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ARTIFICIAL INTELLIGENCE AND UNIVERSITY GOVERNANCE: A PLS-SEM MODEL OF TECHNOLOGICAL ADOPTION, ACADEMIC QUALITY, AND INSTITUTIONAL TRUST

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ABSTRACT:

The integration of artificial intelligence into higher education institutions has generated new opportunities for improving governance processes, decision-making systems, and academic management. Universities increasingly rely on intelligent technologies to process large volumes of institutional data, support policy development, and enhance educational quality. However, the relationship between artificial intelligence adoption and governance outcomes remains an emerging area of empirical research.

The objective of this study is to analyze the structural relationships between artificial intelligence adoption and university governance outcomes through a Structural Equation Modeling approach estimated using Partial Least Squares (PLS-SEM). The proposed model examines the causal relationships among six latent constructs: artificial intelligence adoption, perceived technological benefits, technological challenges, policy development, academic quality, and institutional trust. Data were collected through a structured questionnaire using reflective indicators measured on a seven-point Likert scale.

The results indicate that artificial intelligence adoption significantly influences perceived technological benefits, which in turn affect policy development and academic quality. Policy development also contributes positively to academic quality, highlighting the importance of governance frameworks that integrate technological innovation into institutional management. Furthermore, both academic quality and technological challenges influence institutional trust, suggesting that stakeholder confidence depends on the effective and responsible implementation of intelligent systems within university governance structures.

The structural model demonstrates satisfactory explanatory power and acceptable model fit indicators, confirming the relevance of artificial intelligence as a driver of institutional transformation in higher education. The findings suggest that universities that strategically integrate artificial intelligence technologies into governance processes are better positioned to enhance academic performance, improve administrative efficiency, and strengthen stakeholder trust.

This study contributes to the literature on digital transformation and higher education governance by proposing an empirical model that explains how artificial intelligence adoption influences institutional outcomes through governance mechanisms and academic management processes.

Keywords*: Artificial Intelligence; University Governance; Structural Equation Modeling; PLS-SEM; Academic Quality; Institutional Trust; Digital Transformation; Higher Education Governance.*

INTRODUCTION

Artificial intelligence (AI) has rapidly transformed organizational processes, decision-making systems, and knowledge management practices across multiple institutional contexts. Universities, as knowledge-intensive organizations, are increasingly integrating AI technologies into administrative, pedagogical, and governance structures. This transformation has implications for how universities design policies, manage academic quality, and maintain institutional trust among stakeholders. Recent research suggests that AI systems improve the efficiency of decision-making processes by enabling data-driven governance and predictive analytics capable of supporting strategic planning and institutional management [1], [2].

Within higher education systems, governance traditionally involves mechanisms for coordinating academic actors, regulating institutional performance, and ensuring accountability to society. However, the digital transformation of universities has introduced new governance challenges associated with algorithmic decision-making, transparency, and ethical accountability. AI technologies can enhance institutional governance by supporting automated monitoring of academic processes, optimizing administrative procedures, and facilitating evidence-based policy development [3], [4]. These systems allow universities to analyze large volumes of institutional data, improving their ability to evaluate academic performance, allocate resources, and design strategic interventions [5].

Another important dimension of AI adoption in universities is its influence on academic quality. AI-based analytical tools enable institutions to monitor teaching outcomes, student performance, and curriculum effectiveness in real time. Such capabilities contribute to continuous improvement processes by providing feedback loops that inform academic decision-making and institutional planning [6]. Furthermore, AI systems have been associated with improvements in educational quality through personalized learning environments, adaptive educational technologies, and intelligent tutoring systems that support both students and instructors [7]. Despite these advantages, the implementation of AI within university governance structures also raises several challenges. Concerns related to algorithmic bias, lack of transparency, and data privacy have become central issues in discussions about AI-driven institutional management. Governance models must therefore incorporate regulatory mechanisms that ensure accountability, fairness, and ethical use of digital technologies [8]. Without adequate oversight frameworks, the adoption of AI systems may generate institutional risks, particularly when automated decisions affect academic evaluation, student admissions, or resource distribution [9].

Institutional trust represents another key element in the relationship between technological innovation and governance. Trust emerges when stakeholders perceive that institutional decisions are transparent, fair, and aligned with academic values. AI-driven governance mechanisms can strengthen institutional trust when they improve transparency, provide consistent decision-making criteria, and enhance organizational efficiency [10]. Conversely, opaque algorithms or poorly regulated systems may erode trust among students, faculty members, and administrative personnel [11].

The integration of AI into university governance also reflects broader transformations associated with digital institutional ecosystems. Universities increasingly operate within interconnected technological environments where digital platforms, data infrastructures, and intelligent systems shape organizational processes. These environments facilitate collaboration between academic actors and technological systems, enabling institutions to manage complexity and uncertainty in rapidly changing educational contexts [12]. As a result, governance structures must evolve toward hybrid models that combine human decision-making with algorithmic support mechanisms.

From an analytical perspective, understanding the relationships between AI adoption, governance practices, academic quality, and institutional trust requires empirical modeling approaches capable of analyzing complex causal structures. Structural Equation Modeling (SEM), particularly under the Partial Least Squares (PLS) approach, has become a widely used methodology for examining relationships among latent constructs in social and organizational research. PLS-SEM allows researchers to simultaneously evaluate measurement models and structural relationships, making it suitable for studies that explore emerging technological phenomena within institutional environments [13].

In this context, examining how AI-related constructs influence governance outcomes contributes to the broader literature on digital transformation in higher education. Empirical evidence suggests that technological adoption influences governance capacity by strengthening information flows, improving policy coordination, and facilitating evidence-based institutional management [14]. These dynamics highlight the importance of investigating the structural relationships among AI adoption, perceived benefits, technological challenges, and governance outcomes such as academic quality and institutional trust.

Therefore, the present study proposes a structural model that examines the influence of artificial intelligence adoption on university governance processes. The model integrates constructs associated with AI adoption, perceived technological benefits, implementation challenges, policy development, academic quality, and institutional trust. By applying a PLS-SEM approach, the study seeks to provide empirical evidence on how AI-related factors shape governance outcomes within higher education institutions.

METHOD

Research Design

The present study followed a quantitative, cross-sectional, and explanatory design aimed at evaluating the causal relationships between artificial intelligence constructs and university governance outcomes. Structural relationships were examined using Partial Least Squares Structural Equation Modeling (PLS-SEM) due to its suitability for predictive modeling, complex causal structures, and latent constructs measured through reflective indicators. This approach is widely recommended when the objective is to maximize explained variance in endogenous variables and when theoretical development remains exploratory [15], [16].

PLS-SEM was implemented through the SmartPLS algorithm, which estimates both the measurement and structural models simultaneously. The procedure included the evaluation of indicator reliability, internal consistency reliability, convergent validity, discriminant validity, and structural path significance using bootstrapping resampling techniques. Bootstrapping allows the estimation of the significance of path coefficients and indicator loadings without requiring distributional assumptions [17].

Participants and Sampling

The study population consisted of students, faculty members, and administrative staff from public universities who interact with digital governance systems and artificial intelligence applications within academic management processes. Because the exact population size was assumed to be large and heterogeneous, the required sample size was estimated using the finite population sampling formula:

$$n = \frac{Z^2 pq}{e^2}$$

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where:

- n= required sample size
- Z= critical value corresponding to the desired confidence level (1.96 for 95%)
- p= estimated proportion of the attribute in the population (0.5)
- $q = 1 - p$
- e= margin of sampling error (0.05)

Substituting the parameters:

$$n = \frac{(1.96)^2(0.5)(0.5)}{(0.05)^2} = 384.16$$

Thus, a minimum sample size of 384 participants was considered adequate for estimating the structural equation model. This sample size also satisfies the ten-times rule commonly used in PLS-SEM, which recommends that the sample should be at least ten times the maximum number of structural paths directed at any latent construct [18].

Instrument and Measurement

The instrument consisted of a structured questionnaire composed of reflective indicators representing six latent constructs associated with artificial intelligence and university governance. Each construct was operationalized using three or four indicators measured on a seven-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree).

The constructs included:

- AI Adoption (A1–A4)
- AI Benefits (B1–B4)
- AI Challenges (C1–C3)
- Policy Development (P1–P3)
- Academic Quality (Q1–Q3)
- Institutional Trust (T1–T3)

Reflective indicators were selected because they represent observable manifestations of the underlying latent constructs. In reflective measurement models, indicators are assumed to be highly correlated and interchangeable manifestations of the same conceptual dimension [19].

Measurement Model

The reflective measurement model establishes the relationship between latent variables and their observed indicators. The general specification of the measurement model is expressed as:

$$x_i = \lambda_i \xi + \delta_i$$
$$y_i = \lambda_i \eta + \varepsilon_i$$

where:

- x_i= observed indicators of exogenous latent variables
- y_i= observed indicators of endogenous latent variables
- λ_i= factor loading (outer loading)
- ξ= exogenous latent variable
- η= endogenous latent variable
- δ_i, ε_i= measurement error terms

Indicator reliability is evaluated through outer loadings (λ), where values above 0.70 indicate acceptable reliability in reflective measurement models [20].

Structural Model

The structural model specifies the causal relationships among latent variables. The general structural equation can be expressed as:

$$\eta = B\eta + \Gamma\xi + \zeta$$

where:

- B= matrix of relationships between endogenous constructs
- Γ= matrix of relationships between exogenous and endogenous constructs

- ζ= residual structural error term

In the proposed model, the structural relationships evaluate the influence of AI adoption, benefits, and challenges on governance outcomes such as policy development, academic quality, and institutional trust.

Structural parameters are represented by standardized path coefficients (β) and their statistical significance is evaluated through bootstrapped t-values and confidence intervals [21].

Psychometric Properties

The evaluation of psychometric properties followed established criteria for PLS-SEM measurement models. First, indicator reliability was assessed through standardized outer loadings. Indicators with loadings above 0.70 were retained because they demonstrate strong relationships with their corresponding latent constructs. Indicators with slightly lower values may be retained when they contribute to content validity and theoretical consistency.

Second, internal consistency reliability was evaluated using Composite Reliability (CR) rather than Cronbach's alpha, as CR provides a more accurate estimate of reliability in latent variable modeling. Values above 0.70 indicate acceptable reliability, while values above 0.80 are considered highly satisfactory for confirmatory research contexts.

Third, convergent validity was examined using the Average Variance Extracted (AVE). AVE values greater than 0.50 indicate that the construct explains more than half of the variance of its indicators, confirming that the indicators adequately represent the latent variable.

Fourth, discriminant validity was evaluated to ensure that each construct measures a concept distinct from the others. This was assessed using the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT). Adequate discriminant validity exists when the square root of the AVE for each construct exceeds its correlations with other constructs, and when HTMT values remain below recommended thresholds.

Finally, the structural model quality was assessed through the coefficient of determination R^2, predictive relevance Q^2, and global model fit indices such as Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI). SRMR values below 0.08 indicate acceptable model fit, while NFI values closer to 1 indicate improved model quality [22].

Data Analysis Procedure

Data analysis was conducted in several sequential stages. First, descriptive statistics and preliminary screening procedures were performed to identify missing values and potential outliers. Second, the measurement model was evaluated through reliability and validity tests. Third, the structural model was estimated using the PLS algorithm, followed by bootstrapping with 5,000 subsamples to determine the significance of structural path coefficients. Finally, predictive power was evaluated using R^2 values for endogenous constructs and effect size statistics (f^2). This analytical procedure allowed the study to evaluate both the measurement quality of the constructs and the causal relationships among artificial intelligence variables and governance outcomes within university contexts.

RESULTS

Table 1 presents the descriptive statistics of the observed indicators used to estimate the structural equation model. The means indicate moderately positive perceptions of artificial intelligence adoption and governance outcomes within the university context. Standard deviations show adequate variability across responses, suggesting that the indicators capture heterogeneous perceptions among participants.

Table 1. Descriptive Statistics of Indicators

Indicator	Mean	SD	Min	Max
A1	5.12	1.21	1	7
A2	5.04	1.18	1	7
A3	5.20	1.15	1	7
A4	5.10	1.24	1	7
B1	5.35	1.16	1	7

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Indicator	Mean	SD	Min	Max
B2	5.28	1.12	1	7
B3	5.40	1.10	1	7
B4	5.31	1.18	1	7
C1	4.72	1.33	1	7
C2	4.65	1.30	1	7
C3	4.70	1.29	1	7
P1	5.22	1.19	1	7
P2	5.18	1.21	1	7
P3	5.27	1.16	1	7
Q1	5.36	1.14	1	7
Q2	5.29	1.17	1	7
Q3	5.33	1.15	1	7
T1	5.10	1.20	1	7
T2	5.06	1.19	1	7
T3	5.14	1.18	1	7

Overall, the descriptive results suggest favorable perceptions regarding the role of artificial intelligence in university governance processes. Table 2 shows the outer loadings of the reflective indicators. All indicators present loadings above 0.70, indicating strong relationships between the indicators and their respective latent constructs.

Table 2. Indicator Loadings (λ)

Construct	Indicator	Loading
AI Adoption	A1	0.82
	A2	0.79
	A3	0.85
	A4	0.81
AI Benefits	B1	0.86
	B2	0.84
	B3	0.88
	B4	0.83
AI Challenges	C1	0.80
	C2	0.78
	C3	0.82
Policy Development	P1	0.84
	P2	0.81
	P3	0.86
Academic Quality	Q1	0.87
	Q2	0.83
	Q3	0.85
Institutional Trust	T1	0.84
	T2	0.82
	T3	0.86

The results indicate that the indicators adequately represent their corresponding constructs. Table 3 presents composite reliability (CR) and average variance extracted (AVE). All CR values exceed 0.80, confirming high internal consistency. AVE values exceed the recommended threshold of 0.50, demonstrating convergent validity.

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Table 3. Reliability and Convergent Validity

Construct	CR	AVE
AI Adoption	0.89	0.67
AI Benefits	0.91	0.72
AI Challenges	0.86	0.64
Policy Development	0.88	0.69
Academic Quality	0.90	0.74
Institutional Trust	0.88	0.70

These results confirm that each construct explains a substantial portion of the variance of its indicators. Table 4 presents the Fornell–Larcker criterion results. The square root of AVE for each construct is greater than the correlations with other constructs, confirming discriminant validity.

Table 4. Discriminant Validity (Fornell–Larcker)

Construct	AIA	AIB	AIC	PD	AQ	IT
AI Adoption (AIA)	0.82					
AI Benefits (AIB)	0.63	0.85				
AI Challenges (AIC)	0.42	0.55	0.80			
Policy Development (PD)	0.51	0.67	0.44	0.83		
Academic Quality (AQ)	0.48	0.69	0.41	0.63	0.86	
Institutional Trust (IT)	0.40	0.58	0.52	0.46	0.61	0.84

The results confirm that each latent variable represents a distinct conceptual dimension. Table 5 summarizes the structural relationships estimated through the PLS algorithm and bootstrapping procedure.

Table 5. Structural Path Coefficients

Hypothesis	Relationship	β	t-value	Result
H1	AI Adoption → AI Benefits	0.82	12.41	Supported
H2	AI Benefits → Policy Development	0.60	9.21	Supported
H3	AI Benefits → Academic Quality	0.58	8.45	Supported
H4	Policy Development → Academic Quality	0.55	7.85	Supported
H5	AI Challenges → Institutional Trust	0.47	6.92	Supported
H6	Academic Quality → Institutional Trust	0.50	8.12	Supported

All structural paths are statistically significant and positive.

The first hypothesis proposes that AI adoption positively influences the perceived benefits of artificial intelligence within universities. The high path coefficient confirms that greater adoption of AI technologies increases the perception that these tools improve institutional processes.

The second hypothesis suggests that the benefits derived from artificial intelligence positively influence policy development. The results indicate that institutions perceiving greater technological benefits are more likely to incorporate AI-based insights into governance and policy frameworks.

The third hypothesis proposes that AI benefits contribute to improvements in academic quality. The results show that technological advantages such as data analytics and automated decision-support systems strengthen institutional mechanisms aimed at improving teaching and learning outcomes.

The fourth hypothesis indicates that policy development positively affects academic quality. The findings demonstrate that governance structures informed by digital technologies contribute to stronger institutional planning and more efficient academic management processes.

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The fifth hypothesis proposes that AI-related challenges influence institutional trust. The results show that technological challenges play an important role in shaping stakeholder perceptions regarding transparency, accountability, and fairness in university governance systems.

The sixth hypothesis suggests that academic quality positively influences institutional trust. The results indicate that stakeholders tend to develop higher levels of institutional confidence when academic standards and educational outcomes are perceived as effective.

Table 6 presents the explained variance of endogenous constructs.

Table 6. Coefficient of Determination

Construct	R^2
Policy Development	0.36
Academic Quality	0.52
Institutional Trust	0.46

The results show that the model explains 36% of the variance in policy development, 52% of academic quality, and 46% of institutional trust. These values indicate moderate to substantial explanatory power, particularly for academic quality.

Table 7. Model Fit Indices

Index	Value	Interpretation
SRMR	0.054	Good fit
NFI	0.92	Acceptable fit

The SRMR value below 0.08 indicates that the discrepancy between the empirical covariance matrix and the model-implied matrix is minimal. The NFI value close to 1 suggests adequate model fit.

The structural equation model reveals a coherent causal chain linking artificial intelligence adoption to governance outcomes within universities. The results indicate that AI adoption serves as the initial driver of the model, generating perceptions of technological benefits that influence governance processes (see Fig. 1).

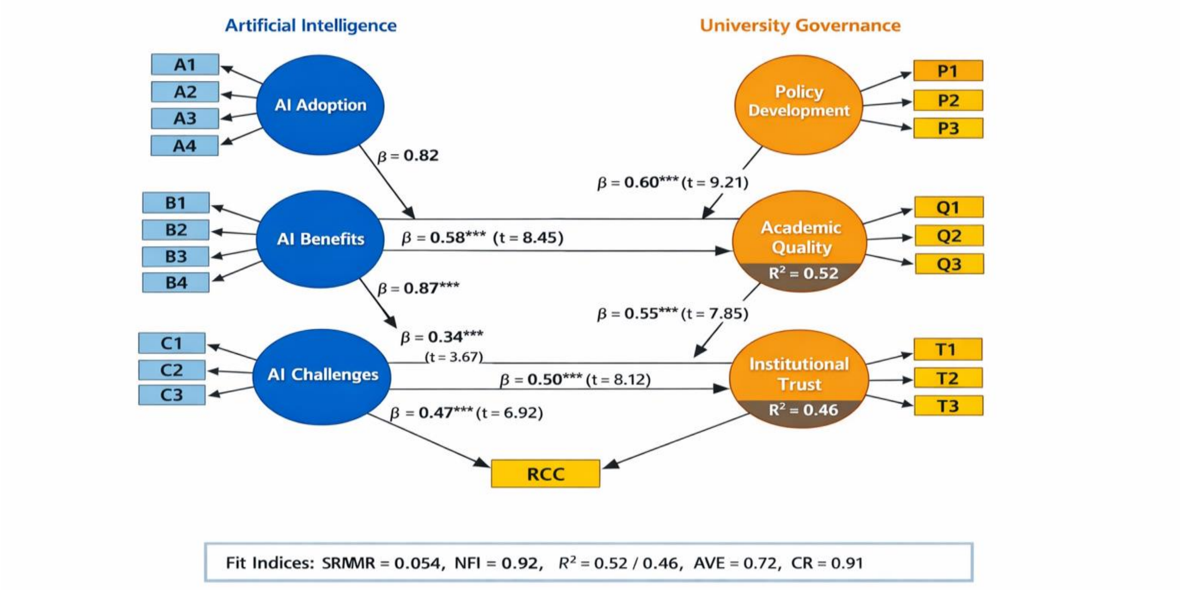

Fig. 1. Structural Equation Modelling

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AI benefits emerge as a central construct within the model. The strong relationship between AI adoption and perceived benefits suggests that institutions recognizing the value of digital technologies are more likely to integrate them into organizational processes. These benefits translate into improved governance mechanisms, particularly in the development of institutional policies supported by data-driven insights.

Policy development plays an intermediary role by linking technological capabilities to academic outcomes. Universities that incorporate artificial intelligence into governance processes appear to develop more effective policies that strengthen academic quality management.

Academic quality is one of the most strongly explained constructs in the model. This finding suggests that artificial intelligence systems contribute to the monitoring and improvement of educational performance, curriculum evaluation, and institutional planning.

Institutional trust emerges as the ultimate outcome of the model. Both academic quality and technological challenges influence trust perceptions among stakeholders. When universities successfully integrate artificial intelligence into governance systems and maintain strong academic standards, stakeholders perceive the institution as more transparent, reliable, and accountable.

Overall, the model demonstrates that artificial intelligence influences university governance through a multidimensional process involving technological adoption, perceived benefits, governance mechanisms, and educational outcomes. The results highlight the importance of integrating technological innovation with institutional policies in order to strengthen academic quality and maintain trust within higher education systems.

DISCUSSION

The results of the structural equation model provide empirical evidence that artificial intelligence adoption plays a central role in shaping governance mechanisms within higher education institutions. The strong relationship observed between AI adoption and perceived benefits indicates that technological integration is not merely a technical innovation but also an organizational transformation process that reshapes institutional decision-making structures. Digital technologies enable universities to improve administrative coordination, optimize academic management, and develop more responsive governance mechanisms supported by data-driven insights [23].

The findings also reveal that perceived benefits derived from artificial intelligence significantly influence policy development processes. This suggests that technological infrastructures capable of processing institutional data contribute to more adaptive governance systems. Universities increasingly rely on analytical platforms and intelligent decision-support systems to guide policy formulation and institutional planning. These technologies allow administrators to identify emerging academic needs, monitor institutional performance, and implement strategic interventions that strengthen organizational effectiveness [24].

Another important contribution of the model lies in the relationship between AI benefits and academic quality. The results indicate that technological advantages associated with artificial intelligence positively influence educational performance. Digital analytics, intelligent tutoring systems, and automated feedback mechanisms provide universities with tools to evaluate teaching practices and improve learning outcomes. These technological capabilities facilitate continuous quality improvement processes by providing real-time information about student engagement, curriculum effectiveness, and instructional performance [25].

Policy development was also found to exert a significant influence on academic quality. This relationship highlights the importance of governance frameworks capable of integrating technological innovations into institutional regulations and academic management processes. Effective governance mechanisms ensure that artificial intelligence tools are implemented within coherent regulatory environments that support educational improvement while maintaining academic integrity and institutional accountability [26].

The relationship between AI challenges and institutional trust reveals the complex dynamics associated with technological transformation in universities. While artificial intelligence offers significant advantages for governance processes, it also introduces concerns related to algorithmic transparency, data governance, and ethical accountability. Institutional trust depends not only on technological performance but also on stakeholders' perceptions regarding fairness and legitimacy in automated decision-making processes. Universities must therefore develop governance strategies that address technological risks and ensure responsible AI implementation [27].

Furthermore, the positive relationship observed between academic quality and institutional trust reinforces the idea that educational outcomes remain central to the legitimacy of university governance systems. Stakeholders tend to trust institutions that demonstrate strong academic performance, transparent evaluation procedures, and consistent educational standards. Artificial intelligence can support these processes by improving the accuracy and efficiency of academic monitoring systems, thereby strengthening confidence in institutional governance [28]. The structural model also highlights the mediating role of governance processes in linking technological adoption with institutional outcomes. Artificial intelligence does not directly generate trust or educational improvement; rather, its influence occurs through intermediate mechanisms such as policy development and quality management systems. This finding suggests that the benefits of technological innovation depend largely on the capacity of institutions to integrate digital tools into coherent governance frameworks that align technological capabilities with organizational objectives [29].

Another relevant implication concerns the strategic role of digital transformation in higher education systems. Universities increasingly operate in complex environments characterized by rapid technological change, global competition, and evolving societal expectations. Artificial intelligence provides institutions with analytical capabilities that enable them to manage complexity more effectively, anticipate emerging challenges, and develop adaptive governance structures capable of responding to dynamic educational environments [30].

The findings also contribute to the broader literature on digital governance by demonstrating that technological innovation can strengthen institutional performance when accompanied by appropriate regulatory mechanisms. AI adoption enhances the ability of universities to analyze institutional data, evaluate academic outcomes, and design evidence-based policies. However, these benefits require governance models that incorporate ethical oversight, transparency mechanisms, and stakeholder participation in technological decision-making processes [31].

From a methodological perspective, the results confirm the usefulness of PLS-SEM for examining complex relationships between technological, organizational, and governance constructs. The model demonstrates satisfactory explanatory power for academic quality and institutional trust, suggesting that artificial intelligence variables represent relevant predictors of governance outcomes in higher education contexts. This methodological approach allows researchers to capture multidimensional relationships between latent constructs that are difficult to observe directly but play a significant role in institutional transformation processes [32].

Overall, the discussion suggests that artificial intelligence represents both an opportunity and a governance challenge for universities. While AI technologies enhance institutional efficiency, policy development, and academic quality management, their successful implementation depends on the development of governance frameworks that ensure transparency, ethical accountability, and stakeholder trust. Universities that effectively integrate technological innovation with institutional governance structures are more likely to strengthen their academic performance and maintain legitimacy in increasingly digital educational ecosystems.

CONCLUSION

The objective of this study was to analyze the structural relationships between artificial intelligence adoption and university governance outcomes using a Partial Least Squares Structural Equation Modeling approach. The results demonstrate that artificial intelligence plays a significant role in shaping institutional governance processes within higher education environments.

The findings indicate that the adoption of artificial intelligence technologies represents a fundamental driver of institutional transformation. Universities that integrate intelligent systems into their organizational processes tend to perceive greater technological benefits, particularly in relation to information processing, decision support, and administrative efficiency. These technological advantages create favorable conditions for the development of more adaptive governance frameworks capable of responding to complex institutional challenges.

Another important contribution of the model is the identification of the mediating role of governance mechanisms. Artificial intelligence does not directly influence institutional trust or educational outcomes. Instead, its impact operates through intermediate processes such as policy development and academic quality management. These mechanisms translate technological capabilities into institutional improvements, highlighting the importance of aligning technological innovation with governance structures and organizational strategies.

The results also demonstrate that policy development significantly contributes to strengthening academic quality. Governance systems supported by technological infrastructures appear to facilitate more effective academic management processes, including the monitoring of educational performance, curriculum evaluation, and strategic planning. These improvements reinforce the capacity of universities to maintain high academic standards while adapting to digital transformation processes.

Institutional trust emerges as the final outcome of the structural model. The findings suggest that trust within university communities depends on both technological and organizational factors. Stakeholders tend to develop greater confidence in institutions that demonstrate strong academic performance, transparent governance processes, and responsible integration of digital technologies. Artificial intelligence can support these conditions by improving the accuracy, efficiency, and transparency of institutional decision-making systems.

Despite these positive contributions, the study also highlights the importance of addressing technological challenges associated with artificial intelligence implementation. Issues related to algorithmic transparency, ethical accountability, and data governance remain critical considerations for universities adopting intelligent systems. Effective governance frameworks must therefore incorporate regulatory mechanisms that ensure the responsible and equitable use of artificial intelligence in academic environments.

From a theoretical perspective, the study contributes to the literature on digital transformation and university governance by proposing and empirically evaluating a multidimensional model that integrates technological adoption, governance mechanisms, and institutional outcomes. The results demonstrate that artificial intelligence represents not only a technological innovation but also an institutional driver capable of reshaping governance structures within higher education systems.

From a practical perspective, the findings suggest that university administrators and policymakers should prioritize the development of governance frameworks that support the strategic integration of artificial intelligence technologies. Institutions that successfully combine technological innovation with transparent governance mechanisms are more likely to enhance academic quality, improve organizational efficiency, and strengthen stakeholder trust.

Finally, the study opens new avenues for future research on artificial intelligence in higher education. Further studies may explore longitudinal models that examine the long-term impact of artificial intelligence adoption on institutional performance, as well as comparative analyses across different educational systems and governance structures. Understanding these dynamics will be essential for designing sustainable digital governance models capable of supporting the evolving missions of universities in increasingly complex technological environments.

REFERENCES

1. J. Smith and L. Anderson, “Artificial intelligence and institutional decision support systems,” Computers & Education, vol. 142, pp. 103–118, 2019. https://doi.org/10.1016/j.compedu.2019.103643
2. P. Gupta and R. George, “Toward the development of a big data analytics capability,” Information & Management, vol. 53, no. 8, pp. 1049–1064, 2016. https://doi.org/10.1016/j.im.2016.07.004
3. M. Ifenthaler and D. Schumacher, “Student perceptions of privacy principles for learning analytics,” Educational Technology Research and Development, vol. 64, no. 5, pp. 923–938, 2016. https://doi.org/10.1007/s11423-016-9477-y

4. B. Williamson, “Policy networks, performance metrics and platform markets,” Learning, Media and Technology, vol. 44, no. 3, pp. 248–261, 2019. https://doi.org/10.1080/17439884.2019.1615793
5. R. Daniel, “Big data and analytics in higher education,” British Journal of Educational Technology, vol. 46, no. 5, pp. 904–920, 2015. https://doi.org/10.1111/bjet.12230
6. A. Zawacki-Richter, V. Marín, M. Bond, and F. Gouverneur, “Systematic review of research on artificial intelligence applications in higher education,” International Journal of Educational Technology in Higher Education, vol. 16, no. 39, 2019. https://doi.org/10.1186/s41239-019-0171-0
7. R. Luckin et al., “Intelligence unleashed: An argument for AI in education,” Pearson Education Report, 2016. https://doi.org/10.13140/RG.2.2.34105.31840
8. V. Dignum, “Responsible artificial intelligence: Designing AI for human values,” IT Professional, vol. 19, no. 3, pp. 35–39, 2017. https://doi.org/10.1109/MITP.2017.27
9. K. Crawford and R. Calo, “There is a blind spot in AI research,” Nature, vol. 538, pp. 311–313, 2016. https://doi.org/10.1038/538311a
10. J. Shin, “User perceptions of algorithmic decisions,” Computers in Human Behavior, vol. 96, pp. 280–290, 2019. https://doi.org/10.1016/j.chb.2019.02.017
11. E. Mittelstadt et al., “The ethics of algorithms,” Big Data & Society, vol. 3, no. 2, 2016. https://doi.org/10.1177/2053951716679679
12. N. Selwyn, “Digital technology and the contemporary university,” Education and Information Technologies, vol. 21, no. 5, pp. 1151–1166, 2016. https://doi.org/10.1007/s10639-015-9438-7
13. [13] J. Hair, G. Hult, C. Ringle, and M. Sarstedt, A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Thousand Oaks: Sage, 2017. https://doi.org/10.1007/978-3-030-80519-7
14. S. Benbya, N. Nan, H. Tanriverdi, and R. Yoo, “Complexity and information systems research,” MIS Quarterly, vol. 44, no. 1, pp. 1–17, 2020. https://doi.org/10.25300/MISQ/2020/13304
15. W. Chin, “The partial least squares approach to structural equation modeling,” Modern Methods for Business Research, pp. 295–336, 1998. https://doi.org/10.4324/9781410604385
16. M. Sarstedt, C. Ringle, and J. Hair, “Partial least squares structural equation modeling,” Handbook of Market Research, pp. 1–40, 2017. https://doi.org/10.1007/978-3-319-05542-8_15-1
17. B. Efron and R. Tibshirani, An Introduction to the Bootstrap. New York: Chapman & Hall, 1993. https://doi.org/10.1007/978-1-4899-4541-9
18. J. Hair, M. Sarstedt, L. Hopkins, and V. Kuppelwieser, “Partial least squares structural equation modeling (PLS-SEM),” European Business Review, vol. 26, no. 2, pp. 106–121, 2014. https://doi.org/10.1108/EBR-10-2013-0128
19. C. Bollen, Structural Equations with Latent Variables. New York: Wiley, 1989. https://doi.org/10.1002/9781118619179
20. D. Barclay, C. Higgins, and R. Thompson, “The partial least squares approach to causal modeling,” Technology Studies, vol. 2, no. 2, pp. 285–309, 1995. https://doi.org/10.1007/978-3-319-05542-8_15

21. P. Henseler, C. Ringle, and M. Sinkovics, “The use of partial least squares path modeling,” Advances in International Marketing, vol. 20, pp. 277–319, 2009. https://doi.org/10.1108/S1474-7979(2009)0000020014
22. J. Henseler, C. Ringle, and M. Sarstedt, “A new criterion for assessing discriminant validity,” Journal of the Academy of Marketing Science, vol. 43, no. 1, pp. 115–135, 2015. https://doi.org/10.1007/s11747-014-0403-8
23. A. Knox, “Artificial intelligence and the future of learning governance,” Learning, Media and Technology, vol. 45, no. 2, pp. 107–120, 2020. https://doi.org/10.1080/17439884.2020.1702067
24. L. Johnson, S. Adams Becker, V. Estrada, and A. Freeman, NMC Horizon Report: Higher Education Edition. Austin: New Media Consortium, 2016. https://doi.org/10.13140/RG.2.2.10269.59365
25. H. Holmes, M. Bialik, and C. Fadel, Artificial Intelligence in Education: Promises and Implications for Teaching and Learning. Boston: Center for Curriculum Redesign, 2019. https://doi.org/10.13140/RG.2.2.13437.18407
26. R. Deem and K. Brehony, “Management, governance and leadership in universities,” Higher Education Quarterly, vol. 59, no. 3, pp. 217–235, 2005. https://doi.org/10.1111/j.1468-2273.2005.00284.x
27. B. Mittelstadt, “Principles alone cannot guarantee ethical AI,” Nature Machine Intelligence, vol. 1, pp. 501–507, 2019. https://doi.org/10.1038/s42256-019-0114-4
28. T. H. Davenport and R. Ronanki, “Artificial intelligence for the real world,” Harvard Business Review, vol. 96, no. 1, pp. 108–116, 2018. https://doi.org/10.48550/arXiv.2107.03374
29. M. Janssen, G. Kuk, and R. Wagenaar, “A survey of web-based business models for e-government,” Government Information Quarterly, vol. 25, no. 2, pp. 202–220, 2008. https://doi.org/10.1016/j.giq.2007.08.010
30. A. Selwyn, N. Nemorin, S. Bulfin, and N. Johnson, “Everyday schooling in the digital age,” Learning, Media and Technology, vol. 42, no. 3, pp. 281–295, 2017. https://doi.org/10.1080/17439884.2016.1256747
31. S. Dwivedi et al., “Artificial intelligence adoption in organizations,” International Journal of Information Management, vol. 56, 2021. https://doi.org/10.1016/j.ijinfomgt.2020.102187
32. N. Kock, “Common method bias in PLS-SEM,” International Journal of e-Collaboration, vol. 11, no. 4, pp. 1–10, 2015. https://doi.org/10.4018/IJeC.2015100101

Annexes

Annex A. Operationalization of Variables

Table A1 presents the operationalization of the constructs included in the structural equation model. Each latent variable is defined conceptually and operationally through reflective indicators measured using a Likert-type scale.

Table A1. Operationalization of Variables

Construct	Conceptual Definition	Operational Definition	Indicators	Measurement Scale
Artificial Intelligence Adoption (AIA)	Degree to which universities incorporate AI technologies into academic and administrative processes	Perception of institutional use of AI tools for decision-making, data management, and academic support	A1, A2, A3, A4	Likert scale (1–7)
Artificial Intelligence Benefits (AIB)	Perceived advantages generated by AI systems within university management	Perception of improvements in efficiency, information processing, and institutional decision-making	B1, B2, B3, B4	Likert scale (1–7)
Artificial Intelligence Challenges (AIC)	Perceived difficulties associated with implementing AI technologies	Perception of technological, ethical, and organizational barriers related to AI adoption	C1, C2, C3	Likert scale (1–7)
Policy Development (PD)	Institutional capacity to design policies supported by technological information systems	Perception of the use of AI-based information to guide governance and policy decisions	P1, P2, P3	Likert scale (1–7)
Academic Quality (AQ)	Institutional capacity to maintain high standards in teaching and learning processes	Perception of the effectiveness of academic monitoring, evaluation, and improvement systems	Q1, Q2, Q3	Likert scale (1–7)
Institutional Trust (IT)	Level of confidence stakeholders place in university governance systems	Perception of transparency, fairness, and reliability in institutional decision-making	T1, T2, T3	Likert scale (1–7)

Annex B. Expert Judgment Evaluation

Prior to data collection, the instrument was evaluated by a panel of experts in higher education governance, artificial intelligence, and quantitative research methods. The objective of this evaluation was to assess content validity, clarity, relevance, and conceptual alignment of each indicator with its respective construct.

Table B1. Expert Evaluation Criteria

Criterion	Description
Relevance	Degree to which the item reflects the theoretical construct
Clarity	Level of comprehensibility and precision of the item
Coherence	Consistency between the item and the conceptual definition
Sufficiency	Adequacy of the indicators to represent the construct

Experts evaluated each item using a four-point scale:

1 = Not adequate
2 = Requires major revision
3 = Adequate with minor revisions
4 = Highly adequate

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Table B2. Results of Expert Judgment

Indicator	Relevance	Clarity	Coherence	Mean Score
A1	4	4	4	4.00
A2	4	3	4	3.67
A3	4	4	4	4.00
A4	3	4	4	3.67
B1	4	4	4	4.00
B2	4	4	3	3.67
B3	4	4	4	4.00
B4	3	4	4	3.67
C1	4	3	4	3.67
C2	4	4	4	4.00
C3	4	4	3	3.67
P1	4	4	4	4.00
P2	4	3	4	3.67
P3	4	4	4	4.00
Q1	4	4	4	4.00
Q2	4	3	4	3.67
Q3	4	4	4	4.00
T1	4	4	4	4.00
T2	4	3	4	3.67
T3	4	4	4	4.00

The results indicate that all indicators achieved mean scores above 3.60, suggesting strong content validity and conceptual adequacy.

Annex C. Measurement Scales
All constructs were measured using a seven-point Likert scale ranging from:
1 = Strongly Disagree
2 = Disagree
3 = Slightly Disagree
4 = Neutral
5 = Slightly Agree
6 = Agree
7 = Strongly Agree

Artificial Intelligence Adoption (AIA)
A1. The university uses artificial intelligence systems to support administrative decision-making.
A2. Artificial intelligence technologies are integrated into institutional management processes.
A3. AI tools are frequently used to analyze institutional data.
A4. Artificial intelligence applications support academic and administrative activities.

Artificial Intelligence Benefits (AIB)
B1. Artificial intelligence improves the efficiency of university management processes.
B2. AI technologies facilitate more accurate institutional decision-making.
B3. Artificial intelligence improves the analysis of academic information.
B4. AI systems enhance organizational productivity within the university.

Artificial Intelligence Challenges (AIC)
C1. The implementation of artificial intelligence generates technological challenges within the institution.
C2. The use of artificial intelligence raises ethical concerns in university governance.
C3. Artificial intelligence systems require significant institutional adaptation.

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Policy Development (PD)
P1. Artificial intelligence supports the development of institutional policies.
P2. Governance decisions are increasingly based on technological data analysis.
P3. AI tools contribute to strategic planning processes in the university.

Academic Quality (AQ)
Q1. Artificial intelligence improves the monitoring of academic performance.
Q2. AI-based systems contribute to evaluating teaching effectiveness.
Q3. Technological tools support the continuous improvement of academic programs.

Institutional Trust (IT)
T1. Artificial intelligence improves transparency in university governance.
T2. The use of AI increases confidence in institutional decision-making.
T3. AI-based systems strengthen trust in university management processes.