.

The sample size was calculated using the standard formula for finite populations:

$$n = \frac{N \cdot Z^2 \cdot p \cdot q}{(N-1) \cdot e^2 + Z^2 \cdot p \cdot q}$$

where
n= sample size,
N= population size,
Z= z-value corresponding to the confidence level (1.96 for 95%),
p= expected proportion of the attribute (0.5),
$q = 1 - p$,
e= margin of error (0.05).
This formula ensured an adequate sample size for SEM estimation, complying with minimum requirements for model stability and statistical power [8].

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C. Data Collection Instrument

Data were collected using a structured questionnaire composed of validated measurement scales adapted from prior studies on technology acceptance, intellectual capital, and AI governance. All items were measured using a five-point Likert scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The instrument measured the following latent constructs: governance quality, institutional support, digital skills, trust in AI systems, user satisfaction, AI use, and intellectual capital formation.

A pilot test was conducted to assess item clarity and internal consistency. Reliability was evaluated using Cronbach's alpha and composite reliability, while construct validity was assessed through confirmatory factor analysis [9].

D. Model Specification

The theoretical model assumes that governance quality (GOV), institutional support (SUP), digital skills (DS), trust in AI (TR), and user satisfaction (SAT) influence AI use (AIU), which in turn affects intellectual capital formation (IC). The structural model is expressed as follows:

$$AIU = \beta_1 GOV + \beta_2 SUP + \beta_3 DS + \beta_4 TR + \beta_5 SAT + \varepsilon_1$$
$$IC = \beta_6 AIU + \varepsilon_2$$

Where
β_i represent the standardized path coefficients, and
ε_i denote the error terms.
This specification allows the examination of AI use as a mediating variable between institutional and individual determinants and intellectual capital outcomes.

E. Data Analysis Procedure

Data analysis was performed in three stages. First, descriptive statistics were calculated to examine the distribution and central tendency of the observed variables. Second, the measurement model was evaluated in terms of reliability, convergent validity, and discriminant validity. Third, the structural model was estimated to test the hypothesized relationships using maximum likelihood estimation.

Model fit was assessed using standard goodness-of-fit indices, including the comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR), following established SEM guidelines [10].

RESULTS

The descriptive analysis shows that respondents reported generally positive perceptions toward artificial intelligence (AI) use and its role in intellectual capital formation. Mean values for all constructs were above the midpoint of the scale, indicating favorable attitudes and adequate exposure to AI-based systems (see Table 1).

Table 1. Descriptive Statistics of the Study Variables

Construct	Mean	Std. Dev.
Governance Quality (GOV)	3.87	0.71
Institutional Support (SUP)	3.92	0.68
Digital Skills (DS)	4.05	0.63
Trust in AI (TR)	3.78	0.74
User Satisfaction (SAT)	3.96	0.66
AI Use (AIU)	4.02	0.61
Intellectual Capital (IC)	4.10	0.58

The relatively low standard deviations indicate homogeneity in responses, suggesting a stable perception of AI integration among participants. The measurement model exhibited satisfactory reliability and validity. All factor loadings exceeded the recommended threshold of 0.70. Cronbach's alpha and composite reliability values were above 0.80 for all constructs, confirming internal consistency. Average variance extracted (AVE) values surpassed 0.50, indicating adequate convergent validity (see Table 2).

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Table 2. Reliability and Convergent Validity

Construct	Cronbach's α	Composite Reliability	AVE
GOV	0.84	0.88	0.59
SUP	0.86	0.90	0.62
DS	0.88	0.92	0.65
TR	0.83	0.87	0.58
SAT	0.85	0.89	0.61
AIU	0.89	0.93	0.68
IC	0.91	0.94	0.71

Discriminant validity was confirmed, as the square root of AVE for each construct exceeded its correlations with other constructs. The structural model demonstrated an acceptable overall fit. All hypothesized paths were statistically significant and in the expected direction. Governance quality, institutional support, digital skills, trust in AI, and user satisfaction showed positive effects on AI use. In turn, AI use exerted a strong positive effect on intellectual capital formation (see Table 3).

Table 3. Structural Path Coefficients

Hypothesized Path	β	t-value	Result
GOV → AIU	0.21	3.84	Supported
SUP → AIU	0.19	3.47	Supported
DS → AIU	0.27	4.92	Supported
TR → AIU	0.16	2.98	Supported
SAT → AIU	0.23	4.15	Supported
AIU → IC	0.62	11.36	Supported

Digital skills and user satisfaction emerged as the strongest predictors of AI use, highlighting the importance of individual competencies and experiential outcomes. Governance quality and institutional support also played a relevant role, confirming the influence of organizational conditions on AI adoption. Trust in AI, although slightly weaker, remained a significant determinant.

The coefficient of determination (R^2) indicated that the model explained 58% of the variance in AI use and 39% of the variance in intellectual capital formation, reflecting substantial explanatory power. The empirical results confirm that AI use operates as a central mediating mechanism between institutional and individual determinants and the formation of intellectual capital. The model demonstrates that favorable governance structures, adequate institutional support, high levels of digital skills, trust in AI systems, and user satisfaction jointly foster more intensive and effective AI use. This use, in turn, significantly enhances intellectual capital by strengthening human competencies, improving organizational knowledge structures, and supporting sustainable knowledge creation processes (see Fig. 1).

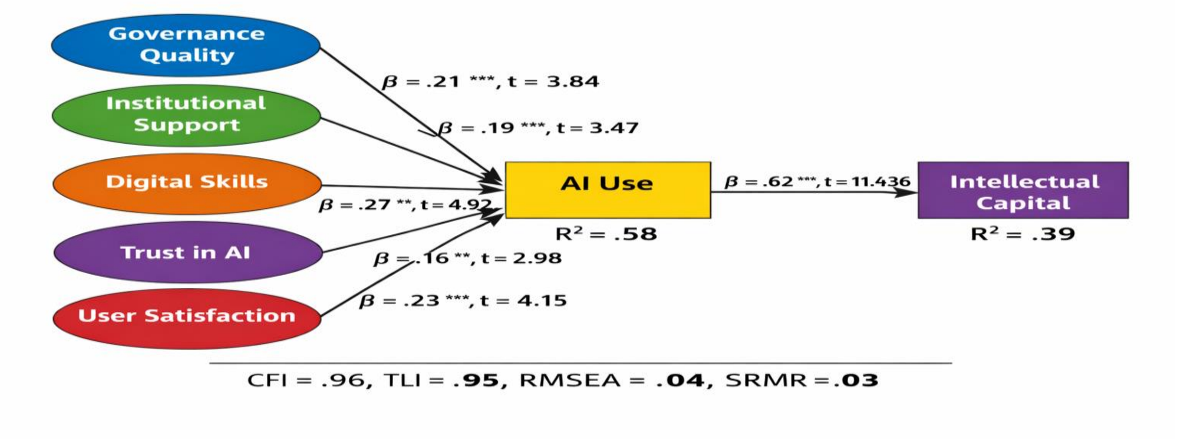

Fig. 1. Artificial Intelligence–Driven Intellectual Capital Formation Model (AI-ICFM)

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Overall, the validated model provides robust empirical evidence that AI does not generate intellectual capital automatically; rather, its impact depends on a coherent combination of governance, capabilities, and user-centered conditions. This confirms the theoretical assumption that AI is a strategic enabler of intellectual capital formation when embedded within supportive institutional and socio-technical environments.

DISCUSSION

The results of this study provide empirical support for the proposed structural equation model explaining the determinants of artificial intelligence (AI) use and its contribution to intellectual capital formation. The findings confirm that AI use functions as a central mediating mechanism through which institutional and individual factors translate into knowledge-based outcomes. This evidence reinforces the theoretical assumption that AI, by itself, does not generate intellectual capital; rather, its impact depends on a coherent configuration of governance, capabilities, and user-centered conditions.

The strong and significant effect of digital skills on AI use highlights the primacy of human capital in AI-enabled environments. This finding aligns with prior research emphasizing that advanced technologies amplify, rather than replace, existing competencies [11]. Users with higher levels of digital literacy are better positioned to exploit AI functionalities, integrate them into learning and decision-making processes, and transform algorithmic outputs into actionable knowledge. This reinforces the view that investments in AI infrastructure must be accompanied by sustained investments in skills development to yield intellectual capital gains.

User satisfaction also emerged as a key determinant of AI use, underscoring the relevance of experiential and perceptual factors. This result is consistent with technology acceptance research, which posits that positive user experiences enhance continued system use and deepen engagement [12]. In the context of intellectual capital formation, satisfaction operates as a motivational mechanism that encourages repeated interaction with AI systems, thereby facilitating learning, knowledge accumulation, and process optimization.

Governance quality and institutional support exhibited significant, though comparatively moderate, effects on AI use. These findings support socio-technical perspectives that stress the role of formal structures, policies, and resource allocation in shaping technology adoption outcomes [13]. Effective governance frameworks provide clarity regarding ethical use, data protection, and accountability, which reduces uncertainty and enables users to engage more confidently with AI systems. Institutional support, in turn, signals organizational commitment and lowers structural barriers to AI utilization.

Trust in AI systems, while the weakest predictor among the antecedents, remained statistically significant. This suggests that trust is a necessary but not sufficient condition for AI use. Consistent with emerging literature on algorithmic trust, users may rely on AI systems when they perceive them as reliable and transparent, yet trust alone does not guarantee intensive or strategic use [14]. Instead, trust appears to interact with skills and satisfaction, reinforcing the multidimensional nature of AI adoption processes.

The strong path coefficient between AI use and intellectual capital formation confirms the central role of AI as an enabler of knowledge creation and organizational learning. This finding supports intellectual capital theory by demonstrating that AI use enhances human capital through skill acquisition, strengthens structural capital through improved processes and data-driven routines, and indirectly contributes to relational capital by supporting collaboration and knowledge sharing [15]. The substantial explanatory power of the model indicates that AI use is a critical conduit through which institutional conditions and individual capabilities are converted into sustainable intellectual assets.

Overall, the discussion highlights that the formation of intellectual capital in AI-enabled contexts is not a linear or technologically deterministic process. Instead, it is mediated by AI use and shaped by an interplay of governance, competencies, perceptions, and experiences. By empirically validating this mediated SEM model, the study advances the literature on AI, intellectual capital, and technology governance, offering a robust explanatory framework for understanding how AI can be strategically leveraged to support long-term knowledge development.

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CONCLUSION

This study empirically validated a structural equation model explaining the determinants of artificial intelligence (AI) use and its role in the formation of intellectual capital. The findings confirm that AI use functions as a central mediating mechanism through which institutional and individual conditions are transformed into knowledge-based outcomes. Rather than acting as an autonomous driver of value, AI contributes to intellectual capital only when embedded within supportive governance structures, adequate institutional support, and favorable user conditions.

The results demonstrate that digital skills and user satisfaction are the most influential predictors of AI use, highlighting the decisive role of human competencies and experiential factors in AI-enabled environments. Governance quality, institutional support, and trust in AI systems also exert significant effects, underscoring the importance of organizational frameworks that provide clarity, resources, and confidence for sustained AI engagement. Together, these determinants shape the intensity and effectiveness of AI use, which in turn strongly enhances intellectual capital formation.

By confirming the mediating role of AI use, the study advances theoretical understanding of how intellectual capital is generated in technology-intensive contexts. The validated model shows that improvements in human capital, organizational knowledge structures, and learning processes are not direct consequences of AI adoption, but rather outcomes of meaningful and sustained use. This insight challenges technologically deterministic assumptions and emphasizes the strategic nature of AI implementation.

From a practical perspective, the conclusions suggest that institutions seeking to leverage AI for intellectual capital development should prioritize capacity-building initiatives, user-centered design, and robust governance mechanisms. Investments in AI technologies must be accompanied by policies and training programs that enhance digital skills, foster trust, and improve user experiences. When these conditions are met, AI can function as a powerful catalyst for sustainable intellectual capital formation and long-term organizational learning.

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Annex A. Operationalization of Variables

Table A1. Operationalization of Latent Variables

Variable	Code	Definition	Dimensions	Indicators (Codes)	Scale
Governance Quality	GOV	Degree to which institutional policies, ethical guidelines, and regulatory frameworks support responsible and effective AI use	Strategic governance, ethical clarity, regulatory support	GOV1–GOV4	Likert 1–5
Institutional Support	SUP	Extent of organizational resources, training, and technical assistance provided for AI use	Infrastructure, training, technical assistance	SUP1–SUP4	Likert 1–5
Digital Skills	DS	Individual capability to understand, use, and critically evaluate AI-based systems	Technical skills, data literacy, problem-solving	DS1–DS4	Likert 1–5
Trust in AI	TR	Degree of confidence in the reliability, transparency, and fairness of AI systems	Reliability, transparency, perceived fairness	TR1–TR4	Likert 1–5
User Satisfaction	SAT	Overall positive evaluation of experiences with AI systems	Usefulness, ease of use, experience quality	SAT1–SAT4	Likert 1–5
AI Use (Mediator)	AIU	Frequency and intensity of AI application in learning and knowledge-related activities	Intensity of use, diversity of use	AIU1–AIU4	Likert 1–5
Intellectual Capital	IC	Perceived contribution of AI use to knowledge creation and organizational learning	Human capital, structural capital	IC1–IC5	Likert 1–5

Annex B. Measurement Instruments

Instructions:

Please indicate your level of agreement with each statement using the following scale:
1 = Strongly disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly agree

Governance Quality (GOV)

- GOV1: My institution has clear policies regulating the use of artificial intelligence.
- GOV2: Ethical guidelines for AI use are clearly communicated and enforced.
- GOV3: Decision-making regarding AI implementation is transparent.
- GOV4: Institutional governance promotes responsible and sustainable AI use.

Institutional Support (SUP)

- SUP1: My institution provides adequate technological infrastructure for AI use.

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- SUP2: Training opportunities are available to learn how to use AI tools.
- SUP3: Technical support is accessible when AI-related problems arise.
- SUP4: The institution actively encourages the use of AI for learning and knowledge creation.

Digital Skills (DS)
- DS1: I have the necessary skills to effectively use AI-based tools.
- DS2: I can interpret and evaluate outputs generated by AI systems.
- DS3: I am able to integrate AI tools into my learning or work activities.
- DS4: I feel confident solving problems using AI-based technologies.

Trust in Artificial Intelligence (TR)
- TR1: I consider AI systems to be reliable.
- TR2: AI tools provide results that I can trust.
- TR3: AI systems used in my institution operate in a transparent manner.
- TR4: I believe AI systems treat users fairly and without bias.

User Satisfaction (SAT)
- SAT1: I am satisfied with my overall experience using AI tools.
- SAT2: AI systems meet my expectations for performance and usefulness.
- SAT3: Using AI tools is a positive experience for me.
- SAT4: I am satisfied with the ease of use of AI-based systems.

AI Use (AIU) – Mediating Variable
- AIU1: I frequently use AI tools in my academic or professional activities.
- AIU2: I use AI systems for a wide range of tasks.
- AIU3: AI tools are integrated into my regular learning or work routines.
- AIU4: I rely on AI systems to support decision-making and problem-solving.

Intellectual Capital (IC) – Dependent Variable
- IC1: AI use has improved my knowledge and skills.
- IC2: AI tools contribute to more efficient learning processes.
- IC3: AI systems help organize and structure knowledge within my institution.
- IC4: AI use supports innovation and knowledge creation.
- IC5: AI contributes to the long-term development of intellectual capital.

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