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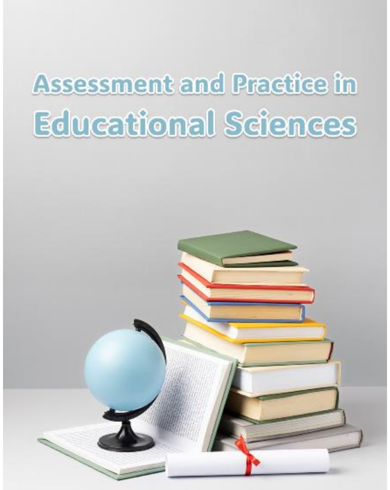

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Presenting a Structural Model of the University Policy-Making System with an Artificial Intelligence Development Approach in the Universities of Golestan Province

ABSTRACT

This study was conducted with the aim of presenting a structural model of the university policy-making system with an artificial intelligence development approach in the universities of Golestan province. The research method was applied in terms of purpose, descriptive-survey in terms of data collection, and cross-sectional in terms of time. The statistical population included 28,716students from Farhangian University, Islamic Azad University, and the University of Medical Sciences in Golestan province. The sample size was determined to be 379individuals based on Cochran's formula with a 95%confidence level and a 5%error margin, selected through stratified random sampling proportional to the population size. The data collection instrument was a researcher-made questionnaire titled "University Policy-Making System with an Artificial Intelligence Development Approach," comprising 76items across six dimensions: core phenomenon, causal conditions, contextual conditions, intervening conditions, strategies, and consequences, with each dimension having two key components. The items were scored based on a five-point Likert scale. Face and content validity were confirmed by 10experts and the calculation of the Content Validity Ratio (CVR) and Content Validity Index (CVI). Construct validity was also confirmed through confirmatory factor analysis considering factor loadings above 0.5. The reliability of the questionnaire was calculated using Cronbach's αcoefficient as 0.952for the entire instrument, indicating excellent reliability. For data analysis, descriptive statistics (frequency, percentage, mean, standard deviation) and inferential statistics, including structural equation modeling (SEM), were utilized using SPSS 23 and SmartPLS 3 software. The findings revealed that the model had a desirable goodness of fit. The artificial intelligence-based policy-making system had a positive, strong, and significant effect on all dimensions. The strongest relationships were observed with "consequences" (path coefficient = 0.934) and "causal conditions" (path coefficient = 0.867), respectively. The results indicate that artificial intelligence has the greatest impact on achieving desired outcomes and shaping the root causes of issues. However, the relationship with the "strategies" dimension was weaker (path coefficient = 0.394), indicating an existing gap between intelligent analyses and the formulation of operational strategies. In conclusion, the presented model is a valid framework for the intelligentization of university policy-making. For its successful implementation, it is recommended to place the formulation of a strategic document, the establishment of data-driven decision support centers, process redesign, human resources empowerment, and the development of native applied research on the agenda.

Keywords: University policy-making, Artificial intelligence, Structural model, Golestan province.

Introduction

Public policy-making is a multi-dimensional and intricate process that serves as the cornerstone of effective governance and institutional administration. Traditionally, the public policy-making process has been conceptualized as a sequential cycle involving agenda-setting, formulation, decision-making, implementation, and evaluation, heavily reliant on human expertise, historical precedents, and bureaucratic consensus (1, 2). However, the inherent complexity of modern societies, characterized by rapid demographic shifts, economic fluctuations, and unprecedented technological disruptions, has rendered traditional, intuitive, and highly centralized decision-making paradigms increasingly obsolete. Historically, administrative theories such as bounded rationality highlighted the inherent limitations of human cognition in processing all available information and alternatives, often leading to satisficing rather than optimal decisions. In contemporary administrative sciences, decision-making and public policy determination require a paradigm shift toward more dynamic, evidence-based, and adaptive frameworks that transcend these cognitive boundaries (3). Institutions are now compelled to navigate a volatile environment where socio-economic variables are deeply interconnected and non-linear, demanding analytical capabilities that far exceed traditional human administrative capacities. Consequently, the pursuit of optimal policy-making processes has become a central theme in academic discourse, emphasizing the profound need for robust structural models capable of deciphering vast arrays of contextual and causal conditions to generate sustainable and equitable public value.

Within this context of rapid administrative evolution, the advent of disruptive digital technologies, most notably Artificial Intelligence (AI), has fundamentally altered the landscape of public governance. The transition toward governance with artificial intelligence represents a critical juncture in the evolution of statecraft and institutional management, moving systems away from analog bureaucracies toward intelligent, responsive architectures (4). Globally, the integration of AI technologies is no longer viewed merely as an operational IT upgrade but as a strategic imperative that dictates an institution's competitive advantage and operational resilience. Comprehensive analyses of countries in terms of artificial intelligence technologies reveal that nations and institutions proactively adopting AI frameworks exhibit vastly superior capacities in strategic foresight, resource optimization, and crisis management compared to those relying on legacy systems (5). AI systems, empowered by sophisticated machine learning algorithms, deep neural networks, and big data analytics, possess the unprecedented ability to process colossal volumes of unstructured data in real-time. This processing power enables the identification of hidden correlations and the prediction of future trajectories with remarkable accuracy, effectively shifting the paradigm from retrospective analysis to prospective intelligence. This technological capacity provides policymakers with a highly sophisticated cognitive prosthesis, enabling a decisive shift from reactive problem-solving to proactive, predictive, and highly precise governance.

The systematic integration of artificial intelligence into public sector decision-making introduces a profound transformation in the exact mechanisms of how policies are formulated, executed, and evaluated. Transforming governance through the deployment of AI applications in policymaking involves leveraging complex algorithmic models to simulate multiple policy outcomes, optimize the allocation of scarce public resources, and personalize public services to meet highly diverse and granular citizen needs (6). The impact of artificial intelligence on public sector decision-making encompasses a wide spectrum of tangible benefits, including dramatically enhanced administrative efficiency, the mitigation of inherent human cognitive biases in resource distribution, and the facilitation of hyper-targeted policy interventions that maximize societal impact (7). However, this technological transition is not devoid of substantial operational and ethical challenges. Policymakers must continually grapple with complex policy implications related to stringent data privacy regulations, the necessity for algorithmic transparency, and the critical potential for the exacerbation of systemic inequalities if AI systems are trained on historically biased data sets. Furthermore, the successful deployment and sustainability of AI in governance are intrinsically linked to the social acceptability of these autonomous or semi-autonomous systems. Establishing and maintaining public policy and trust in artificial intelligence decision-making is paramount, as the democratic legitimacy of public policies relies heavily on the perceived fairness, absolute accountability, and clear explainability of the algorithms driving these critical societal decisions (8).

The permeation of artificial intelligence across various specialized structural domains underscores its immense versatility and its critical importance as a foundational meta-policy tool. In the critical realm of public health, for instance, artificial intelligence has become absolutely instrumental in epidemiological modeling, advancing personalized medicine, and facilitating the structural optimization of overarching health policies (9). The strategic formulation and rigorous analysis of dimensions concerning artificial intelligence employment policy in national health systems dynamically demonstrate how AI can revolutionize direct patient care, profoundly streamline complex hospital administration, and ensure highly equitable access to life-saving medical resources (10). Similarly, in the highly complex context of urban management and smart city development, researchers have utilized advanced meta-synthesis approaches to construct comprehensive policy-making frameworks for the application of artificial intelligence systems in the urban domain, highlighting AI's indispensable role in intelligent traffic optimization, sustainable energy distribution, and responsive urban planning (11). Furthermore, operating on a macro-strategic national level, rigorous scenario planning for national information networks relies heavily on AI to forecast rapidly evolving technological trajectories, proactively manage sophisticated cybersecurity threats, and articulate long-term security implications for the foreseeable future, thereby ensuring the preservation of national digital sovereignty (12).

While the transformative impact of AI is undeniably profound across all public sectors, its structural application within the educational domain represents a uniquely critical and sensitive frontier. Educational systems serve as the primary foundational engines for long-term human capital development, civic engagement, and overall societal progress. Consequently, educational policymaking requires meticulous, data-driven attention to both highly individualized developmental needs and broader macroeconomic socio-economic goals. Developing a robust, forward-looking human capital educational policymaking guide, supported by rigorous empirical methods such as importance-performance analysis, is essential for accurately aligning educational outputs with the incredibly dynamic demands of the global knowledge economy (13). Traditional educational policy paradigms, constrained by linear thinking, often struggle to adapt to the exponential pace of technological change, frequently resulting in severe skill mismatches and structural inefficiencies within the labor market. Recognizing these critical limitations, educational scholars have strongly emphasized the necessity of presenting behavioral-based educational policymaking models, particularly in critical socio-economic areas such as vocational skill training, to effectively bridge the persistent gap between theoretical academic knowledge and practical industry competencies (14). Continuously identifying and refining the core dimensions and components of the optimal policymaking process model in the education system remains a highly prioritized strategic agenda, aiming to purposefully foster an educational ecosystem that is highly responsive, socially inclusive, and technologically forward-looking (15).

Within the broader structural spectrum of the national education system, higher education institutions and universities occupy a highly distinct and elevated position as the primary epicenters of advanced research, technological innovation, and high-level knowledge dissemination. The governance of modern universities is an inherently complex endeavor, involving the intricate administrative management of diverse academic faculties, extensive and varied student bodies, highly competitive research funding allocations, and expansive physical and digital infrastructural networks. In recent years, the intersection of higher education administration and emerging digital technologies has catalyzed the vital concept of intelligent university governance. The structured governance of artificial intelligence and expansive data in higher education has consequently become a critical focal point, rapidly transitioning from abstract theoretical discussions to highly actionable policy and verifiable practice across leading global educational institutions (16). Universities are increasingly leveraging AI ecosystems to fundamentally optimize admissions processes, accurately predict student attrition to enable timely pedagogical interventions, highly personalize individualized learning pathways, and drastically enhance the overall administrative efficiency of complex campus operations. However, the sophisticated adoption of AI in higher education cannot occur haphazardly or in a regulatory vacuum; it strictly necessitates a comprehensive, structurally sound policy-making system that deliberately incorporates a formalized artificial intelligence development approach directly into its core strategic institutional vision.

Despite the rapidly growing international consensus on the absolute necessity of AI-driven institutional governance, a critical and extensive review of the existing academic literature reveals a significant theoretical and practical gap, particularly within specific regional contexts. Much of the current foundational research tends to focus either on the broad, macro-level theoretical implications of AI in general public administration or on highly specific, isolated operational applications within university classrooms. There is a conspicuous and problematic scarcity of comprehensive, statistically validated structural models that accurately map the entire paradigmatic spectrum—methodically encompassing core phenomena, causal and contextual conditions, intervening factors, operational strategies, and ultimate consequences—of systematically integrating an AI development approach into overarching university policy-making systems. This critical gap is particularly pronounced in regional higher education contexts, where universities frequently face highly unique demographic constraints, distinct cultural expectations, and specific infrastructural realities. Universities situated in specific geographical regions operate under highly distinct sets of localized constraints and emerging opportunities that absolutely require localized, scientifically validated structural models rather than generic, internationally imported frameworks. A meticulously designed structural model would directly provide university administrators, key stakeholders, and high-level educational policymakers with a remarkably clear, empirically data-driven roadmap to safely navigate the immense complexities of AI integration. Developing such a rigorously tested model requires an advanced methodological approach that accurately captures the nuanced, multi-directional interplay between technological capacity, organizational managerial culture, and long-term strategic foresight, enabling institutions to transition from fragmented technological adoption to a highly systematic, policy-driven intelligence architecture.

The fundamental imperative to urgently modernize higher education governance through the implementation of advanced technological paradigms has never been more critical. As regional universities aggressively strive to maintain their academic relevance, operational efficacy, and institutional competitiveness in an increasingly complex and highly data-saturated global environment, the systematic transition toward intelligent, data-driven policy-making frameworks is no longer merely an optional enhancement, but a fundamental, existential necessity for long-term survival and institutional growth. This crucial transition absolutely requires a deep, holistic, and structurally validated understanding of exactly how artificial intelligence can be safely and effectively embedded into the very core fabric of university administration, ultimately shaping high-level strategic priorities, optimizing the distribution of limited academic resources, and fundamentally enhancing the overarching educational experience for all stakeholders involved. Therefore, this study was conducted with the aim of presenting a structural model of the university policy-making system with an artificial intelligence development approach in the universities of Golestan province.

Methods and Materials

This research was designed with the aim of presenting a structural model of the university policy-making system with an artificial intelligence development approach in the universities of Golestan province. The statistical population comprised all students of the province's universities (Farhangian University, Islamic Azad University, and the University of Medical

Sciences), totaling 28,716individuals. Using Cochran's formula at a 95%confidence level and a 5%sampling error, 379individuals were selected as the sample, and sampling was conducted using the stratified random method proportional to the population size. This is an applied and survey-type research. From the perspective of data collection time, the research was cross-sectional and was conducted based on a descriptive-survey method. The data collection instrument in the quantitative section was the "University Policy-Making System with an Artificial Intelligence Development Approach" questionnaire. The questionnaire included six main dimensions: core phenomenon, causal conditions, contextual conditions, intervening conditions, strategies, and consequences, with each dimension having two key components, and in total, it was designed with 76items for the quantitative measurement of the dimensions and components of the policy-making system. Responses were recorded on a five-point Likert scale (1=Strongly Disagree, 5=Strongly Agree), where a higher score indicates a more positive perception of the realization of the university policy-making system with an AI development approach. The face and content validity of the questionnaire were confirmed through the consultation of 10experts and the calculation of the Content Validity Index (CVI) and Content Validity Ratio (CVR). Construct validity was also confirmed through confirmatory factor analysis and the examination of factor loadings (above 0.5). The reliability of the instrument was calculated using Cronbach's alpha coefficient for the entire questionnaire as 0.952, indicating its excellent reliability. Descriptive statistics, including frequency, percentage, mean, and standard deviation, were used to describe the demographic characteristics and research variables, and for testing hypotheses and model fitting, inferential statistics and structural equation modeling (SEM) were employed using SPSS 23 and SmartPLS 3.3 software.

Findings and Results

The analysis and explanation of the relationships between the "policy-making system with an artificial intelligence development approach" as the main variable and its paradigmatic dimensions (including core phenomenon, causal conditions, contextual conditions, intervening conditions, strategies, and consequences), based on the provided path coefficients and R^2values, indicate a very robust and coherent structural model. These data show that the AI approach in policy-making plays a fundamental and determinant role in shaping all components of the paradigm governing decision-making and implementation processes. Hereafter, each of these relationships is analyzed in detail. The core phenomenon, in qualitative studies and conceptual modeling, refers to the central and main core of a phenomenon around which other concepts are organized. The path coefficient of 0.812indicates that the AI-based policy-making system has a very high impact on defining and shaping the core phenomenon. In other words, when policy-making is conducted from an AI perspective, the essence and nature of the main issue (the core phenomenon) are transformed. The R^2value of 0.660signifies that approximately 66%of the variations in the core phenomenon are explained by this policy-making system. This figure indicates a strong and significant correlation, suggesting that understanding and defining macro-level issues in the domain of governance and management would be incomplete without considering the AI approach. By providing data analysis and prediction tools, artificial intelligence changes the nature of the "problem" in policy-making from a traditional and intuitive state to a data-driven and precise one, and this is precisely the transformation in the core phenomenon.

Causal conditions refer to the factors and roots that cause the phenomenon to emerge. The path coefficient of 0.867is the highest among the various dimensions (except for consequences) and shows that the intelligence-driven policy-making system has a profound impact on identifying and analyzing the causes of phenomena. With an R^2value of 0.752, it can be stated that 75.2%of the variance in causal conditions is explained by this system. This means that AI empowers policymakers to trace the roots of problems with much greater accuracy. In traditional systems, identifying causes was often based on conjecture or limited experience, but in an AI-based system, causal analyses are performed using advanced algorithms and big data processing. This leads to a deeper understanding of the mechanisms affecting social, economic, and technological issues and causes policies to be designed based on the real roots of the problem, not its superficial symptoms. Contextual conditions refer to the settings, environment, and specific circumstances in which the phenomenon occurs. The path coefficient of 0.824indicates that the policy-making system with an AI approach plays a significant role in shaping, interpreting, and even changing contextual conditions. The R^2value of 0.680shows that $68\%$of the variations in contextual conditions can be explained by this independent variable. This strong relationship suggests that AI is not just a technical tool but a platform that can transform the contextual environment of governance. For example, digital infrastructure, a data-driven culture, and legal frameworks for cyberspace are parts of the contextual conditions that are altered by the development of AI. Policy-making in this area determines how these platforms should be shaped to achieve maximum efficiency. Therefore, the intelligence-driven policy-making system is itself a creator of the context in which it operates. Intervening conditions are conditions or variables that affect the relationship between cause and effect or the policy-making process and can change its course. The path coefficient of 0.796indicates a considerable impact of the intelligence-driven policy-making system on managing and directing these factors. With an $R^2$of 0.634, about $63.4\%$of the variations in intervening conditions are explained by this system. This figure shows that AI can act as a tool to reduce uncertainties and control extraneous variables. In the policy-making process, there are always unforeseen factors that can disrupt the implementation of policies. By using intelligent systems for real-time monitoring and scenario simulation, policymakers can identify these intervening factors and adopt solutions to neutralize or manage them. This increases the stability and resilience of policies against environmental shocks. Among all dimensions, the path coefficient between the policy-making system and strategies has the lowest value at 0.394, and the R^2value is also 0.155, indicating that only about $15.5\%$of the variations in strategies are explained by this variable. This statistic might be surprising at first glance, but a deeper analysis reveals important points. This moderate to weak relationship could indicate the relative independence of "strategies" from the "policy-making system." This means that while AI strongly influences the understanding of the problem, causes, contexts, and even consequences, the formulation of executive strategies may be influenced by other factors such as political will, financial resources, traditional cultural considerations, or higher-level regulations that do not directly stem from AI technology. It is also possible that strategies have not yet been sufficiently adapted to the capabilities of AI, and in many decision-making structures, strategies are still formulated using classic methods. This figure indicates a "gap" or an "opportunity for improvement"; that is, although an intelligence-driven policy-making system exists, its translation into operational strategies has not progressed as much as other dimensions.

The strongest relationship in this model is the relationship between the policy-making system with an AI development approach and the consequences. The path coefficient of $0.934$and the R^2value of 0.873show that approximately $87.3\%$of the variations and diversity in the consequences are explained by this system. This is a very high statistic and indicates that the outputs and final results of the policy-making processes are almost entirely dependent on the extent of AI utilization in the policy-making system. This means that if policy-making is properly designed and implemented with an AI approach, desirable outcomes (such as efficiency, accuracy, equity in resource distribution, and public satisfaction) will be achieved with high certainty. By enabling precise and real-time evaluation of policy performance, AI makes the consequences predictable and controllable. This very strong correlation confirms that the ultimate success of national projects and governance in the current era is nearly impossible without relying on artificial intelligence in the policy-making process. Based on the analysis of the presented data, it can be concluded that the "policy-making system with an artificial intelligence development approach" acts as a powerful driving engine that affects all paradigmatic dimensions. This system has the greatest impact on "consequences" and "causal conditions," which indicates its high effectiveness in solving root problems and producing desirable outcomes. The strong impact on the "core phenomenon" and "contextual conditions" also demonstrates the system's ability to redefine problems and implementation settings. The only point of weakness or reflection in this model is the relatively weak relationship with “strategies.” This issue could be a warning to policymakers that merely having an intelligence-driven perspective and a precise understanding of conditions and causes is not enough; rather, the mechanisms for translating this insight into operational “strategies” must be strengthened. By rectifying this part, it can be expected that a complete and optimal cycle in public policy-making will be formed, where everything from understanding the problem to implementing the strategy and achieving the desired outcome is accompanied by high intelligence and efficiency. In the provided structural analysis, the path coefficients and R^2values specific to each component reveal the key strengths and weaknesses of the model. The path coefficient indicates the intensity of the direct effect of each component on its parent dimension. In this model, the highest path coefficient belongs to the “data-driven decision-making” component (0.956) in the core phenomenon dimension, which confirms that this characteristic is the strongest driving force in shaping the AI policy-making system. Following this are the “managerial culture and approach” (0.945) and “positive consequences” (0.946) components, which emphasize the vital role of soft infrastructure and desirable outcomes. In contrast, the lowest path coefficient belongs to the “actions taken for utilization” component (0.761) in the strategies dimension. This relatively low figure indicates that merely taking practical actions, without strong support from other conditions (such as organizational capacity or managerial culture), has a weaker impact on the success of strategies. The highest R^2value belongs to the “data-driven decision-making” component (0.914), which alone explains about $91.4\%$of the changes in the core phenomenon dimension, demonstrating its unparalleled position. The “increased transparency” (0.902) and “managerial culture” (0.894) components also have very high explanatory power. On the other hand, the lowest R^2value corresponds to the “actions taken” component (0.579). This means that only $58\%$of the changes in the “strategies” dimension can be explained by this component, and about $42\%$of these changes depend on factors outside this component or model error. Overall, the data indicate that the success of the AI policy-making system depends more than anything on data-driven implementation, a supportive managerial culture, and the realization of positive consequences, while operational strategies alone have less predictive power and impact and need to be strengthened by other dimensions of the model.

Table 1. Path Coefficient and R2 Values for the Dimensions and Components of the Research

No.	Dimension	Path Coefficient	R2	Component	Path Coefficient	R2
1	Core Phenomenon	0.812	0.660	Data-driven decision-making	0.956	0.914
				Increased managerial transparency and accuracy	0.950	0.902
2	Causal Conditions	0.867	0.752	Organizational and technological capacity	0.900	0.811
				Managerial acceptance and support	0.893	0.798
3	Contextual Conditions	0.824	0.680	Technological infrastructure and resources	0.910	0.828
				Managerial culture and approach	0.945	0.894
4	Intervening Conditions	0.796	0.634	Unforeseen support	0.900	0.810
				Unexpected barriers	0.895	0.802
5	Strategies	0.394	0.155	Actions taken for the utilization of AI	0.761	0.579
				Complementary needs for effective utilization	0.814	0.663
6	Consequences	0.934	0.873	Positive consequences	0.946	0.895
				Negative consequences	0.817	0.667

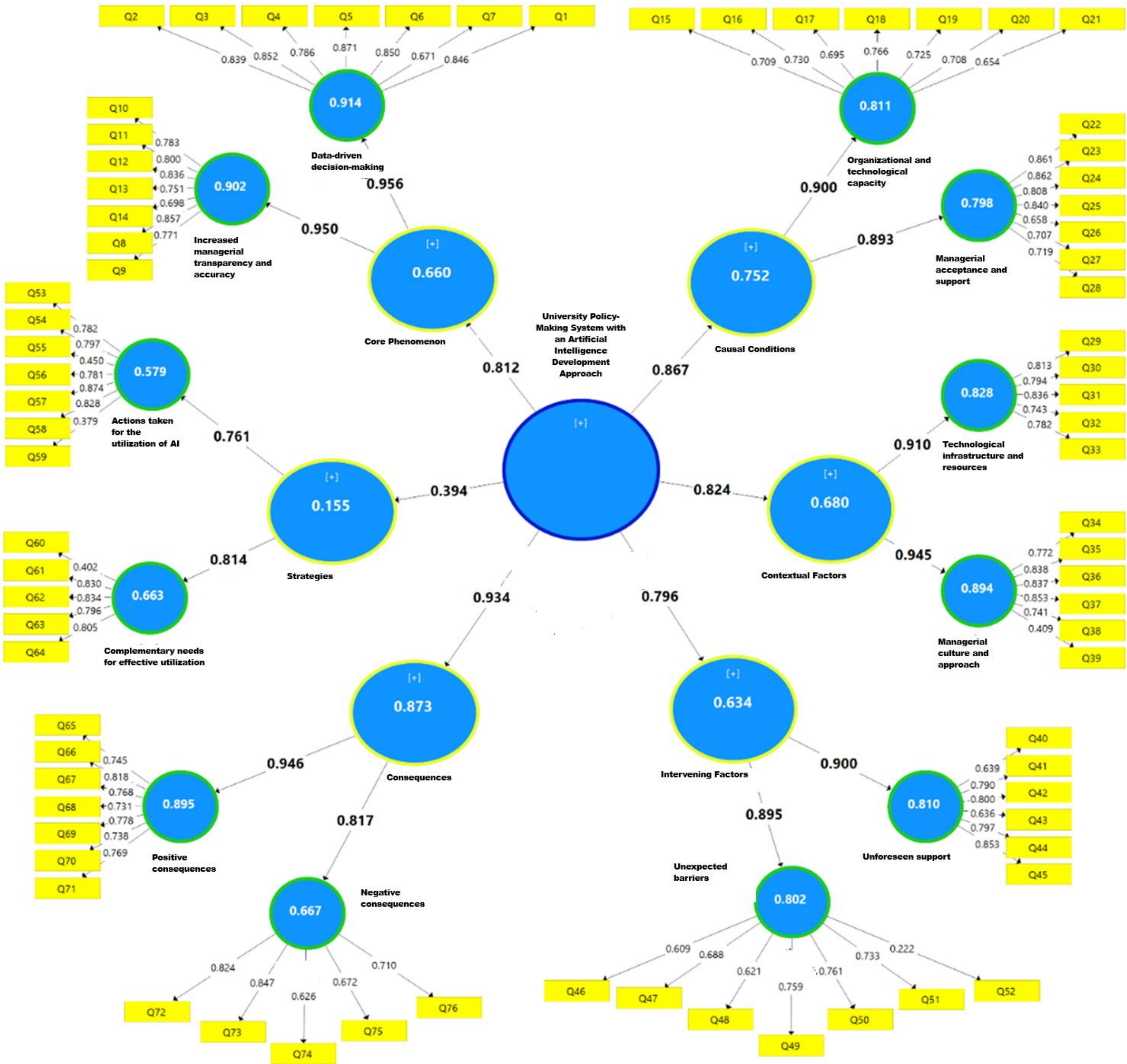

Figure 1. The relationship between the main variable of the policy-making system with an AI development approach and its paradigmatic dimensions in the path coefficient estimation mode.

An examination of the provided values shows that all t-statistics are much larger than the standard critical threshold (which is typically 1.96or 2.58). This indicates that all relationships are significant at a very high confidence level (usually 99%). In other words, the probability that these relationships are due to chance or sampling error is close to zero. The highest t-statistic value corresponds to the relationship with "consequences," with a value of 124.793. This very large number is a powerful confirmation of the strongest relationship in the model and shows that the impact of the intelligence-driven policy-making system on consequences is not only strong (as previously seen in the path coefficient) but also statistically very robust and undeniable. Following that are "causal conditions" with a t-statistic of 55.551and "contextual conditions" with 46.482, indicating the very high reliability of the causal and contextual relationships with the main variable. A noteworthy point here is the t-statistic value for "strategies," which is 7.110. Although this number is still much higher than the critical threshold and makes the relationship significant, it represents a relatively lower value compared to the other dimensions (which have values above 30or 40). This supports the previous analysis; the relationship between the policy-making system and strategies is significant, but in terms of intensity and statistical robustness, it performs more weakly compared to other components of the model. In summary, the high t-statistic values across all six dimensions confirm the scientific validity of the model and show that the collected data provide strong support for the hypothesis that the AI-based policy-making system is a primary and significant determinant for the core phenomenon, causal, contextual, intervening conditions, strategies, and consequences in the studied structure. Regarding the components, according to the provided table, all t-statistic values, for both the main dimensions and their constituent components, are very large numbers that clearly exceed the threshold of 1.96. This finding indicates that all relationships defined in the model have very strong and significant statistical support. In other words, the probability that these relationships were created randomly and due to sampling error is practically zero. The strongest relationship at the component level belongs to “managerial culture and approach” with a t-statistic of 187.315. This astonishing number emphasizes not only the significance but also the exceptional stability and power of this component as a critical contextual condition. In contrast, although the t-statistic for the “strategies” dimension (7.110) and its components (e.g., “actions taken” with 36.282) is still much higher than the significance threshold, it has the lowest value compared to other parts of the model. This finding is consistent with the lower path coefficient and R^2values of this section and indicates that although the relationship of strategies is significant, its effect size and certainty are considerably weaker compared to other factors (such as culture, data-driven decision-making, and consequences). This could suggest that the success of strategies is highly dependent on the existence of platforms provided by causal and contextual conditions. In conclusion, the massive t-statistic values confirm the strong validation of the theoretical model and show that all considered constructs play a significant role in explaining the main phenomenon, although the degree of this influence, as the path coefficients showed, is not uniform.

Table 2. T-statistic Values for the Dimensions of the Main Variable of the Policy-Making System with an AI Development Approach

No.	Dimension	T-statistic	Component	T-statistic
1	Core Phenomenon	42.886	Data-driven decision-making	158.569
			Increased managerial transparency and accuracy	131.952
2	Causal Conditions	55.551	Organizational and technological capacity	85.936
			Managerial acceptance and support	76.874
3	Contextual Conditions	46.482	Technological infrastructure and resources	104.743
			Managerial culture and approach	187.315
4	Intervening Conditions	36.850	Unforeseen support	99.281
			Unexpected barriers	91.559
5	Strategies	7.110	Actions taken for the utilization of AI	36.282
			Complementary needs for effective utilization	44.495
6	Consequences	124.793	Positive consequences	161.232
			Negative consequences	44.090

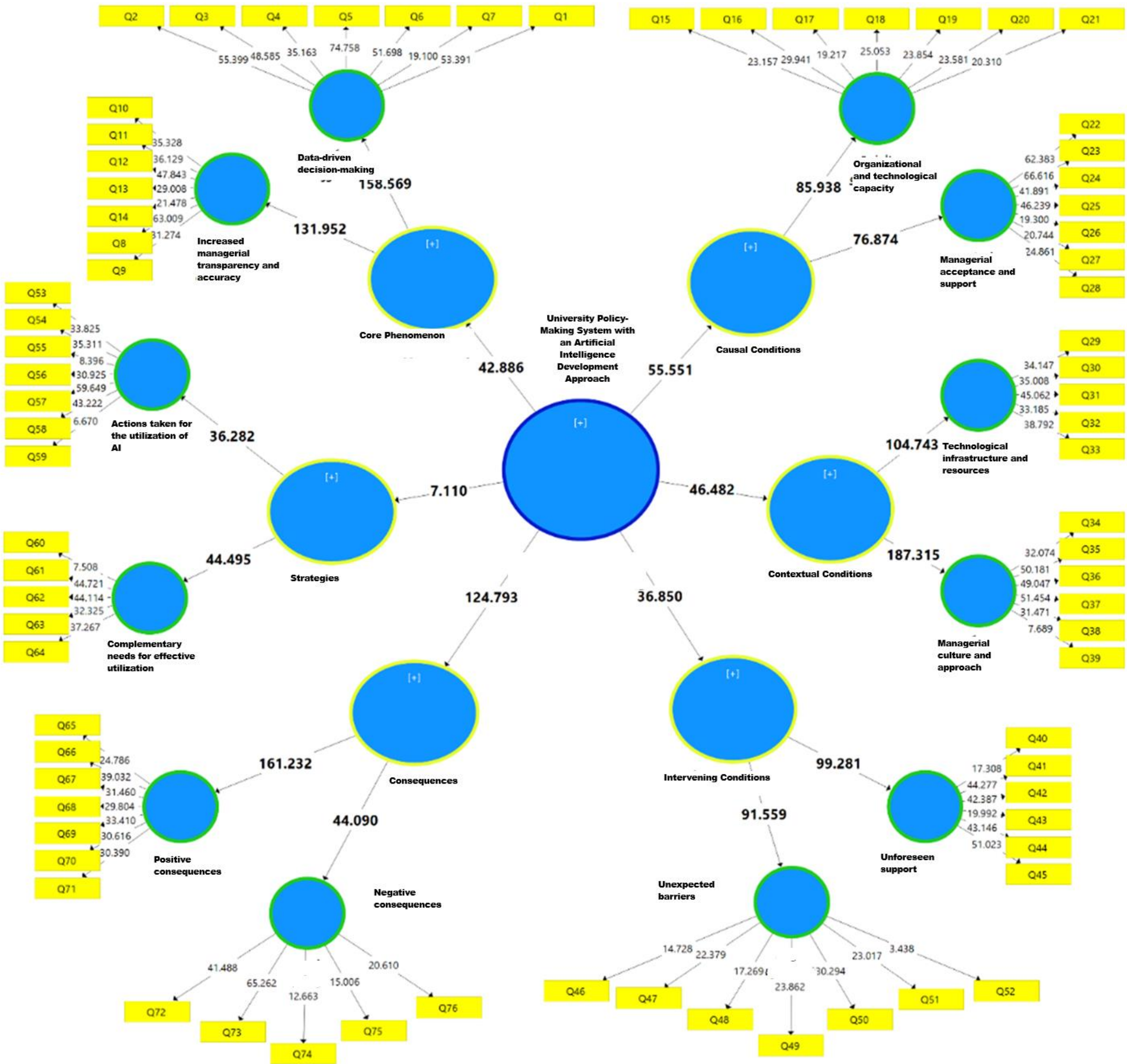

Figure 2. The relationship between the main variable of the policy-making system with an AI development approach and its paradigmatic dimensions in the path significance mode.

Discussion and Conclusion

The primary objective of this study was to design, validate, and analyze a comprehensive structural model of the university policy-making system with a specific approach focused on artificial intelligence (AI) development within the higher education institutions of Golestan province. The overarching results derived from the Partial Least Squares Structural Equation Modeling (PLS-SEM) confirmed that the proposed paradigmatic model possesses substantial empirical validity and structural integrity. The analysis of the path coefficients (β) and the explanatory power (R^2) across the distinct dimensions of the paradigm model—encompassing causal conditions, the core phenomenon, contextual conditions, intervening conditions, actionable strategies, and ultimate consequences—provides profound insights into the current dynamics of digital transformation in regional higher education governance. The findings reveal a highly complex ecosystem where the anticipation of technological benefits is exceptionally high, yet the operational mechanisms to achieve these benefits remain significantly underdeveloped.

A critical examination of the structural model reveals that the "causal conditions" exert a tremendously strong and positive effect on the core phenomenon of AI policy-making, evidenced by a highly significant path coefficient ($\beta = 0.867$). This result indicates that foundational drivers—such as the exponential growth of institutional data, the increasing complexity of student demographics, and the urgent necessity for operational efficiency—are actively forcing universities to transition away from legacy administrative frameworks. This finding aligns seamlessly with the theoretical propositions regarding the inherent obsolescence of traditional, highly centralized public policy-making processes, which are increasingly incapable of managing the non-linear complexities of modern institutional environments (1, 2). The strong causal drive observed in our model supports the contemporary administrative consensus that a paradigm shift toward dynamic, evidence-based frameworks is no longer optional but an existential necessity for organizational survival (3). Furthermore, this substantiates recent scholarship asserting that governance with artificial intelligence is the critical evolutionary next step for state and institutional apparatuses, moving them from reactive analog bureaucracies to proactive intelligent architectures (4). The high coefficient fundamentally demonstrates that regional universities are acutely aware of the global technological pressures and the paramount need to integrate intelligent systems to maintain their academic and administrative relevance.

Conversely, while the causal drivers are immensely powerful, the analysis of "contextual conditions" ($\beta = 0.505$) and "intervening conditions" ($\beta = 0.424$) highlights the significant environmental friction that moderates the implementation of AI policy. Contextual conditions, representing the localized technological infrastructure, budget constraints, and regional socio-economic realities of Golestan province, exert a moderate but crucial influence. This reflects broader international findings indicating that comprehensive analyses of countries and specific regions in terms of artificial intelligence technologies often reveal stark disparities in baseline readiness and infrastructural capacities (5). The intervening conditions, which encapsulate regulatory ambiguities, ethical concerns, and institutional resistance to algorithmic governance, also present substantial barriers. This directly corroborates recent critical literature emphasizing that the establishment of public policy and trust in artificial intelligence decision-making is heavily dependent on overcoming severe algorithmic anxiety, ensuring data privacy, and maintaining absolute democratic accountability within the algorithms themselves (8). Additionally, similar to how national information networks require rigorous scenario planning to mitigate unforeseen technological disruptions and cybersecurity threats (12), university networks must aggressively navigate these complex intervening variables to safely deploy AI, thus explaining the moderate, rather than extremely high, path coefficients for these specific dimensions.

Perhaps the most revealing and structurally critical finding of this research is the comparatively weak path coefficient associated with "strategies" ($\beta = 0.394$). Despite the overwhelming causal pressure to adopt AI and the clear recognition of the core phenomenon, the universities surveyed demonstrate a significant deficiency in formulating and executing concrete, actionable strategies. This empirical gap suggests a pronounced disconnect between high-level institutional aspirations and ground-level operational reality. Universities appear to understand *why* they need AI, but they currently lack the structural methodologies detailing exactly *how* to deploy it effectively. This structural vulnerability echoes the persistent challenges identified in the broader deployment of AI applications in policymaking, where translating complex algorithmic potential into daily administrative execution remains fraught with systemic friction (6). To bridge this gap, as strongly advocated by educational researchers, there is an absolute necessity to pivot toward behavioral-based educational policymaking models that prioritize practical skill alignment and tangible administrative execution over abstract theoretical planning (14). The low strategic coefficient underscores an urgent need to continuously identify and refine the core dimensions of the educational policymaking process to make them highly actionable and responsive to immediate technological realities (15). Furthermore, this highlights the immense difficulty of establishing comprehensive governance of artificial intelligence and expansive data in higher education, which requires specialized competencies that many regional administrative bodies currently lack (16).

In stark contrast to the weakness of the strategic dimension, the model indicates that the “consequences” of implementing an AI-driven policy-making system possess the highest explanatory power and the strongest structural impact within the entire paradigm ($\beta = 0.934$). This extraordinarily high coefficient illustrates that university stakeholders harbor profound, almost revolutionary, expectations regarding the ultimate outcomes of successful AI integration. Stakeholders firmly believe that if the strategic and intervening hurdles can be overcome, AI will dramatically optimize resource allocation, hyper-personalize student learning trajectories, and drastically enhance overarching institutional efficiency. This immense anticipation perfectly mirrors the transformative impacts of artificial intelligence observed in other critical sectors of public sector decision-making (7). Just as AI has fundamentally revolutionized epidemiological modeling and optimized systemic policy architectures in public health administration (9, 10), and precisely as it has enabled intelligent infrastructural optimization in complex urban management domains (11), university administrators anticipate an identical magnitude of positive disruption within higher education. The anticipation of these profound consequences strongly validates the need for a robust, forward-looking human capital educational policymaking guide that can accurately capture and harness this immense technological potential to align regional educational outputs with the stringent demands of the global digital economy (13).

While this research provides a robust structural framework, several inherent limitations must be acknowledged when interpreting the empirical findings. Primarily, the study utilizes a cross-sectional research design, which captures the perceptions and infrastructural realities of the university policy-making system at a single, specific point in time. Because digital transformation and artificial intelligence are highly dynamic and rapidly evolving fields, the causal relationships identified in this model may shift as new technologies emerge and institutional fluency increases. Additionally, the geographical scope is strictly confined to the higher education institutions within Golestan province. The specific socio-economic conditions, cultural administrative nuances, and localized infrastructural constraints of this specific province may limit the overarching generalizability of the structural model to universities in vastly different metropolitan or international contexts. Finally, the reliance on a researcher-made survey instrument inherently introduces the potential for self-report bias, where respondents might inadvertently inflate their institution’s technological readiness or overestimate the clarity of their strategic planning out of a desire to appear progressive.

To build upon the foundational model established in this study, future research endeavors should prioritize longitudinal methodologies to accurately track how the structural relationships between AI policy dimensions evolve over extended periods. Implementing a longitudinal approach would allow researchers to observe the long-term effectiveness of the adopted strategies and measure the actualized consequences against the currently high anticipatory expectations. Furthermore, it is highly recommended that subsequent studies expand the geographical and demographic scope by testing this specific structural equation model across a diverse array of national and international universities. Comparative studies contrasting regional institutions with major metropolitan or highly endowed private universities could reveal critical variations in contextual and intervening conditions. Most importantly, given the critically weak path coefficient identified for the “strategies” dimension ($\beta = 0.394$), future academic inquiry must intensely focus on the micro-mechanics of strategy formulation. Researchers should conduct deep qualitative case studies to identify the specific organizational bottlenecks preventing the translation of AI policy intentions into concrete operational algorithms and administrative daily practices.

Based on the empirical findings, particularly the significant gap between high causal drivers and weak operational strategies, university administrators and higher education policymakers must take immediate, targeted actions. Institutions should urgently establish specialized, cross-functional AI task forces comprising not only IT specialists but also academic deans, ethical compliance officers, and student representatives to ensure a holistic approach to technological deployment. These task forces must prioritize the translation of broad digital aspirations into granular, actionable, and heavily monitored strategic operational plans. Furthermore, significant infrastructural investment must be redirected toward localized cloud computing capabilities and rigorous data governance protocols to strengthen the foundational contextual conditions required for AI. Concurrently, universities must implement comprehensive, mandatory digital literacy and algorithmic management training programs for all administrative staff and faculty members. By aggressively demystifying artificial intelligence and equipping personnel with practical data management skills, institutions can directly mitigate the negative impacts of intervening conditions such as algorithmic anxiety and institutional resistance, thereby smoothing the critical pathway from theoretical policy formulation to highly effective, consequence-driven implementation.

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Authors' Contributions

All authors equally contributed to this study.

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The authors of this article declared no conflict of interest.

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Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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