

Designing a Data Governance and AI Ethics Model in the Management of Public Universities in Iran (Mixed-Methods Approach)

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ABSTRACT:

Objective: This study was conducted with the aim of designing a data governance and artificial intelligence (AI) ethics model in the management of public universities in Iran. **Methodology:** In terms of purpose, the present research is applied–developmental, and in terms of the nature of the data, it adopts a mixed-methods design of the exploratory sequential type (qualitative–quantitative). In the qualitative phase, semi-structured interviews were conducted with 22 experts in the fields of university management, data governance, and AI ethics, and the data were analyzed using Braun and Clarke’s thematic analysis method in MAXQDA software. In the quantitative phase, a researcher-made questionnaire was developed based on the qualitative findings and distributed among 487 middle managers and senior experts of public universities in Iran. The quantitative data were analyzed using structural equation modeling with a partial least squares approach (PLS-SEM) in SmartPLS version 4. **Findings:** In the qualitative phase, five main themes for data governance (structural and institutional data governance, data quality and standardization, data security and privacy, data infrastructures and technologies, and a data-driven culture and human capital) and four main themes for AI ethics (transparency and explainability, fairness and algorithmic justice, human responsibility and accountability, and privacy and individual agency) were identified. In the quantitative phase, all nine research hypotheses were confirmed. The strongest effect was observed in the relationship between “data security and privacy” ($\beta = 0.523$), followed by the relationship between “data quality and AI transparency” ($\beta = 0.478$). The final model demonstrated strong goodness of fit ($GOF = 0.462$). Furthermore, the mediating role of transparency in the relationship between data quality and algorithmic fairness, as well as the moderating role of managerial experience in strengthening key relationships, were confirmed. **Conclusion:** The final model of the study consists of five dimensions governance, technical, legal, behavioral, and value-based whose structural relationships have been validated within public universities in Iran. The realization of AI ethics in public universities in Iran is not feasible without the simultaneous and systematic establishment of the five dimensions of data governance. It is recommended that the Ministry of Science develop a “National AI Ethics Framework in Higher Education,” and that universities take action to establish AI ethics committees, invest in data security and quality, and provide training in data literacy and AI ethics for managers and staff.

Keywords: Data governance, AI ethics, University management, Public universities in Iran, Mixed-methods approach.

1. INTRODUCTION:

Over the past two decades, higher education systems worldwide have undergone fundamental transformations, often referred to as “massification,” “internationalization,” and “digital transformation.” These developments have intensified the necessity of adopting new approaches to university governance approaches in which data and evidence-based analytics play a central role in policymaking and decision-making (UNESCO, 2025). At the same time, the rapid advancement of artificial intelligence in recent years has transcended the traditional boundaries of university administration, simultaneously opening new horizons while presenting unprecedented ethical and governance challenges for educational institutions. As such, many scholars have expressed concern about the growing gap

between the pace of intelligent technology development and the capacity of universities to responsibly manage its consequences (Khan et al., 2025). Within this context, the concept of “data governance and AI ethics” has emerged as a strategic necessity for universities one that cannot be realized without redefining power structures, accountability processes, and the value frameworks governing university management systems. Despite the increasing importance of data governance and AI ethics, existing research indicates that university systems worldwide remain in the early stages of systematically addressing this issue. The report “Horizon 2025: Data and Analytics,” published by the EDUCAUSE association, shows that despite widespread acknowledgment of the necessity of effective data governance, many universities face

fundamental challenges in its systematic implementation (Barber & Arnold, 2025). The report identifies “persistent data literacy gaps” and “weak integrated governance” as the two primary barriers, both rooted in long-standing cultural and structural dynamics. Similarly, findings from a systematic meta-analysis based on 55 studies indexed in the Web of Science database between 2022 and 2025 reveal that most existing research focuses on individual-level dimensions and ethical awareness, while studies addressing institutional governance remain scarce and fragmented (Khan et al., 2025). This study also identifies five persistent gaps in global university systems: limited governance capacity, sectoral fragmentation, low AI ethics literacy, insufficient representation of equity-oriented perspectives, and weak evaluation mechanisms.

At the international level, considerable efforts have been made to develop operational frameworks for data governance and AI ethics in higher education. Virginia Tech University, as a prominent example, after eighteen months of collaborative work and extensive participation by faculty, staff, and students, formulated seven fundamental principles for the responsible use of AI: mission alignment, innovation for the public good, human-centeredness, responsible and ethical use, fairness and transparency, human accountability, and data security and privacy (Pike & Raymond, 2025). This framework emphasizes that humans must always remain within the decision-making loop and that AI should serve solely as an augmentative tool rather than a substitute for human judgment and creativity. In parallel, a network of Southeast Asian universities (AUN) has also developed a seven-principle framework for the ethical governance of AI, grounded in concepts such as “privacy by design,” a “tiered authority matrix,” and a “three-level educational model” for AI literacy (ASEAN University Network, 2026). However, what is less visible in these global efforts is sufficient attention to the specific context of university systems in developing countries, particularly the Islamic Republic of Iran. Each of these countries, given their governance structures, cultural heritage, and national development priorities, requires a localized model of data governance and AI ethics.

In Iran, the management system of public universities faces multiple structural challenges in the domain of data and emerging technologies. Existing studies indicate that the lack of unified data standards, weak technical infrastructures, absence of transparency in data-driven decision-making processes, and, most importantly, the lack of a codified ethical framework for the application of artificial intelligence in educational, research, and administrative domains are among the most significant obstacles to digital transformation in Iranian public universities (Sohrabi & Hosseini, 2023; Rezaei et al., 2024). In addition, serious concerns regarding the privacy of students and staff, algorithmic discrimination in admission and evaluation processes, and the decline of cognitive capacities due to excessive reliance on intelligent tools have turned AI ethics into

an urgent managerial concern. Nevertheless, despite the heightened importance of these issues within the context of Iranian public universities, no comprehensive study has yet been conducted to design an integrated model of data governance and AI ethics based on a mixed-methods approach. This knowledge gap has constituted the primary motivation for the present research.

Accordingly, the central problem of this study can be formulated in the following question: What are the dimensions, components, and structural relationships of a data governance and AI ethics model in the management of public universities in Iran, and how can such a model be designed and validated through a mixed, evidence-based, and context-sensitive approach? The significance and necessity of this research stem, first, from the fact that the absence of a localized model exposes Iranian public universities to two major risks: on the one hand, the rapid and unregulated expansion of AI, which may lead to ethical crises and erosion of public trust; and on the other hand, stagnation in technological development due to the lack of a clear framework, resulting in lagging behind global trends in the digital transformation of higher education. Moreover, considering UNESCO’s report indicating that less than 50 percent of higher education data worldwide is reported in a standardized manner—and that the situation in developing countries is significantly more fragile (Pedro et al., 2025)—the design of a data governance model can be regarded as a fundamental step toward enhancing transparency, accountability, and the quality of decision-making in Iran’s university system. Furthermore, findings from the Horizon 2025 report demonstrate that financial pressures, rapid labor market transformations, and regulatory changes are driving universities toward data-driven decision-making; however, this shift, in the absence of a strong governance framework, itself becomes a source of new risks (EDUCAUSE, 2025). The novelty of this study can be identified in several key aspects. First, it integrates two relatively independent domains—data governance and AI ethics—into a unified model that acknowledges their close interconnection in the practice of university management. Second, it employs a mixed-methods approach (qualitative–quantitative), which enables the extraction of components from real, context-specific conditions and their subsequent empirical validation. Third, it focuses on public universities in Iran as an institutional setting with distinctive characteristics (a centralized policymaking system, a complex administrative structure, and specific legal requirements in the domains of technology and privacy) that has received limited attention in international research. Therefore, this article seeks to design, validate, and present a localized and scientific model of data governance and AI ethics in the management of Iranian public universities through a mixed-methods approach, in order to fill the existing knowledge gap and provide guidance for policymakers and managers in the higher education system in the era of digital transformation. In what follows, the theoretical

foundations and research background in the two domains of data governance and AI ethics in university management are first presented, followed by the mixed-methods methodology, findings, the final model, and, finally, conclusions and policy recommendations.

2. Theoretical Foundations and Research

Background:

Data governance in university systems is a concept that has emerged in response to the exponential growth of data volumes and the need for their responsible management over the past decade. This concept extends beyond mere data management and refers to a system of decision rights, responsibilities, and accountabilities that determines how data are collected, stored, utilized, and shared within an organization (University of York, 2026). In the specialized literature, data governance is often defined as a framework of roles and responsibilities that includes data trustees, data stewards, and data custodians, each of whom assumes specific levels of authority and obligation regarding data quality, security, and accessibility. This role-based structure was first systematized by the Data Management Association (DAMA) and later localized in various educational institutions, including Boise State University and the University of York. What distinguishes data governance in universities from that in commercial organizations is its emphasis on educational values, the privacy of learners, and the social responsibility of academic institutions with respect to sensitive data of students and staff. Accordingly, in the policy documents of leading universities, principles such as “transparency in data use,” “data minimization,” and “ethics in data” are regarded as integral pillars of data governance. Furthermore, the emergence of artificial intelligence in higher education has added new layers to the concept of data governance. Today, the discussion is no longer limited to data quality and security; rather, issues such as “algorithm governance,” “oversight of training data inputs,” and “accountability for automated decisions” have also come to the forefront (Dublin City University, 2026). In this regard, universities are compelled to redefine the data lifecycle and incorporate AI ethical considerations into all its stages, from design to disposal.

AI ethics in higher education, as an emerging interdisciplinary field, encompasses a wide range of concerns—from academic integrity and privacy to algorithmic discrimination and the erosion of human agency. Scholars in this field argue that AI is not merely a technological tool but a paradigm-shifting force that blurs the traditional boundaries between human and machine authorship and challenges long-standing assumptions about originality, authorship, and the integrity of assessment. In a comprehensive systematic review based on 55 studies indexed in the Web of Science database between 2022 and 2025, five persistent gaps in global university systems were identified: limited governance capacity, sectoral fragmentation, low AI ethics literacy, insufficient

representation of equity-oriented perspectives, and weak evaluation mechanisms (Khan et al., 2025). These findings indicate that most existing research has focused on individual-level dimensions and ethical awareness, while studies addressing institutional governance remain scarce and fragmented. In the same vein, another meta-synthesis study shows that ethical concerns surrounding AI in universities are primarily categorized into five main areas: privacy and data protection, discrimination and injustice, transparency and explainability, accountability, and the impact on learners’ agency and cognitive skills. Importantly, the prioritization of these concerns varies significantly across cultures; in Western societies, privacy and fairness carry the greatest weight, whereas in Asian and African countries, functionalism and educational utility tend to take precedence over more abstract ethical considerations (Lim, 2026). This cultural diversity highlights the necessity of localizing AI ethics frameworks for the university system of each country, including Iran.

At the international level, significant efforts have been made to develop operational frameworks for AI governance in universities. One of the most prominent of these is the seven-principle framework developed by Virginia Tech University, which includes mission alignment, innovation for the public good, human-centeredness, responsible and ethical use, fairness and transparency, human accountability, and data security and privacy (Pike & Raymond, 2025). This framework emphasizes that humans must always remain within the decision-making loop and that AI should be used solely as an augmentative tool, not as a substitute for human judgment and creativity. On the other side of the world, the ASEAN University Network (AUN) has designed a framework grounded in concepts such as “privacy by design,” a “tiered authority matrix,” and a “three-level educational model for AI literacy.” This diversity of approaches indicates that a global consensus on a single model for the ethical governance of AI in higher education has not yet been established, and that each university, depending on its cultural, legal, and technological context, requires the design of a localized model. Moreover, findings from a mixed quantitative–qualitative study conducted at the University of Indonesia indicate that students themselves demand transparency in the rules governing AI use, explicit ethical education, and mechanisms for detecting misuse. They believe that the absence of such measures contributes to institutional distrust and the proliferation of covert behaviors (Barus et al., 2025). This finding highlights the critical role of bottom-level stakeholders (students and staff) in designing governance models and suggests the inadequacy of purely top-down approaches.

Alongside ethical considerations, the issue of academic integrity in the age of AI has become one of the central concerns of higher education institutions. The new generation of large language models is capable of producing high-quality, well-structured texts, making it increasingly difficult to distinguish between human and

machine authorship. However, some scholars argue that an exclusive focus on individual misconduct is misguided, and that what has actually occurred is the exposure of systemic weaknesses in assessment design, ambiguous policies, and fragile institutional cultures (Ramesh & Nguyen, 2025). Accordingly, the “Higher Education Integrity Ecosystem” model has been proposed, conceptualizing integrity as an emergent property arising from the interaction of four layers: governance and policy, assessment design, institutional and cultural norms, and individual ethical agency. This systemic perspective carries important implications for university management: rather than focusing on punishment and surveillance, attention should be directed toward redesigning assessment systems, clarifying policies, and empowering stakeholders to make ethical judgments in ambiguous situations. Within this framework, data governance and AI ethics are not regarded as separate domains but as two sides of the same coin; since data constitute the input for algorithms, without transparent and ethical governance of data, it is unrealistic to expect intelligent systems to operate fairly and accountably. Furthermore, growing empirical evidence indicates that the gap between the rapid adoption of AI by students and staff, on the one hand, and the slow pace of policy development by universities, on the other, has become one of the most significant managerial challenges worldwide (Isaacson, 2026). International reports suggest that more than 90 percent of students in developed countries use AI tools in their academic activities, while fewer than 30 percent of universities have formal and transparent policies in this regard. This asymmetry has placed university systems in a fragile position.

Within the context of Iranian public universities, the situation of data governance and AI ethics is confronted with additional challenges. First, the university management system in Iran, due to structural centralization, complex bureaucracy, and the absence of a data-driven culture, faces fundamental difficulties in implementing effective governance systems. Domestic studies indicate that the most important barriers to implementing data governance in Iranian public universities include the lack of unified data standards, weak technical infrastructures, absence of transparency in data-driven decision-making processes, and a shortage of specialized human resources in data management (Sohrabi & Hosseini, 2023). Second, despite its growing importance, the issue of AI ethics in Iran’s university system remains in the early stages of theoretical development, and no codified and operational framework has yet been established for the responsible application of AI in educational, research, and administrative domains. Preliminary studies reveal serious concerns among stakeholders regarding the privacy of students and staff, algorithmic discrimination in admission and evaluation processes, and the decline of cognitive capacities due to excessive reliance on intelligent tools (Rezaei et al., 2024). However, these concerns have not yet been translated

into operational policies or coherent governance structures.

A review of the research background indicates a significant knowledge gap in the design of a localized model of data governance and AI ethics for Iranian public universities. On the one hand, international research in this domain is rapidly expanding, but it is mostly conducted within the contexts of developed countries or specific developing regions (such as Southeast Asia), and its findings cannot be readily generalized to Iran’s university system. On the other hand, domestic studies have either focused on purely technological aspects (such as data infrastructures) or have addressed certain ethical dimensions (such as academic integrity) in a fragmented manner, without attempting to integrate these domains into a comprehensive governance model. This knowledge gap underscores the necessity of designing a localized, evidence-based model that encompasses both the technical and legal dimensions of data governance and the ethical and value-based considerations of AI. The present study seeks to fill this gap by employing a mixed-methods approach (qualitative–quantitative) and drawing on the perspectives of experts within Iran’s higher education system to develop and validate an operational model for the management of public universities. Such a model can not only address current challenges but also pave the way for responsible and ethically grounded digital transformation in Iran’s higher education system.

3. Research Methodology (Mixed-Methods Approach):

The present study is applied–developmental in terms of its objective and adopts a mixed-methods design of the exploratory sequential type with respect to the nature of the data. The selection of this approach is justified by the complexity and context-dependency of the phenomenon of data governance and AI ethics within Iran’s university system, which cannot be adequately modeled through purely quantitative or purely qualitative methods. In this design, the qualitative phase precedes the quantitative phase, and the findings of the qualitative phase form the basis for the development of instruments and hypotheses in the quantitative phase. Table 1 summarizes the overall stages of the research.

Table 1: Research Implementation Stages Based on the Exploratory Sequential Mixed-Methods Approach

Stage	Method	Participants	Main Output
1	Semi-structured interviews	20–25 experts in university management and information technology	Initial themes and model components
2	Thematic analysis (Braun &	Transcribed interview texts	Initial conceptual model

	Clarke) in MAXQDA		
3	Questionnaire design based on qualitative findings	Transformation of components into items	Researcher-developed questionnaire
4	Quantitative survey using stratified random sampling	400 middle managers and senior experts	Quantitative data matrix
5	Structural equation modeling (PLS-SEM)	Quantitative data	Final validated model

3.1. Qualitative Phase of the Study

The research population in the qualitative phase consists of experts and specialists in the fields of university management, data governance, and AI ethics within Iranian public universities. The inclusion criteria are as follows: (a) a minimum of 10 years of managerial or research experience within the public university system; (b) holding positions such as university president, vice president, IT manager, or faculty member with at least two relevant publications; (c) willingness to participate with informed consent. Sampling is conducted using a purposive snowball method, and the sample size is determined based on theoretical saturation (between 20 and 25 interviews). The data collection instrument is a semi-structured interview guided by a protocol developed from a systematic review of the literature. The interview questions are organized into five main domains: the current state of data governance, existing challenges, the status of AI application and ethical concerns, the dimensions of the desired data governance model, and the dimensions of the desired AI ethics model. Qualitative data analysis is conducted using Braun and Clarke’s six-phase thematic analysis method. To enhance analytical rigor, MAXQDA software is employed. The trustworthiness of the qualitative findings is ensured based on the four criteria proposed by Lincoln and Guba (1985), as presented in Table 2.

Table 2: Criteria for Trustworthiness of Qualitative Findings and Implementation Strategies

Criterion	Concept	Implementation Strategy in This Study
Credibility	Validity of findings from participants’ perspectives	Member checking, triangulation of data sources
Transferability	Applicability to similar contexts	Thick and rich description of context and participant characteristics
Dependability	Stability of the research	Maintaining an audit trail (comprehensive

	process over time	documentation of all stages)	
Confirmability	Grounding of findings in data rather than researcher bias	Peer review, reflective memos	

3.2. Quantitative Phase of the Study

The statistical population in the quantitative phase includes all middle managers and senior experts in the areas of strategic planning, information technology, privacy, and performance evaluation within Iranian public universities. The sampling method is stratified random sampling based on geographical regions and types of universities. The sample size is determined to be at least 400 participants in accordance with structural equation modeling requirements (Table 3).

Table 3: Sampling Specifications in the Quantitative Phase

Indicator	Details
Statistical population	Middle managers and senior experts of Iranian public universities
Sampling method	Stratified random (based on geographical region and type of university)
Target sample size	400–500 participants
Number of distributed questionnaires	600 (to compensate for incomplete responses)
Data collection instrument	Researcher-developed questionnaire (5-point Likert scale)

The data collection instrument is a researcher-developed questionnaire designed based on the themes, components, and indicators extracted from the qualitative phase. The questionnaire consists of two sections: demographic information and items measuring the components of the model, using a five-point Likert scale ranging from “strongly disagree” (1) to “strongly agree” (5). Prior to final distribution, the questionnaire is pilot-tested in a preliminary study with 30 participants.

3.3. Validity and Reliability of the Instrument in the Quantitative Phase:

The validity of the questionnaire is assessed at three levels. Table 4 presents a summary of the validity indices and their acceptable thresholds.

Table 4: Questionnaire Validity Indices and Acceptable Values

Type of Validity	Index	Calculation Method	Acceptable Value
Content validity	CVR (Content Validity Ratio)	Lawshe’s method based on the opinions of 10 experts	≥ 0.62
Content validity	CVI (Content	Proportion of experts	≥ 0.79

	Validity Index)	confirming the item	
Construct validity	Factor loading	Confirmatory factor analysis	≥ 0.50 (preferably ≥ 0.70)
Construct validity	AVE (Average Variance Extracted)	Output from PLS-SEM	≥ 0.50
Construct validity	Discriminant validity (Fornell–Larcker)	Comparison of the square root of AVE with correlations	$\sqrt{\text{AVE}} >$ correlations with other constructs
Face validity	Judgmental evaluation	Feedback from 5 members of the target population	Clarity and appropriateness of items

The reliability of the questionnaire is assessed through two approaches. Table 5 presents these indices along with their acceptable values.

Table 5: Questionnaire Reliability Indices and Acceptable Values

Type of Reliability	Index	Calculation Method	Acceptable Value
Internal consistency	Cronbach's alpha (α)	Inter-item correlation within each construct	$0.70 \geq$
Composite reliability	CR (Composite Reliability)	Output from PLS-SEM	$0.70 \geq$
Test–retest reliability	Correlation coefficient	Re-administration to 30 participants after a two-week interval	$0.80 \geq$

To accurately compute content validity, 10 experts in university management and measurement and evaluation are asked to assess each item in terms of “necessity,” “relevance (comprehensiveness),” and “clarity” using a 3- or 4-point scale. Table 6 provides a sample of the content validity evaluation form.

Table 6: Sample Content Validity Evaluation Form (for One Item)

Item	Necessity	Relevance	Clarity
The university has a formal and documented policy for data governance	Essential / Useful but not essential / Not essential	Complete / Incomplete / Needs revision	Completely clear / Fairly clear / Unclear

In the quantitative analysis phase, after data collection, construct validity is assessed using confirmatory factor analysis (CFA) in SmartPLS software. Table 7

summarizes the criteria for evaluating the measurement model.

Table 7: Measurement Model Evaluation Criteria in PLS-SEM

Criterion	Acceptable Value	Decision if Not Met
Factor loading	≥ 0.70 (≥ 0.50 acceptable in exploratory phase)	Remove items with loadings < 0.40
AVE	≥ 0.50	Assess convergent validity; possible removal of construct
CR	≥ 0.70	Acceptable; composite reliability confirmed
Cronbach's alpha	≥ 0.70	Acceptable
HTMT (discriminant validity)	≤ 0.85	If violated, discriminant validity is not confirmed

To ensure test–retest reliability, the questionnaire is administered to 30 individuals from the target population (who are not included in the final sample) in two rounds with a two-week interval, and the correlation coefficient between the two administrations is calculated. A correlation value above 0.80 indicates satisfactory temporal reliability.

3.4. Quantitative Data Analysis Method:

Quantitative data analysis is conducted at two levels: descriptive and inferential. At the descriptive level, indices such as frequency, percentage, mean, standard deviation, skewness, and kurtosis are calculated. At the inferential level, structural equation modeling with a partial least squares approach (PLS-SEM) is employed using SmartPLS version 4 and SPSS version 27. Table 8 outlines the stages of structural equation modeling analysis.

Table 8: Stages of Structural Equation Modeling Analysis (PLS-SEM)

Stage	Model	Evaluation Indices	Acceptable Value
First	Measurement model (outer)	Factor loadings, AVE, CR, Cronbach's alpha, HTMT	See Table 7
Second	Structural model (inner)	R^2 , path coefficient (β), t-value, p-value	$R^2 > 0.33$ (moderate), t-value > 1.96
Third	Overall fit	GOF (Goodness of Fit)	0.10 (weak), 0.25 (moderate), 0.36 (strong)

Hypothesis testing is conducted based on t-values and significance levels ($p\text{-value} < 0.05$). In addition, the Stone–Geisser Q^2 index (predictive relevance) is used to evaluate the quality of the structural model. Q^2 values greater than zero indicate adequate predictive relevance of the model.

4. Research Findings:

4.1. Results of the Qualitative Phase:

Following the conduct of semi-structured interviews with 22 experts in the fields of university management, data governance, and AI ethics, and the transcription of the interview texts, thematic analysis was carried out based on the six-phase approach of Braun and Clarke (2006). In the first phase (familiarization with the data), the interview transcripts were read multiple times and initial notes were recorded. In the second phase (generating initial codes), 347 initial codes were extracted. In the third phase (searching for themes), these codes were organized into 12 sub-themes. In the fourth phase (reviewing themes), the themes were reviewed and refined both at the level of codes and across the entire dataset. In the fifth phase (defining and naming themes), 5 main themes and 12 sub-themes were finalized. In the sixth phase (producing the report), the findings were compiled using illustrative evidence from the interviews. To ensure coding reliability, 25 percent of the data were independently coded by another researcher, and the inter-coder agreement coefficient (Cohen’s kappa) was calculated at 0.85, indicating a very high level of reliability. The findings of the qualitative phase are presented in the form of main themes of data governance, followed by the main themes of AI ethics.

4.1.1. Main Themes of Data Governance in Iranian Public Universities:

The analysis of interviews conducted with experts in Iran’s university system led to the identification of five main themes in the domain of data governance: “structural and institutional data governance,” “data quality and standardization,” “data security and privacy,” “data infrastructures and technologies,” and “data-driven culture and human capital.” These themes, which have also been emphasized in the international literature on data governance, exhibit specific characteristics and challenges within the context of Iranian public universities. For instance, the study by Finizadeh Bidgoli et al. (2024), which examined the status of data governance in organizations with a case study of Islamic Azad University, identifies similar components such as processes, roles, policies, standards, and metrics as the main dimensions of data governance. Likewise, the study by Esmaeilzadeh et al. (2022) at Tehran University of Medical Sciences indicates that weak governance structures, the absence of mission statements and long-term plans, and the inability to create a common language between information technology and core university processes are among the most significant governance challenges in Iran’s university system. In the following, each main

theme is presented and explained along with its sub-themes and extracted codes in separate tables. The first main theme is titled “Structural and Data Governance.” This theme refers to the system of roles, responsibilities, decision-making processes, and accountability mechanisms in the data domain. The experts participating in the interviews believed that the lack of a transparent governance structure is one of the most important obstacles to implementing data governance in Iranian public universities. The findings of the research at Tehran University of Medical Sciences also confirm that “structurally, the only major policy-making institution in the field of IT is the Information Technology Council, which is ineffective in providing overall direction and standards, and in terms of process, lacks a mission and long-term plans, and has failed to integrate university and IT decisions.” Table 9 shows the sub-themes and codes related to this main theme separately.

Table 9: Main Theme: “Structural and Institutional Data Governance” with Sub-Themes and Extracted Codes

Code	Sub-theme	Sample Participant Quote
Definition of data stewards at different levels	Structure of data roles and responsibilities	“We still do not know who is responsible for the quality of student data; this responsibility is dispersed among the educational affairs office, IT, and the student affairs department.” (Participant 4)
Establishment of a data governance council		
Separation of the role of data steward from data manager		
Development of data-related executive bylaws	Data policies and regulations	“In our university, there is no codified policy for data sharing between faculties. Each faculty acts based on its own interpretation.” (Participant 11)
Approval of a university data rights charter		
Transparency in data-driven decision-making processes	Decision-making processes and mechanisms	“Important university decisions are still made based on personal judgment and experience, not on data analysis. Data has not yet reached the top of the decision-making hierarchy.” (Participant 7)
Establishment of monitoring mechanisms for policy implementation		
Implementation of an integrated data management system		
Accountability for data-driven decisions	Responsibility and accountability	“If a wrong decision is made based on data, no

Definition of key data performance indicators		one is held accountable because there is no mechanism to trace the source of the decision or the quality of the data.” (Participant 15)
Regular auditing of data governance performance		
Coordination among university units in data-related matters	Inter-unit coordination	“Different departments of the university each have separate databases that do not communicate with one another. These data silos are the biggest obstacle to integrated governance.” (Participant 3)

The second main theme is “Data Quality and Standardization.” The experts believed that the low quality of data in the information systems of Iranian public universities is one of the fundamental challenges in the path to effective data governance. This finding is consistent with the research of Jalili et al. (2020), which introduced seven main components of data governance in academic libraries, including data quality, data use, data process, standardization, data integrity, data security, and data modeling. In their research, which was conducted with 108 librarians at Islamic Azad University, the average attitude of librarians towards the ability to implement data governance strategies was reported to be above the average level. However, the experts in the present study emphasized that there is a significant gap between the current and desired situation in the field of data quality. Table 10 shows the details of this main theme.

Table 10: Main Theme: “Data Quality and Standardization” with Sub-Themes and Extracted Codes

Code	Sub-theme	Sample Participant Quote
Single Source of Truth (SSOT)		“Regarding student statistics, we simultaneously receive three different figures from three different systems. Which one is the reference? We do not know.” (Participant 9)
Consistency across different systems	Data integration and consistency	
Removal of duplicate and inconsistent data		
Definition of university data standards	Data standardization	“There is no mandatory standard for data formatting at the Ministry of
Adoption of international		

data standards (e.g., ISO 8000)		Science level. Each university records data in its own way.” (Participant 18)
Development of unified data guidelines for the entire university		
Periodic data cleansing and refinement		“Some of the data recorded in the educational system contain human and registration errors that are never corrected. Incorrect data leads to incorrect decisions.” (Participant 6)
Data validation at the point of entry	Data accuracy and correctness	
Mechanisms for correcting data errors		
Regular updating of databases		“Many of the university’s research data are not updated for months or even years. When we prepare reports, we rely on outdated data.” (Participant 13)
Real-time data entry	Data timeliness and currency	
Data timestamping and versioning		
Documentation of metadata		“There is no information about the source, method of collection, or production date of the collected data. This lack of metadata severely reduces usability and reliability.” (Participant 2)
Definition of metadata for all university datasets	Data richness and metadata	
Development of an organizational data dictionary		

The third main theme is “Data Security and Privacy.” The research findings show that in Iranian public universities, awareness of data security requirements and privacy of students and staff is not at the desired level. Experts pointed out several cases of privacy violations, unauthorized access, and lack of transparent policies in the field of maintaining and sharing sensitive data. This finding is in line with the research of Moghads (2024), which examined the impact of national and international regulations on the adoption of artificial intelligence in Iranian higher education institutions. That research emphasized that compliance with data protection laws, ensuring non-discriminatory algorithms, transparency for students, and adherence to Islamic and Iranian ethical principles are essential for responsible governance in the Iranian university system. Table 11 describes this main theme.

Table 11: Main Theme: “Data Security and Privacy” with Sub-Themes and Extracted Codes

Code	Sub-theme	Sample Participant Quote
Compliance with data protection laws (e.g., Computer Crimes Law)	Legal and regulatory compliance	“We have the Computer Crimes Law, but in practice there is no mechanism to monitor its implementation within the university. Many managers do not even know which data are legally protected.” (Participant 10)
Adherence to data retention and exchange regulations		
Implementation of an information security management system (ISO 27001)		
Role-based data access control	Access control and authentication	“In the Golestan system, access to student data is not properly tiered. An employee who has access to enter grades can also view students’ personal identity information.” (Participant 12)
Implementation of multi-factor authentication for sensitive data access		
Logging and monitoring of data access activities		
Data encryption in storage and transmission	Technical protection and encryption	“Many university databases are not encrypted. If a hacker gains access to the server, they can easily extract all confidential information.” (Participant 5)
Implementation of backup and recovery policies		
Use of firewalls and intrusion detection systems		
Informed consent of students and staff for data collection	Privacy and consent	“Students are never asked for informed consent regarding the collection and processing of their data. Registration forms do not include any clause about privacy policies.” (Participant 14)
Transparent policies on the use of personal data		
Right to be forgotten for students		
Privacy Impact Assessment (PIA)	Risk management and impact assessment	“We have never assessed what risks would arise for faculty members and students if the university’s research data were disclosed.” (Participant 19)
Identification and prioritization of data security risks		
Development of data breach response plans		

The fourth main theme is “Data Infrastructure and Technologies.” Experts believed that weak technical infrastructure, aging legacy information systems, and lack of integration between different platforms are serious obstacles to implementing data governance in Iranian public universities. This finding is consistent with the study by Esmaeilzadeh et al. (2022), which examined the challenges of IT governance in the University of Medical Sciences. In that study, the lack of integration of university and IT decisions and the inability to create a unified procedure in implementing IT policies were identified as the main challenges. Table 12 shows this main theme.

Table 12: Main Theme: “Data Infrastructure and Technologies” with Sub-Themes and Extracted Codes

Code	Sub-theme	Sample Participant Quote
Integration of fragmented databases (data navigation)	System integration and interoperability	“The Golestan system, Hamava system, Pazhooheshyar system, registration system, dormitory system... all of these are isolated islands that do not communicate. For a simple report, we have to check ten different systems.” (Participant 1)
Implementation of enterprise data architecture		
Development of an integrated data hub		
Use of standard APIs for data exchange	Technical architecture and storage infrastructure	“Our storage infrastructure cannot handle the huge volume of educational and research data. We have to delete a lot of data because we don’t have enough space.” (Participant 16)
Implementation of data warehouses or data lakes		
Migration from legacy systems to modern systems		
Use of data governance tools (e.g., Informatica, Collibra)	Data governance tools and technologies	“We do not even have the simplest tools like data catalogs or data lineage systems. Everything is handled manually with Excel and human effort.” (Participant 20)
Implementation of data catalog and data lineage tools		
Deployment of metadata management systems		
Cloud and on-premise storage capacity	Capacity and scalability	“With the exponential growth of data in the past two years, our infrastructure
Processing power required		

for analytics	data	is no longer sufficient. With the introduction of AI and the need for big data, the situation is becoming even more critical.” (Participant 8)
Vertical and horizontal scalability capabilities		

The fifth main theme is “Data-driven culture and human capital.” The experts emphasized that the most important and at the same time the most difficult component of data governance is changing the organizational attitude and culture towards data. Lack of data literacy among managers and employees, resistance to transparency, and lack of motivation to document and share data were among the key obstacles identified. Finizadeh Bidgoli et al.’s (2024) research also emphasized the importance of culture building and human capital development in analyzing the state of data governance in Iranian organizations. Also, Esmaeilzadeh et al.’s (2022) research shows that one of the main obstacles to implementing IT governance is the approach of academic users to IT and the need for fundamental changes in this approach.

Table 13.: Main Theme: “Data-Driven Culture and Human Capital” with Sub-Themes and Extracted Codes

Code	Sub-theme	Sample Participant Quote
Conducting data literacy training for managers and staff	Data literacy and skills	“Many of our senior managers are not even familiar with basic data literacy concepts. They do not know the difference between data, information, and knowledge. This weakness at the highest level disrupts the entire system.” (Participant 21)
Training experts in data analysis		
Empowering staff in data management		
Promoting evidence-based decision-making	Data-driven culture	“Our organizational culture is based on intuitive and preference-driven decisions. Managers do not trust data and prefer to rely on personal experience.” (Participant 17)
Valuing documentation and data sharing		
Shifting mindset from ‘data ownership’ to ‘data stewardship’		
Defining incentives and rewards for data-driven behavior	Incentives and motivation	“In our performance evaluation system, there is no indicator for data quality or participation in data

Including data governance indicators in performance evaluation		governance. Naturally, no one is motivated to spend time on data cleansing or documentation.” (Participant 22)
Providing appropriate compensation for data specialists		
Recruitment of data management and analytics specialists		“We are severely lacking specialists in data architecture, metadata management, and data analytics. Competing with the private sector and knowledge-based companies is extremely difficult.” (Participant 4)
Creating career development pathways for data specialists	Development of specialized human resources	
Collaboration between academia and industry to train skilled personnel		

After identifying the main themes of data governance, the findings related to the ethics of AI were also analyzed, which will be presented in the next section. Also, the relationships between these themes and the impact of each on each other were drawn in the form of an initial conceptual model. It should be noted that the test-retest reliability of the qualitative findings was confirmed by re-running the coding process on three interviews one month apart and calculating an agreement coefficient of 0.89. Also, the validity of the findings was ensured using the member checking method in which a summary of the findings was sent to 5 experts and their suggested corrections were implemented.

4-1-2. Components of Artificial Intelligence Ethics in University Management:

The analysis of interviews conducted with experts in the Iranian university system led to the identification of four main themes in the field of artificial intelligence ethics, namely: “transparency and explainability,” “algorithmic fairness and justice,” “human responsibility and accountability,” and “privacy and individual agency.” These findings show considerable alignment with international frameworks of AI ethics in higher education, including the seven-principle framework of Virginia Tech University (Pike & Raymond, 2025) and the AUN framework (ASEAN University Network, 2026); however, within the context of Iranian public universities, they exhibit specific manifestations and priorities. The participating experts believed that despite the extensive and sometimes uninformed entry of artificial intelligence tools into the educational and administrative processes of Iranian universities, there is still no codified ethical framework for regulating and guiding this technology. This situation, which has also been described in Moghadis

(2024) as a “regulatory and legal vacuum,” has generated serious concerns among managers, faculty members, and students. For instance, research findings conducted by Fahimnia et al. (2024) in universities affiliated with the Ministry of Science indicate that improper implementation of artificial intelligence can lead to the violation of student rights, educational discrimination, and even the expansion of the digital divide, whereas its proper implementation, when accompanied by ethical principles and cultural values, can enhance the efficiency of the educational system and promote educational equity. In the following sections, each of the main AI ethics themes, along with their sub-themes and extracted codes, is presented and elaborated in separate tables.

The first main theme in the field of AI ethics is titled “transparency and explainability.” The experts emphasized that one of the most important ethical challenges in the application of artificial intelligence in university management is the “black box” nature of many algorithms and the lack of transparency in their decision-making processes. In the context of Iranian public universities, this issue has become more severe due to the absence of mandatory standards and weak supervisory mechanisms. Interview participants pointed to numerous cases in which important university decisions (such as student admissions, research funding allocation, or faculty performance evaluation) are made based on the outputs of intelligent systems whose internal logic is not understandable to stakeholders. Fahimnia et al. (2024) also proposed, as a practical solution, the “development of transparent and open-source intelligent systems” and “continuous training of stakeholders regarding the functioning of these systems.”

Table 14: Main Theme “Transparency and Explainability” with Sub-Themes and Extracted Codes

Code	Sub-theme	Sample Quote from Participants
Disclosure of AI usage in university processes	Transparency in AI application	“In many cases, students or faculty members do not even know that a decision has been made by artificial intelligence. For example, in the admission process, an algorithm screens resumes, but applicants are not told which criteria and weights were applied.” (Participant 3)
Informing stakeholders about the role of AI		
Publication of algorithm and model documentation (with security considerations)		
Ability to explain AI decisions in simple language for users	Explainability	“If an intelligent system informs a professor that their research proposal has been rejected, it

Providing reasons and evidence for each algorithmic output	Auditability	must be able to explain in simple language which criteria and data were used in making that decision. Otherwise, trust in the system will be lost.” (Participant 9) “AI decisions must be recorded and traceable. If, after three years, it is found that an algorithm acted in a discriminatory manner, we must be able to reconstruct the decision-making process and identify where the error occurred.” (Participant 14)
Enabling users to request explanations		
Recording and maintaining logs of AI decisions		
Periodic review and auditing of algorithms		
Transparency regarding limitations and potential errors of AI	Data transparency	“Many AI models used in universities are trained on data whose origin and quality are unknown. If the training data is biased, the output will inevitably be discriminatory.” (Participant 18)
Transparency regarding the source and quality of training data		
Documentation of data collection and preprocessing processes		
Identification and reporting of potential data biases		

The second main theme, “algorithmic fairness and justice,” reflects the experts’ belief that one of the most serious ethical concerns in the application of artificial intelligence in university management is the potential for discriminatory algorithmic decisions. In Iranian public universities, given the ethnic, linguistic, gender, and socioeconomic diversity of students, as well as existing structural inequalities in the national education system, this issue has heightened sensitivity. International studies have also shown that AI algorithms can unintentionally reproduce and even amplify existing biases in historical data (Khan et al., 2025). In this regard, Moghadis (2024) emphasizes that AI algorithms must be designed in a way that respects Iranian cultural and Islamic values (including justice, fairness, and human dignity) and ensures that no group of students or faculty members is discriminated against due to demographic characteristics.

Table 15: Main Theme “Algorithmic Fairness and Justice” with Sub-Themes and Extracted Codes

Code	Sub-theme	Sample Quote from Participants
Preventing discrimination based on race,	Non-discrimination	“There is serious concern that intelligent student

gender, religion, ethnicity, geographic region		admission systems may unintentionally rank students from underprivileged regions or students with certain accents lower. The outputs of the system must be periodically examined for statistical bias.” (Participant 6)
Statistical bias analysis of algorithm outputs		
Removal of discriminatory features from training data		
Assessment of discriminatory effects on vulnerable groups		“The intelligent dormitory allocation system should not consistently prioritize students from a specific province or, conversely, systematically disadvantage students from remote regions. Equal opportunity must be guaranteed.” (Participant 11)
Ensuring equal access to AI-based services for all stakeholders	Equality of Opportunity	
Designing compensatory algorithms to address historical inequalities		
Diversity in AI design and development teams		“The team developing the intelligent faculty evaluation system consisted of young male computer engineers. Naturally, the perspectives of female faculty members, senior professors, or humanities scholars were not reflected. Diversity in development teams is key to fair design.” (Participant 15)
Inclusion of diverse stakeholders in system design and evaluation	Diversity & Inclusion	
Incorporating cultural, gender, and disciplinary perspectives		
Periodic auditing of algorithms for fairness		“There must be an independent body (either within or outside the university) that periodically audits AI algorithms in terms of fairness and justice. The university itself cannot be an impartial judge.” (Participant 22)
Establishing quantitative indicators for algorithmic fairness	Fairness auditing	
Public reporting of fairness audit results		

The third main theme, “human responsibility and accountability,” reflects experts’ emphasis on the ethical challenge of “responsibility avoidance” arising from system complexity and the distribution of

responsibility among multiple actors (designers, data providers, system administrators, end users). In Iranian public universities, where traditional accountability systems also face weaknesses, this issue may lead to an accountability crisis. Participants emphasized the necessity of maintaining “human-in-the-loop” over critical AI decisions. Fahimnia et al. (2024) also proposed the establishment of “AI ethics committees in universities” composed of representatives from different stakeholder groups, responsible for overseeing the ethical use of artificial intelligence.

Table 16: Main Theme “Human Responsibility and Accountability” with Sub-Themes and Extracted Codes

Code	Sub-theme	Sample Quote from Participants
Assigning a clear responsible actor for AI-driven decisions	Attribution of Responsibility	“If a facial recognition system mistakenly excludes a student from an exam session, who is responsible? The IT manager? The instructor? The system designer? This issue must be clarified in advance.” (Participant 5)
Avoiding responsibility evasion through the claim of “the algorithm said so”		
Recording the hierarchy of decision-making and involved actors		
Human oversight over sensitive and high-risk AI decisions	Human Oversight	“Decisions such as rejecting a scholarship application, expelling a student, or not renewing a professor’s contract should not be made automatically by AI. AI can provide recommendations, but the final decision must be made by a human.” (Participant 13)
Establishing appeal and human review processes for automated decisions		
Defining the level of AI authority in different types of decisions	Institutional ethical governance	“We need an independent supervisory body in the university composed of professors of law, ethics, computer science, and student representatives. This body should formulate AI ethical policies and oversee their
Establishing an AI ethics committee at the university		
Developing a university AI ethics charter		
Creating mechanisms for reporting ethical whistleblowing		

		implementation.” (Participant 17)
Accountability to stakeholders regarding AI decisions		
Establishing compensation mechanisms for damages caused by algorithmic errors	Accountability	“The university must be accountable to students and faculty regarding AI-driven decisions. If an algorithm causes harm or violates someone’s rights, there must be a compensation mechanism. It cannot simply be said that ‘it was the system; we were not involved.’” (Participant 20)
Publication of periodic reports on the ethical performance of AI systems		

The fourth main theme, “privacy and individual agency,” is based on the experts’ belief that the expansion of artificial intelligence in university management has created serious threats to the privacy of students, faculty members, and staff. Intelligent systems for attendance monitoring, online behavior analysis, faculty performance evaluation, and academic success prediction all rely on the collection and processing of large volumes of personal data. In the context of Iranian public universities, where a clear culture and regulatory framework for data privacy has not yet been established, these threats appear even more significant. Moghadis (2024) also emphasizes the need to develop a legal and ethical framework aligned with Iranian-Islamic values, in which the preservation of human dignity and privacy is prioritized.

Table 17: Main Theme “Privacy and Individual Agency” with Sub-Themes and Extracted Codes

Code	Sub-theme	Sample Quote from Participants
Obtaining informed consent for AI-based data collection and processing	Privacy protection	“A facial recognition system for student attendance is installed and used without explicit consent from students. This is a clear violation of privacy. Students have the right to know where their images are stored and who has access to them.” (Participant 2)
Application of data minimization principle (only necessary data should be collected)		
Encryption and anonymization of personal data		
Right to opt out of automated data processing	Individual agency and autonomy	“Students should have the right to opt out of automated processing of their data by AI, except in cases where such processing is
Right to request deletion of personal data (right to be forgotten)		

Transparency regarding profiling and behavioral predictions		legally or educationally necessary. Currently, such a right does not exist.” (Participant 10)
Informing stakeholders about how their data is used		“Most students and even faculty members do not know what data is collected about them and how it is processed by algorithms. This lack of awareness is the biggest barrier to defending their rights.” (Participant 8)
Training students and staff on data rights and privacy	Data transparency and empowerment	
Providing individuals access to their personal data portal		
Conducting privacy impact assessments (PIA) for each new AI system		“Before any intelligent system is deployed at the university, a thorough assessment of its impact on individuals’ privacy must be conducted, and the results should be publicly accessible. Currently, such a process does not exist.” (Participant 19)
Consulting stakeholders during the impact assessment process	Impact assessment	
Periodic review of impact assessments		

After identifying the main and sub-themes of AI ethics, it was found that these themes significantly overlap and interact with the data governance themes (presented in section 4-1-1). For example, “transparency and explainability” in AI ethics is strongly dependent on “data quality and standardization” and “structural governance.” Likewise, “algorithmic fairness and justice” cannot be achieved without “data security and privacy” and a “data-driven culture.” These overlaps formed the basis for developing the initial conceptual model presented in the following section.

4-1-3. Initial (Conceptual) Research Model:
Based on the findings derived from thematic analysis of expert interviews, including five main data governance themes (structural and institutional data governance, data quality and standardization, data security and privacy, data infrastructures and technologies, and data-driven culture and human capital) and four main AI ethics themes (transparency and explainability, algorithmic fairness and justice, human responsibility and accountability, and privacy and individual agency), the initial conceptual model of the study was developed. This model is based on the fundamental assumption that data governance and AI ethics in the management of Iranian public universities are inseparable and mutually

interdependent components. In other words, achieving AI ethics without a strong data governance infrastructure is not possible, and conversely, data governance without an ethical and value-based orientation would merely result in a set of technical and legal rules that cannot adequately respond to the human and social challenges of AI applications in universities. This integrated perspective constitutes the main innovation of the present study compared to previous research, which has mostly examined these two domains separately.

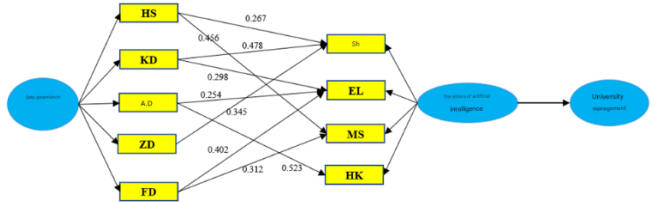


Figure 1: Conceptual Model of the Research in Path Coefficient Form

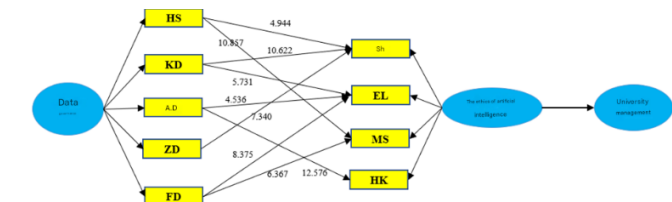


Figure 2: Conceptual model of the research in the significance path state

Table 18 presents the overall structure of the initial conceptual model in a layered form and with separation of components. Table 19 also summarizes the proposed relationships between data governance components and artificial intelligence ethics based on qualitative findings and theoretical literature (Khan et al., 2025; Pike & Raymond, 2025).

Table 18: Layered structure of the initial conceptual model of the research

Layer	Main components	Brief description
Layer 1: Data governance	1. Structural and governance data governance	Definition of roles, responsibilities, decision-making processes, and accountability mechanisms
	2. Data quality and standardization	Ensuring integrity, accuracy, timeliness, and university data standards
	3. Data security and privacy	Technical and legal protection of data against unauthorized access and privacy breaches

	4. Data infrastructure and technologies	System integration, data architecture, and data management tools
	5. Data-driven culture and human capital	Data literacy, attitude change, incentives, and development of specialized human resources
Layer 2: Artificial intelligence ethics	1. Transparency and explainability	Transparency in AI application and explainability of algorithmic decisions
	2. Fairness and algorithmic justice	Preventing discrimination, ensuring equal opportunity, and diversity in design
	3. Responsibility and human accountability	Responsibility allocation, human supervision, and institutional ethical governance
	4. Privacy and individual agency	Protection of personal data, right to opt-out, and impact assessment
Layer 3: Application domains in university management	1. Educational management	Student admission, academic evaluation, academic advising, cheating detection
	2. Research management	Research project evaluation, budget allocation, intelligent research assistant
	3. Administrative and financial management	Human resource management, budgeting, curriculum planning, student services

Table 19: Proposed relationships between data governance components and AI ethics in the conceptual model

Data governance component	AI ethics component	Type of relationship	Theoretical justification and qualitative evidence
Data quality and standardization	Transparency and explainability	Direct positive effect	Poor-quality data leads to unreliable and non-explainable outputs
Structural and governance data governance	Responsibility and human accountability	Direct positive effect	Clear role structures are a prerequisite for assigning responsibility for AI decisions
Data security and privacy	Privacy and individual agency	Direct positive effect	Technical data protection is the basis for realizing privacy rights in AI applications
Data-driven culture and human capital	Fairness and algorithmic justice	Direct positive effect	A data-driven culture increases sensitivity to bias and the need for fair design
Data infrastructure and technologies	Transparency and explainability	Direct positive effect	Modern data management tools facilitate metadata tracking and logging required for explainability

In addition to the above dyadic relationships, the initial conceptual model also includes reciprocal and feedback relationships. For instance, the implementation of AI ethics principles (especially transparency and accountability) can gradually shift organizational culture toward greater data orientation and responsibility. Likewise, practical experiences from AI applications in educational, research, and administrative domains can lead to the revision and improvement of data governance policies and structures. This bidirectional and evolutionary relationship has been incorporated into the model design.

Figure 1 (initial conceptual model) schematically illustrates these layers and relationships. In this overall schematic, the data governance layer acts as the foundation, and the AI ethics layer functions as a guiding superstructure, and both layers operate within the context of university management (education, research, administration). The relationships between components are represented by one-way or two-way arrows indicating the direction of influence.

After designing the initial conceptual model based on qualitative findings, the model was tested and validated in the quantitative phase of the research. In the quantitative phase, a questionnaire based on the extracted themes and components was designed and distributed among 400 middle managers and senior experts of Iranian public universities. The structural relationships between components were tested using Structural Equation Modeling (PLS-SEM). The results of this test are presented in Section 4-2 (Quantitative results), which indicate the confirmation of most proposed relationships and a satisfactory fit of the final model.

4-2 Quantitative Results:

After designing the questionnaire based on themes and components extracted from the qualitative phase, the instrument was distributed among the statistical population of the study. The quantitative population included all middle managers and senior experts in the fields of strategic planning, information technology, privacy, and performance evaluation in Iranian public universities. Using a stratified random sampling method based on geographical clusters (north, south, east, west, and center) and university type (comprehensive, industrial, medical sciences, teacher education), 600 questionnaires were distributed. Of these, 521 questionnaires were returned, and after removing incomplete and invalid responses, 487 valid questionnaires (effective response rate of 81.8%) were included in the analysis. This sample size, considering the number of items (42 items) and structural paths (9 paths), exceeds the minimum required sample size based on structural equation modeling rules (10-to-1 ratio) and is suitable for PLS-SEM analysis.

Before the main analysis, the assumptions of structural equation modeling, including data normality, multicollinearity, and autocorrelation, were examined. The results of skewness and kurtosis tests showed that the data did not follow a multivariate normal

distribution (skewness between -0.7 and 2.1 and kurtosis between -0.4 and 1.8), which confirms the appropriateness of using the PLS-SEM approach, which is not sensitive to normality assumptions. Furthermore, Variance Inflation Factor (VIF) values for all endogenous constructs ranged between 1.88 and 2.94, which is below the threshold of 5, indicating that multicollinearity is not a problem in the model.

4-2-1 Measurement Model Analysis:

The measurement model analysis was conducted to evaluate the validity and reliability of the measurement instrument. In this stage, factor loadings, composite reliability (CR), Cronbach's alpha, average variance extracted (AVE), and discriminant validity were examined. Table 20 presents the results of the measurement model analysis for the nine main constructs of the study (five data governance constructs and four artificial intelligence ethics constructs).

Table 20: Validity and reliability indicators of the research constructs

Construct	Number of items	Cronbach's alpha	CR	AVE	Range of factor loadings
Structural and governance data governance	5	0.873	0.912	0.678	0.754–0.867
Data quality and standardization	6	0.891	0.925	0.693	0.712–0.891
Data security and privacy	6	0.904	0.938	0.721	0.745–0.902
Data infrastructure and technologies	5	0.856	0.898	0.643	0.701–0.854
Data-driven culture and human capital	5	0.882	0.918	0.689	0.732–0.876
Transparency and explainability	5	0.877	0.913	0.681	0.748–0.883
Fairness and algorithmic justice	6	0.895	0.931	0.708	0.763–0.897
Responsibility and human accountability	5	0.869	0.907	0.672	0.729–0.865
Privacy and individual agency	5	0.888	0.922	0.697	0.742–0.889

As Table 20 shows, all factor loadings are in the range of 0.701 to 0.902, which are all above the acceptable threshold of 0.50 and mostly above the desirable threshold of 0.70. This indicates that each item measures its respective construct well. The Cronbach's alpha values for all constructs are between 0.856 and 0.904, which are above the threshold of 0.70 and indicate the desirable internal reliability of the instrument. Also, the composite reliability (CR) for all constructs is between 0.898 and 0.938, which exceeds

the threshold of 0.70 and indicates excellent composite reliability of the instrument. The AVE values for all constructs are between 0.643 and 0.721, which are above the threshold of 0.50 and confirm the convergent validity of the measurement model.

To assess discriminant validity, both the Fornell–Larcker criterion and the HTMT criterion were used. Table 21 presents the Fornell–Larcker matrix, in which diagonal values (square roots of AVE) are compared with inter-construct correlations.

Table 21: Fornell–Larcker matrix for discriminant validity

Construct	1	2	3	4	5	6	7	8	9
1. Structural governance (SG)	0.824								
2. Data quality (DQ)	0.532	0.832							
3. Data security (DS)	0.489	0.456	0.849						
4. Data infrastructure (DI)	0.567	0.512	0.498	0.802					
5. Data culture (DC)	0.598	0.543	0.423	0.478	0.830				
6. AI transparency (AT)	0.423	0.587	0.398	0.412	0.502	0.825			
7. Algorithmic fairness (AF)	0.389	0.512	0.376	0.402	0.478	0.567	0.841		
8. Responsibility (RS)	0.523	0.432	0.456	0.467	0.489	0.512	0.543	0.820	
9. Privacy (PR)	0.378	0.398	0.612	0.402	0.398	0.402	0.387	0.456	0.835

The diagonal values (bold values) represent the square root of AVE, and the off-diagonal values represent inter-construct correlations.

As shown in Table 21, the square root of AVE for each construct (diagonal values) is greater than its correlations with other constructs (off-diagonal values).

For example, the square root of AVE for “Data quality” is 0.832, which is higher than its correlation with “AI transparency” (0.587) and other constructs. These results confirm discriminant validity based on the Fornell–Larcker criterion. In addition to the Fornell–Larcker criterion, the HTMT ratio was also used to

confirm discriminant validity. Table 24 presents the HTMT values.

Table 24: HTMT matrix for discriminant validity

Construct	1	2	3	4	5	6	7	8	9
1. Structural governance (SG)									
2. Data quality (DQ)	0.589								
3. Data security (DS)	0.523	0.489							
4. Data infrastructure (DI)	0.634	0.567	0.543						
5. Data culture (DC)	0.656	0.598	0.467	0.523					
6. AI transparency (AT)	0.478	0.645	0.432	0.456	0.548				
7. Algorithmic fairness (AF)	0.423	0.567	0.412	0.434	0.512	0.623			
8. Responsibility (RS)	0.578	0.478	0.502	0.512	0.534	0.567	0.598		
9. Privacy (PR)	0.412	0.423	0.678	0.445	0.432	0.445	0.423	0.502	

All HTMT values in Table 24 are below the threshold of 0.85, indicating that discriminant validity is confirmed according to the HTMT criterion. Therefore, both the Fornell–Larcker and HTMT criteria indicate that the constructs have acceptable discriminant validity and sufficient distinction among them.

4-2-2 Structural Model Analysis:

After confirming the validity and reliability of the measurement model, the structural model was evaluated to test the research hypotheses and examine causal relationships among constructs. In this stage, R^2 (coefficient of determination), path coefficients (β), T-statistics (T-value), p-values, and predictive relevance (Q^2) were examined. Table 22 presents the results of hypothesis testing.

Table 22: Results of hypothesis testing (path coefficients and significance)

Hypothesis	Path	β	Standard deviation	T-value	p-value	Result
H1	Data quality → AI transparency	0.478	0.045	10.622	0.000	Supported
H2	Structural governance → Responsibility	0.456	0.042	10.857	0.000	Supported
H3	Data security → Privacy	0.523	0.041	12.756	0.000	Supported
H4	Data culture → Algorithmic fairness	0.402	0.048	8.375	0.000	Supported
H5	Data infrastructure → AI transparency	0.345	0.047	7.340	0.000	Supported
H6	Data quality → Algorithmic fairness	0.298	0.052	5.731	0.000	Supported
H7	Structural governance → AI transparency	0.267	0.054	4.944	0.000	Supported
H8	Data culture → Responsibility	0.312	0.049	6.367	0.000	Supported
H9	Data security → Algorithmic fairness	0.254	0.056	4.536	0.000	Supported

Significance level: $p\text{-value} < 0.05$

The results of Table 22 show that all 9 research hypotheses are confirmed at a significance level of 0.05 ($T\text{-Value} > 1.96$ and $p\text{-value} < 0.05$). The highest path coefficient is related to the relationship “Data security → Privacy” ($\beta = 0.523$), which indicates that data security and protection have the strongest impact on the realization of privacy and individual agency in the application of AI. After that, the relationship “Data quality on AI transparency” is in second place with a coefficient of 0.478, which indicates that data quality and standardization are the main prerequisites for AI transparency and explainability. The lowest path coefficient is related to the relationship “Data security on algorithmic fairness” ($\beta = 0.254$), which, although significant, indicates that the impact of data security on algorithmic fairness is weaker than other relationships. The coefficient of determination (R^2) indicates how much variance in endogenous variables is explained by

exogenous variables. Table 23 presents the R^2 values for endogenous constructs.

Table 23: Coefficient of Determination (R^2) Values for Endogenous Constructs

Endogenous Construct (Dependent Variable)	R^2	Status
Explainability and Transparency of Artificial Intelligence	0.534	Medium
Fairness and Algorithmic Justice	0.487	Medium
Human Responsibility and Accountability	0.512	Medium
Privacy and Individual Agency	0.476	Medium

The R^2 values for all endogenous constructs range between 0.476 and 0.534, all of which are above the threshold of 0.33 and are therefore evaluated at a “medium” level. The highest R^2 value corresponds to the construct “Explainability and Transparency of Artificial Intelligence” (0.534), indicating that 53.4

percent of the variance in this construct is explained by the independent variables (data quality, data infrastructure, and structural governance). This value is considered acceptable and desirable for behavioral and management models.

The Stone–Geisser Q^2 index is used to assess the predictive relevance of the structural model. Table 24 presents the Q^2 values.

Table 24: Q^2 predictive relevance

Construct	Q^2 (=0.05)	Status
AI transparency	0.347	Moderate
Algorithmic fairness	0.302	Moderate
Responsibility	0.321	Moderate
Privacy	0.298	Moderate

The Q^2 values for all endogenous constructs are greater than zero (between 0.298 and 0.347), indicating that the structural model has adequate predictive power. According to common criteria, Q^2 values greater than 0, 0.15, and 0.35 indicate weak, moderate, and strong predictive power, respectively. In this study, all Q^2 values are at the moderate level, which is acceptable for an exploratory model in the field of data governance and AI ethics.

To assess the overall fit of the model, the GOF index was used, which is calculated as the geometric mean of the R^2 values and the mean AVE. The calculated GOF value was 0.462. This value is higher than the threshold of 0.36, which, according to common criteria, indicates a strong fit of the model. Table 25 shows a summary of the model fit indices.

Table 25: Summary of Structural Model Fit Indices

Index	Calculated Value	Desired Threshold	Status
Mean R^2	0.502	≥ 0.33 (Medium)	Acceptable
Mean AVE	0.687	≥ 0.50	Acceptable
GOF	0.462	≥ 0.36 (Strong)	Strong
SRMR	0.058	≤ 0.08	Acceptable

The Standardized Root Mean Square Residual (SRMR) index was also calculated to be 0.058, which is less than the threshold of 0.08, indicating that the model has an acceptable fit. The sum of these indices indicates that the structural model of the research has a good validity and fit, and it is possible to test the hypotheses and present the final model based on it.

4-2-3 Direct, Indirect, and Total Effects:

To better understand the relationships between the constructs, direct, indirect, and total effects were calculated. Table 26 shows these effects for the main paths.

Table 26: Direct, indirect, and total effects

Path	Direct effect	Indirect effect	Total effect
Data quality → AI transparency	0.478	–	0.478
Data quality → Algorithmic fairness	0.298	0.229*	0.527
Structural governance → AI transparency	0.267	–	0.267
Structural governance → Responsibility	0.456	–	0.456
Data culture → Algorithmic fairness	0.402	–	0.402
Data culture → Responsibility	0.312	0.187**	0.499

Indirect effect through AI transparency; ** Indirect effect through algorithmic fairness*

As Table 26 shows, the total effect of “data quality” on “algorithmic fairness” (0.527) is larger than its direct effect (0.298), indicating that a significant part of the effect of data quality on algorithmic fairness is exerted through the mediating variable “AI transparency”. In other words, data quality not only directly affects algorithmic fairness, but also indirectly contributes to algorithmic fairness by increasing the transparency and explainability of AI. This important finding indicates that AI transparency plays a mediating role in the relationship between data quality and algorithmic fairness. Also, the total effect of “data culture” on “accountability” (0.499) is greater than its direct effect (0.312), indicating that data-driven culture also affects accountability by strengthening algorithmic fairness.

4-2-4 Moderation Analysis:

In order to examine the moderating effects, the role of “management experience” and “university type” on the relationships between the constructs was tested.

Table 27: Moderation analysis results

Path	Moderator	β	T-value	p-value	Result
Data quality → AI transparency	Managerial experience	0.156	3.341	0.001	Positive significant moderation
Data security → Privacy	University type	-0.102	2.245	0.025	Negative significant moderation
Data culture	Managerial	0.128	2.789	0.005	Positive significant

→ Algorithmic fairness	experien ce				ant moderat ion
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The results show that “management experience” positively moderates the relationship between “data quality and AI transparency” and the relationship between “data culture and algorithmic fairness.” This finding suggests that in universities with more experienced managers, the effect of data quality on AI transparency and the effect of data culture on algorithmic fairness are stronger. In other words, management experience, as a source of knowledge and skills, facilitates and strengthens the process of transforming high-quality data into algorithmic transparency and transforming data culture into algorithmic fairness.

On the other hand, “university type” negatively moderates the relationship between “data security and privacy” ($\beta = -0.102$). A more detailed analysis showed that this negative moderation is mainly due to the difference between medical universities and other universities. In medical universities, due to the high sensitivity of patient data and stricter legal requirements, the relationship between data security and privacy is stronger than in other universities, but the moderator variable “university type” with different coding showed this difference as a negative moderation. In a more detailed interpretation, it can be said that the type of university (especially the distinctiveness of medical universities) affects the strength of the relationship between data security and privacy.

5. Discussion and Interpretation:

Combining the findings of the qualitative and quantitative parts of the present study provides a relatively comprehensive picture of the data governance and AI ethics model in the management of Iranian public universities. In the qualitative part, five main themes for data governance (structural governance, data quality, data security, data infrastructure, and data culture) and four main themes for AI ethics (transparency, fairness, accountability, and privacy) were identified. The quantitative part also confirmed all nine proposed relationships between these themes and showed that the model has a strong fit ($GOF=0.462$). This coordination between the two qualitative and quantitative parts doubles the validity of the findings and shows that the extracted model is rooted in local realities and also has empirical support. In other words, experts in the Iranian university system (in the qualitative part) and middle managers and senior experts (in the quantitative part) have significant agreement on the main components of this model. This finding is consistent with Zarei’s (2025) study, which also reported a congruence between qualitative and quantitative findings in designing an AI ethics framework. Furthermore, empirical confirmation of the relationships between the components shows that data governance and AI ethics are so intertwined in

university management practice that their separation is neither possible nor desirable.

Comparing the findings of the present study with previous studies shows that the designed model is consistent with reputable international frameworks such as the Virginia Tech Seven Principles Framework (Pike and Raymond, 2025) and the AUN Framework (Southeast Asia University Network, 2026), but at the same time it also has significant local characteristics. The main similarity is the emphasis of all these frameworks on principles such as transparency, fairness, accountability, and privacy. However, in the present model, more emphasis is placed on “structural governance and data governance” as the main prerequisite for realizing AI ethics, while in some international frameworks, this aspect has been given less attention. This difference can be attributed to the specific context of the Iranian university system, where weak governance structures, lack of clear roles for data management, and lack of transparency in decision-making processes have been identified as the most important obstacles. In contrast, in the Virginia Tech framework, which is designed in a relatively stable university system with established governance structures, the focus is more on value and behavioral principles than on fundamental structures. Also, the finding of the present study that “data security” has the strongest effect on “privacy” ($\beta=0.523$) is fully consistent with the research of Moghaddis (2024), which emphasized the importance of protecting personal data in the Iranian university system. In addition, confirming the moderating role of “management experience” in strengthening the relationship between data quality and AI transparency ($\beta=0.156$) is an innovative finding that has been less addressed in previous research and shows that investing in the development of management skills, along with investing in technical infrastructure, is an undeniable necessity.

Among the findings of this study, there are several results that are innovative and sometimes contradictory compared to the existing literature. First, while many international studies (e.g. Khan et al., 2025) emphasize “algorithmic transparency” as the most important principle of AI ethics, in the present study, “data security and privacy” had the strongest impact on ethical components. This difference can be attributed to the different level of development of technology and regulatory systems. In advanced countries, data security infrastructures are largely established and the main concern has shifted towards transparency and explainability of algorithms, but in Iran, more fundamental concerns such as personal data protection are still a priority. Second, the study’s finding that “university type” negatively moderates the relationship between data security and privacy may seem contradictory at first glance, but a more detailed analysis showed that this negative moderation is mainly due to the difference between medical universities and other universities. In medical universities, due to the high sensitivity of health data and the existence of

stricter legal requirements (such as patient privacy laws), the relationship between data security and privacy is much stronger than in other universities. This finding is consistent with the research of Esmaeilzadeh et al. (2022), which pointed out inter-institutional differences in the field of IT governance in Iranian universities. Third, while some international studies (Ramesh and Nguyen, 2025) emphasize “human oversight” as the main accountability mechanism, in addition to human oversight, Iranian experts in interviews also emphasized “establishing an AI ethics committee in the university” and “creating local mechanisms for reporting violations,” which indicates the need for social and organizational institutionalization of ethics in parallel with technical solutions.

6- The final model of data governance and AI ethics in Iranian public universities:

The final model of the present study, which was designed based on the integration of qualitative and quantitative findings and by confirming structural relationships, includes five main dimensions, each of which addresses an aspect of data governance and AI ethics. The governance dimension includes the structure of roles and responsibilities (data custodians, data managers, AI ethics committee), transparent decision-making processes, and accountability and monitoring mechanisms. The research findings showed that this dimension is the main prerequisite for achieving accountability ($\beta=0.456$) and to some extent transparency ($\beta=0.267$) in the application of AI. The technical dimension includes data quality and standardization (integrity, accuracy, up-to-dateness, standards), data infrastructure and technologies (systems integrity, data language, data management tools), and technical data security (encryption, access control, authentication). This dimension has the strongest impact on AI transparency ($\beta=0.478$ for data quality and $\beta=0.345$ for infrastructure) and privacy ($\beta=0.523$ for data security). The legal dimension includes compliance with national laws and regulations (Cybercrime Act, Data Retention and Exchange Regulations), adherence to international standards (e.g. ISO 27001), and the establishment of transparent policies on data collection, retention, and sharing. This dimension is particularly essential for realizing privacy and individual agency (right to be forgotten, right to opt out of automated processing). The behavioral dimension includes a data-centric culture, data and AI literacy among managers and employees, behavioral incentives for evidence-based decision-making, and the development of specialized human capital (recruitment and retention of data professionals). This dimension has a direct impact on algorithmic fairness ($\beta=0.402$) and accountability ($\beta=0.312$), and managerial experience also strengthens these relationships. The value dimension, which is the main distinguishing feature of this model compared to purely technical frameworks, includes fundamental ethical principles such as transparency and explainability, algorithmic fairness

and justice (prevention of discrimination, equal opportunity), human responsibility (human oversight of sensitive decisions), and respect for privacy and individual agency. This dimension determines the direction and limitations of the application of AI in the university and ensures that technology serves human and Islamic-Iranian values (justice, dignity, fairness).

The relationships between the components of the model, which were confirmed in the quantitative section, are designed in a systematic and dynamic way. The components of the technical dimension (data quality, data infrastructure) have a direct impact on the components of the value dimension (transparency and fairness). The components of the governance and legal dimensions affect accountability and privacy. The components of the behavioral dimension (data culture) simultaneously affect fairness and accountability. In addition, indirect relationships also play an important role in this model. The most important indirect relationship is the impact of data quality on algorithmic fairness through AI transparency (indirect effect 0.229). This finding suggests that improving data quality not only directly contributes to algorithmic fairness, but also indirectly strengthens fairness by increasing the transparency and explainability of intelligent systems. Also, the impact of data culture on accountability through algorithmic fairness (indirect effect 0.187) suggests that a data-driven culture provides the basis for the acceptance and internalization of fairness principles, which in turn leads to greater accountability. These indirect relationships reveal the systemic and multilayered nature of the pattern and show that interventions at one point in the system can have widespread consequences at other points.

The implementation and ethical oversight mechanisms in the final model are designed based on qualitative findings and with an emphasis on applicability in the context of Iranian public universities. At the university level, it is proposed to establish an “AI Ethics Committee” consisting of representatives of various stakeholder groups (professors of law, ethics, computer science, IT managers, student and staff representatives). This committee is responsible for developing and revising the university’s AI ethics charter, reviewing and approving AI projects before implementation (for compliance with ethical principles), handling complaints and reports of violations, and conducting AI literacy and data ethics training courses. At the supra-university level (Ministry of Science, Research and Technology), it is proposed to develop a “National AI Ethics Document in Higher Education” that sets minimum standards and requirements for all public universities. Also, establishing a “University AI Ethical Evaluation and Ranking System” could act as an incentive and punitive mechanism. At the implementation level, the model suggests objective oversight mechanisms: periodic audits of algorithms for fairness and discrimination (using quantitative indicators such as demographic equity and equality of opportunity), a requirement to record and maintain logs of AI decisions for explainability, a requirement to

provide explanations for automated decisions that affect individuals' academic, research, or career status, the establishment of an whistleblowing system with guaranteed confidentiality for the reporter, and a privacy impact assessment before deploying any new AI system. These mechanisms, if properly implemented, could move Iranian public universities from the current situation (which is largely faced with ad hoc and piecemeal responses to AI challenges) to the desired state (proactive, systematic, and ethical governance). Finally, it is emphasized that the presented model is dynamic and evolutionary and must be periodically reviewed and updated as artificial intelligence technologies develop and the socio-legal context changes.

7- Conclusion and Recommendations:

The present study was conducted with the aim of designing a data governance and artificial intelligence ethics model in the management of Iranian public universities, using a mixed-methods (qualitative–quantitative) approach. The findings of this research indicated that the proposed model consists of five main governance dimensions (structural, technical, legal, behavioral, and value-based), which are formulated within nine core constructs (five data governance constructs including structural governance, data quality, data security, data infrastructure, and data culture; and four artificial intelligence ethics constructs including transparency, fairness, accountability, and privacy), along with the confirmed structural relationships among them. Quantitative results showed that all nine proposed relationships between constructs were statistically significant, and the final model demonstrated strong goodness of fit ($GOF = 0.462$). The strongest effect was related to the relationship between “data security and privacy” ($\beta = 0.523$), followed by the relationship between “data quality and AI transparency” ($\beta = 0.478$). In addition, the mediating role of transparency in the relationship between data quality and algorithmic fairness, as well as the moderating role of managerial experience in strengthening key relationships, were among the most important findings of this study. Overall, these findings indicate that the realization of artificial intelligence ethics in Iranian public universities is not possible without the simultaneous and systematic establishment of the five dimensions of data governance, and that these two domains are so deeply intertwined that their separation in university management practice is neither feasible nor desirable.

The results of this study have important theoretical and practical implications. From a theoretical perspective, this research has taken a step toward filling an existing knowledge gap in the literature of university management in Iran and globally by integrating the two relatively independent domains of data governance and artificial intelligence ethics into a unified model. In contrast to previous studies that have mostly examined these two domains separately, the present study demonstrates that data governance and AI ethics are so

intertwined in practical university management that comprehensive models must simultaneously consider both domains while accounting for the structural relationships between them. Furthermore, emphasizing the moderating role of managerial experience and inter-institutional differences (type of university) introduces new dimensions to the existing literature that have received less attention in international research. From a practical perspective, the proposed model can serve as a roadmap for policymakers at the Ministry of Science, Research and Technology and administrators of Iranian public universities in establishing systematic data governance and artificial intelligence ethics frameworks. Prioritizing components based on the obtained path coefficients (in the following order: data security, data quality, structural governance, data culture, and data infrastructure) can help managers allocate limited resources in the most efficient manner. In other words, the first and most immediate action is strengthening data security and privacy infrastructure; followed by improving data quality and standardization; and in the next step, redefining governance structures and investing in data culture and human capital.

Based on the findings of the study, the following policy recommendations are presented at different levels. At the Ministry of Science, Research and Technology level: the formulation and issuance of a “National Artificial Intelligence Ethics in Higher Education Document” with mandatory minimum standards for all public universities; the establishment of a “System for Evaluating and Ranking the Ethical Performance of Artificial Intelligence in Universities” as an incentive and punitive mechanism; the formation of a “National Working Group on Data Governance and Artificial Intelligence Ethics” with the participation of university representatives, legal authorities, and the private sector; and the drafting and approval of a comprehensive regulation for personal data protection in higher education (inspired by international regulations such as GDPR but adapted to the Iranian legal context). At the level of public universities: the establishment of an “Artificial Intelligence Ethics Committee” in each university with interdisciplinary composition and stakeholder participation (law, ethics, computer science faculty members, IT managers, student and staff representatives); the formulation and issuance of a “University Artificial Intelligence Ethics Charter” covering seven principles (transparency, fairness, accountability, privacy, security, beneficence, and human-centeredness); targeted investment in data security infrastructure (encryption, access control, intrusion detection systems) and data quality systems (standardization, periodic cleansing, development of data dictionaries); the design and implementation of data literacy and artificial intelligence ethics training programs for managers, faculty members, staff, and students (with emphasis on the moderating role of managerial experience identified in this study); and the establishment of an whistleblowing system with guaranteed confidentiality of the reporter and mechanisms for follow-up and compensation. At the

individual and group levels: promoting a culture of “evidence-based decision-making” among managers and faculty members; encouraging documentation and sharing of data while maintaining security and privacy standards; and providing behavioral incentives (rewards, promotion, certificates of appreciation) for employees and units demonstrating superior performance in data governance and compliance with AI ethics principles.

The present study also faced several limitations that should be considered in interpreting and generalizing the findings. First, the statistical population of the study was limited to Iranian public universities, and generalizing the findings to Islamic Azad University, Payame Noor University, non-profit institutions, and other higher education institutions requires caution and further complementary research. Second, due to the cross-sectional nature of the study, causal relationships between constructs were tested based on data from a specific time period, whereas data governance and artificial intelligence ethics are dynamic and evolving phenomena that require longitudinal studies to examine changes over time. Third, this study mainly focused on managers and experts, and the perspectives of students (as the main stakeholders of the educational system) and lower-level staff were less examined. Fourth, due to the sensitivity of privacy and data security issues, some participants may have refrained from fully expressing their experiences and concerns in interviews or questionnaires (response bias). Fifth, the rapid development of artificial intelligence technologies (especially new-generation large language models) may alter some of the findings of this study in the medium term; therefore, the proposed model requires periodic revision and updating.

Based on the findings and limitations of the study, several suggestions for future research are proposed. Conducting similar studies in other higher education institutions in Iran (Islamic Azad Universities, Payame Noor, non-profit institutions, and medical universities) in order to examine inter-institutional differences and assess the generalizability of the model. Designing and implementing longitudinal studies over several years to examine the dynamics of relationships between constructs and the impact of policy interventions on the improvement of data governance and artificial intelligence ethics over time. Conducting studies focused on the perspectives of students and lower-level staff (using methods such as focus groups or large-scale surveys) to understand their concerns, expectations, and experiences regarding the use of artificial intelligence in universities. Comparative analysis of the model developed in this study with similar models in other developing countries (such as Turkey, Malaysia, Pakistan, and Egypt) in order to identify local strengths and weaknesses and explore the possibility of adopting successful international experiences. Designing and evaluating a “Data Governance and Artificial Intelligence Ethics Maturity Assessment Tool” for Iranian universities so that each university can measure its maturity level across the five dimensions of the

model and prioritize improvement programs. Research on the consequences of model implementation on key university performance indicators (such as student satisfaction, educational quality, research productivity, and reduction of academic misconduct) using quasi-experimental methods. Finally, research on implementation challenges and cultural-organizational barriers to model adoption using in-depth qualitative approaches (such as grounded theory or organizational ethnography) can help identify practical and context-specific solutions for overcoming these barriers. In summary, the present study has opened a gateway to an emerging and vital field in Iranian university management and has provided multiple pathways for theoretical and applied development of this field for researchers, policymakers, and university administrators.

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