Volume 3, Issue 2, pp 1-12
Article history:
Received 12 January 2026
Revised 15 March 2026
Accepted 28 March 2026
Published online 01 April 2026

Article type:
Original Research

Toward Intelligent Governance of Healthy Digital Learning Systems: A Future-Oriented Model of AI-Supported Blended Learning in Higher Education

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How to cite this article:
Akbari Markhali, F., & Keramatpour, M. (2026). Toward Intelligent Governance of Healthy Digital Learning Systems: A Future-Oriented Model of AI-Supported Blended Learning in Higher Education. *Foresight and Health Governance*, 3(2), 1-12. https://doi.org/10.61838/jfhg.50

ABSTRACT

This article develops a future-oriented model for the intelligent governance of healthy digital learning systems in higher education, drawing on doctoral research conducted at Islamic Azad University. While the original dissertation established a blended learning model supported by artificial intelligence to improve e-learning quality, the present article reinterprets those findings through a governance lens. Rather than treating artificial intelligence as an autonomous driver of educational transformation, the study argues that AI should be governed as an enabling layer that strengthens pedagogical coherence, learner support, and institutional responsiveness within blended environments. A sequential mixed-methods design was used. In the qualitative phase, semi-structured interviews with 15 experts in education, e-learning, and educational technology were analyzed through thematic analysis to identify the core dimensions of the proposed model. In the quantitative phase, data from 384 faculty members and university experts were analyzed using partial least squares structural equation modeling (PLS-SEM), artificial neural networks (ANN), and the MABAC multi-criteria decision-making technique. The findings indicate that the governance architecture of a healthy digital learning system consists of three interrelated domains: blended learning (flexibility, interaction, personalization, and infrastructure/access), AI capabilities (educational data analysis, intelligent recommendation, intelligent support, and automated assessment), and healthy digital learning outcomes, operationalized in the dissertation as e-learning quality (learner satisfaction, learning effectiveness, and educational interaction). The model showed substantial explanatory capacity ($R^2 = 0.712$ in the dissertation summary). Blended learning had a stronger direct effect on e-learning quality ($\beta = 0.574$) than AI capabilities alone ($\beta = 0.437$), whereas AI exerted a very strong enabling effect on blended learning ($\beta = 0.926$). ANN results prioritized learner satisfaction (0.2772) and learning effectiveness (0.1780), while MABAC ranked intelligent support first, intelligent recommendation second, automated assessment third, and educational data analysis fourth. The article concludes that universities should adopt pedagogy-first, support-centered, and ethically governed AI strategies to build resilient and healthy digital learning systems.

Keywords: artificial intelligence; blended learning; digital governance; e-learning quality; higher education; healthy digital learning systems

Introduction

The rapid digitalization of higher education has intensified a long-standing question: how can universities use technology to improve learning quality without allowing technological tools to dictate the terms of education itself? Digital platforms, analytics systems, adaptive tools, and, more recently, generative artificial intelligence have expanded the possibilities of instructional design, student support, and assessment. Yet the proliferation of technological solutions has also exposed structural weaknesses in many university systems, including fragmented implementation, uneven digital access, low interaction quality, limited personalization, and uncertainty about how institutions should govern the expanding role of AI in teaching and learning (Al-Fraihat et al., 2020; Alhabeeb & Rowley, 2018; Anwar et al., 2020; McGill et al., 2014). For that reason, contemporary debates in higher education are shifting from the simple adoption of technology toward the governance of digital learning systems. Governance in this context does not merely refer to formal policy documents. It refers to the set of institutional principles, pedagogical priorities, organizational arrangements, infrastructural commitments, and ethical controls that determine how digital tools are selected, integrated, monitored, and revised over time. This shift is especially important in blended learning environments, where face-to-face and online modalities must function as complementary rather than competing parts of an integrated educational design (Alamri et al., 2021; Bozkurt, 2022; McCarthy & Palmer, 2023; Min & Yu, 2023). The dissertation by Akbari Markhali, on which the present article is based, addressed this challenge by developing a model of blended learning for improving the quality of e-learning in universities through the use of artificial intelligence capabilities. The empirical context was Islamic Azad University, one of the largest higher education networks in Iran. The original study showed that blended learning and AI capabilities jointly contribute to e-learning quality and that the most influential priorities are not purely technological variables, but learner-centered outcomes such as satisfaction and effectiveness. Those results create an opportunity for reinterpretation. Instead of reading the model merely as a technology-enhanced learning framework, it can be understood as a governance architecture for healthy digital learning systems.

In this article, the phrase healthy digital learning systems is used analytically to refer to digitally mediated learning arrangements that are pedagogically coherent, interaction-rich, learner-supportive, accessible, adaptive, and sustainable over time. Within the dissertation, this health condition was empirically represented by the construct of e-learning quality, operationalized through learner satisfaction, learning effectiveness, and educational interaction. Reframing these outcomes as indicators of system health makes it possible to generate a more future-oriented interpretation of the dissertation findings. It also allows the study to speak directly to contemporary concerns about AI governance in higher education, including proportionality, ethics, transparency, and the need to prioritize support over surveillance (Banihashem et al., 2022; Bearman et al., 2023; Bond et al., 2024; Chu et al., 2022). This article therefore differs from the previous article derived from the dissertation. The earlier paper emphasized the design of intelligent learning ecosystems and focused on how AI and blended learning enhance digital education quality. The present article moves beyond enhancement discourse and foregrounds governance. It asks a different interpretive question: what do the dissertation findings imply about how universities should govern AI-supported blended learning if their aim is to cultivate healthy, resilient, and future-ready digital learning systems?

This reframing is timely. Research on AI in higher education increasingly warns against deterministic or solutionist narratives in which AI is assumed to transform education by virtue of technical sophistication alone (Annamalai et al., 2025; Bearman et al., 2023; Bond et al., 2024; Chu et al., 2022; Kuleto et al., 2021; Wang et al., 2024). Evidence suggests that technology is effective only when embedded in sound pedagogical design, adequate infrastructure, staff capability, meaningful interaction, and institutional trust (Al-Fraihat et al., 2020; Mao et al., 2024; McCarthy & Palmer, 2023; McGill et al., 2014). Universities therefore need models that clarify not only what tools can do, but what must be governed if those tools are to contribute to educational quality. By using the dissertation's mixed-methods evidence base and reanalyzing its meaning through a governance-oriented conceptual lens, this article aims to provide such a model. The article has four objectives. First, it reconstructs the dissertation's empirical model in governance terms. Second, it shows that blended learning functions as the primary pedagogical driver of quality, while AI operates as an enabling and amplifying layer. Third, it identifies the strategic priorities that should guide implementation, drawing on the ANN and MABAC results. Fourth, it proposes practical implications for universities that want to move toward healthy and ethically governed digital learning systems. In doing so, the article contributes to current scholarship on blended learning, AI in education, and digital governance by offering a model rooted in empirical evidence yet oriented toward future institutional design.

Literature Review and Conceptual Background

Blended learning has been one of the most widely discussed organizational models for digital transformation in higher education because it offers a pragmatic middle path between conventional face-to-face teaching and fully online delivery (Bozkurt, 2022; Kohnke et al., 2024; Lazarinis et al., 2024; McCarthy & Palmer, 2023; Means et al.). Its strength lies not in mixing modalities for their own sake, but in aligning pedagogical purpose with mode selection. When blended learning is thoughtfully designed, universities can improve flexibility, expand access, increase opportunities for interaction, and accommodate differences in learner pace and need (Liu, 2024; Mariam et al., 2023; Min & Yu, 2023; Nirmala et al., 2025; Pimdee et al., 2024). Systematic reviews and meta-analyses consistently show that blended approaches can improve achievement, engagement, and satisfaction under appropriate conditions (Liu, 2024; Mariam et al., 2023; Means et al.; Rashidi, 2023). However, the literature also makes clear that blended learning does not automatically lead to better outcomes. Its success depends on curriculum design, staff readiness, technological reliability, student support, and institutional coordination (Lazarinis et al., 2024; McCarthy & Palmer, 2023; Min & Yu, 2023; Stöhr & Färnevik, 2020). A second body of scholarship concerns the quality of e-learning. Studies in this area have conceptualized quality through multiple dimensions, including system quality, information quality, service quality, user satisfaction, interaction, and performance outcomes (Al-Fraihat et al., 2020; Alhabeeb & Rowley, 2018; Anwar et al., 2020; Sui & Yang, 2023). This literature is important because it shows that digital learning quality is not reducible to platform functionality. Instead, quality emerges from an interaction between technological infrastructure, instructional design, communication processes, and learner experience. User satisfaction, perceived usefulness, responsiveness, and educational interaction are therefore not peripheral indicators; they are among the clearest signals of whether a digital learning arrangement is functioning well (Al-Fraihat et al., 2020; Alhabeeb & Rowley, 2018; Anwar et al., 2020; Sui & Yang, 2023; Wang et al., 2023).

The third relevant literature concerns artificial intelligence in higher education. AI can support digital learning through data analysis, recommendation systems, feedback automation, intelligent tutoring, predictive analytics, and adaptive assessment (Annamalai et al., 2025; Bearman et al., 2023; Bond et al., 2024; Chu et al., 2022; Kuleto et al., 2021; Mao et al., 2024; Wang et al., 2023; Wang et al., 2024). From an institutional perspective, these capabilities promise scale, responsiveness, and personalization. Yet the literature increasingly emphasizes that AI should not be treated as a neutral upgrade layer. Critical reviews show that higher education discourse often invokes AI in broad, aspirational terms while under-specifying its educational purposes, governance implications, and ethical risks (Bearman et al., 2023; Bond et al., 2024; Chu et al., 2022). Concerns include opacity, algorithmic bias, privacy intrusion, over-reliance on prediction, and the displacement of human judgment in areas where contextual sensitivity is essential (Annamalai et al., 2025; Kuleto et al., 2021; Wang et al., 2024). Consequently, scholars now call for stronger attention to ethics, governance, collaboration, and pedagogical alignment in AI-related educational research and implementation (Bearman et al., 2023; Bond et al., 2024; Chu et al., 2022). Learning analytics provides an especially useful bridge between these discussions. On the one hand, analytics may help institutions identify patterns of participation, provide timely feedback, and support proactive intervention (Banihashem et al., 2022). On the other hand, analytics can introduce ethical dilemmas if data extraction is not balanced by transparency, proportionality, and educational benefit (Kuleto et al., 2021; Wang et al., 2023; Wang et al., 2024). Early work on learning analytics ethics emphasized privacy, informed consent, and institutional responsibility (Kuleto et al., 2021; Wang et al., 2024). More recent scholarship offers practical recommendations for predictive analytics that foreground explanation, human oversight, and student protection (Wang et al., 2023). These debates suggest that AI governance in higher education cannot be limited to compliance. It must also involve value-based decisions about what counts as legitimate support, acceptable automation, and educationally meaningful adaptation.

Taken together, the three literatures point to an unresolved issue. Research has produced rich evidence on blended learning design, e-learning quality, and AI applications, but these strands are often discussed separately. When they are linked, the relationship is frequently framed in enhancement terms: AI enhances blended learning; blended learning enhances e-learning quality. That logic is useful but incomplete. It does not fully explain how institutions should sequence priorities, allocate responsibilities, or decide which AI functions deserve emphasis in contexts where resources, infrastructure, and trust are uneven. In other words, the literature still needs models that connect educational design to governance. This article addresses that need by proposing a future-oriented governance interpretation of the dissertation findings. The model treats blended learning as the pedagogical and organizational backbone of digital education. AI capabilities are conceptualized as a service layer that can strengthen this backbone, but only if institutional governance preserves proportionality and learner-centeredness. Healthy digital learning outcomes—captured empirically through satisfaction, effectiveness, and educational interaction—serve as the test of whether the system is functioning well. This interpretive move is supported by emerging evidence that AI is most valuable when it deepens responsiveness without eroding pedagogy. Personalized recommendation can help learners navigate resources (Alamri et al., 2021; Bond et al., 2024), intelligent support can sustain motivation and access (Annamalai et al., 2025; Bond et al., 2024), automated assessment can accelerate formative feedback when carefully designed (Mao et al., 2024), and data analysis can inform institutional decisions (Banihashem et al., 2022). Yet not all capabilities have equal immediate value for healthy digital learning systems. If institutions prioritize surveillance-heavy or technically impressive functions before building infrastructure, trust, flexibility, and human support, AI can become a source of friction rather than a contributor to quality. A governance model is therefore needed to clarify sequence, balance, and institutional responsibility.

The dissertation used mixed methods to identify a three-part architecture—blended learning, AI capabilities, and e-learning quality. The present article advances that architecture conceptually. It argues that future-oriented governance in higher education should begin from pedagogical coherence, move through ethically governed AI enablement, and be evaluated in terms of system health. In this sense, healthy digital learning systems are not simply digitally advanced systems. They are systems in which technology remains accountable to educational values, institutional capacity, and the lived experience of learners and teachers.

Methodology

This article is based on the doctoral dissertation conducted at Islamic Azad University and retains the empirical design, dataset, and analytical procedures of that study, while offering a distinct conceptual interpretation. The original research adopted a sequential mixed-methods design grounded in pragmatism. This design was appropriate because the study aimed both to identify the components of an AI-supported blended learning model and to test the relationships among those components within a large university context. In the qualitative phase, semi-structured interviews were conducted with 15 experts selected through purposive sampling. Participants had expertise in e-learning, educational technology, blended learning, and related fields of higher education. The interviews were analyzed using thematic analysis in order to identify the major dimensions and subcomponents of the proposed model. The qualitative phase produced three broad domains: blended learning, AI capabilities, and e-learning quality, along with their respective components. In the quantitative phase, questionnaire data were collected from 384 faculty members and university experts through stratified random sampling across regions and academic fields within Islamic Azad University. The sample included both men and women and represented different age and educational backgrounds. Descriptive results in the dissertation indicated a reasonably balanced gender distribution, a large share of respondents above age 35, and representation from bachelor's, master's, and doctoral degree holders. This composition strengthened the relevance of the findings for institutional planning because respondents were familiar with university teaching and educational administration. The questionnaire was developed on the basis of the qualitative findings. Quantitative analysis proceeded in three stages. First, PLS-SEM was used to evaluate the measurement and structural models. This step assessed factor loadings, reliability, convergent validity, collinearity, path coefficients, and explanatory power. Second, latent variable scores extracted from the PLS-SEM model were entered into an artificial neural network to determine the relative importance of quality- and blended-learning-related indicators. Third, the MABAC multi-criteria decision-making technique was used to rank AI capabilities identified in the qualitative phase. The present article reuses those results in full, but the analytic emphasis changes. Rather than focusing primarily on model validation as an end in itself, the study interprets the validated model as an institutional governance framework. The question is not only whether the model fits the data, but also what the pattern of results implies for universities deciding how to govern AI-supported blended learning over the medium and long term.

Table 1. Governance architecture derived from the dissertation findings

Domain	Core components	Governance function
Blended learning	Flexibility; interaction; personalization; infrastructure/access	Establishes the pedagogical and organizational backbone of the digital learning system
AI capabilities	Educational data analysis; intelligent recommendation; intelligent support; automated assessment	Provides an adaptive, service-oriented enablement layer for decision support and learner assistance
Healthy digital learning outcomes (empirically represented as e-learning quality)	Learner satisfaction; learning effectiveness; educational interaction	Indicates whether the system is educationally successful, sustainable, and aligned with learner needs

Research Findings

Overview of the analytical output

The results derived from the dissertation support a robust, multi-layered model of AI-supported blended learning in higher education. The empirical structure identified in the qualitative phase was retained in the quantitative phase and validated through PLS-SEM, ANN, and MABAC analyses. Three higher-order domains were confirmed: blended learning, AI capabilities, and e-learning quality. In the present article, these are interpreted as the pedagogical backbone, the intelligent enablement layer, and the health condition of the digital learning system, respectively. The study sample for the quantitative phase comprised 384 faculty members and university experts, while the qualitative model-building phase drew on 15 expert interviews. The dissertation’s abstract and analytical chapters consistently indicate that the model achieved substantial explanatory power and a coherent internal structure.

Qualitative identification of the model domains

The thematic analysis yielded three central dimensions and their associated components. Blended learning included flexibility, interaction, personalization, and infrastructure/access. AI capabilities included educational data analysis, intelligent recommendation, intelligent support, and automated assessment. E-learning quality comprised learner satisfaction, learning effectiveness, and educational interaction. This qualitative architecture later became the foundation for the measurement and structural models used in the quantitative phase.

Table 2. Core dimensions and components identified from the dissertation

Domain	Components
Blended learning	Flexibility; interaction; personalization; infrastructure/access
AI capabilities	Educational data analysis; intelligent recommendation; intelligent support; automated assessment
E-learning quality	Learner satisfaction; learning effectiveness; educational interaction

Measurement model quality: reliability and convergent validity

The measurement model showed satisfactory psychometric quality across all major constructs. Cronbach’s alpha values ranged from 0.746 to 0.975, composite reliability values ranged from 0.748 to 0.976, and average variance extracted (AVE) values ranged from 0.560 to 0.753. The higher-order constructs also met the relevant thresholds. In particular, blended learning showed alpha = 0.940, composite reliability = 0.941, and AVE = 0.604, while AI capabilities showed alpha = 0.914, composite reliability = 0.915, and AVE = 0.594. E-learning quality demonstrated alpha = 0.975, composite reliability = 0.976, and AVE = 0.560. These values confirm that the retained indicators adequately captured their latent variables and that convergent validity was established across the model.

Table 3. Reliability and convergent validity of the principal constructs

Construct	Cronbach's alpha	Composite reliability	AVE
Learning effectiveness	0.788	0.789	0.702
Automated assessment	0.772	0.778	0.686
Flexibility	0.835	0.840	0.753
Educational data analysis	0.789	0.794	0.703
Interaction	0.799	0.799	0.714
Educational interaction	0.772	0.774	0.687
Intelligent recommendation	0.796	0.798	0.710
Learner satisfaction	0.791	0.791	0.705
Infrastructure/access	0.785	0.788	0.700
Personalization	0.768	0.768	0.683
AI capabilities	0.914	0.915	0.594
Intelligent support	0.746	0.748	0.663
E-learning quality	0.975	0.976	0.560
Blended learning	0.940	0.941	0.604

Structural model results

The structural model demonstrated strong and statistically significant relationships among the main constructs. AI capabilities had a very strong positive effect on blended learning ($\beta = 0.926$, $t = 155.292$, $p < 0.001$), indicating that AI substantially reinforces the operation of blended learning environments. However, when explaining e-learning quality directly, blended learning showed the stronger effect ($\beta = 0.574$, $t = 31.304$, $p < 0.001$), whereas AI capabilities also contributed significantly but to a lesser extent ($\beta = 0.437$, $t = 23.778$, $p < 0.001$). This pattern suggests that pedagogical architecture remains the primary direct driver of quality, while AI functions as a strong enabling layer. The paths from the higher-order constructs to their subdimensions were also uniformly strong and significant. For blended learning, the strongest reflective loading was flexibility ($\beta = 0.937$, $t = 184.451$), followed by infrastructure/access ($\beta = 0.919$, $t = 114.911$), interaction ($\beta = 0.917$, $t = 104.399$), and personalization ($\beta = 0.911$, $t = 105.903$). For the AI-related side of the model, e-learning quality was strongly associated with automated assessment ($\beta = 0.893$, $t = 90.765$), educational data analysis ($\beta = 0.890$, $t = 74.554$), intelligent recommendation ($\beta = 0.902$, $t = 89.520$), and intelligent support ($\beta = 0.865$, $t = 66.516$). AI capabilities were also strongly linked to learning effectiveness ($\beta = 0.927$, $t = 116.786$), educational interaction ($\beta = 0.922$, $t = 129.678$), and learner satisfaction ($\beta = 0.919$, $t = 112.714$). All reported p-values were < 0.001.

Table 4. Main structural paths reported in the dissertation

Path	β	t	p
AI capabilities → blended learning	0.926	155.292	<0.001
AI capabilities → e-learning quality	0.437	23.778	<0.001
Blended learning → e-learning quality	0.574	31.304	<0.001
AI capabilities → learning effectiveness	0.927	116.786	<0.001
AI capabilities → educational interaction	0.922	129.678	<0.001
AI capabilities → learner satisfaction	0.919	112.714	<0.001
E-learning quality → automated assessment	0.893	90.765	<0.001
E-learning quality → educational data analysis	0.890	74.554	<0.001
E-learning quality → intelligent recommendation	0.902	89.520	<0.001
E-learning quality → intelligent support	0.865	66.516	<0.001
Blended learning → flexibility	0.937	184.451	<0.001
Blended learning → interaction	0.917	104.399	<0.001
Blended learning → infrastructure/access	0.919	114.911	<0.001
Blended learning → personalization	0.911	105.903	<0.001

Multicollinearity, predictive relevance, and explanatory power

The collinearity diagnostics were well within acceptable bounds. The dissertation reports VIF values ranging from 1.453 to 4.080, all below the conventional cut-off of 5, indicating that severe multicollinearity was not present in the structural model. This supports the stability of the parameter estimates. The predictive relevance results were also strong. The Q^2 values reported for the endogenous constructs were all above zero and often well above the threshold for strong predictive relevance. Among the most important values, e-learning quality had $Q^2 = 0.547$, blended learning had $Q^2 = 0.514$, infrastructure/access had $Q^2 = 0.587$, personalization had $Q^2 = 0.561$, and intelligent support had $Q^2 = 0.491$. These values indicate that the model has meaningful out-of-sample predictive utility for the most important endogenous constructs.

The R^2 results further confirm the strength of the model. The dissertation reports $R^2 = 0.985$ for e-learning quality and $R^2 = 0.857$ for blended learning. At the subdimension level, flexibility had $R^2 = 0.879$, learning effectiveness had $R^2 = 0.858$, educational interaction had $R^2 = 0.851$, learner satisfaction had $R^2 = 0.845$, infrastructure/access had $R^2 = 0.844$, interaction had $R^2 = 0.841$, personalization had $R^2 = 0.829$, intelligent recommendation had $R^2 = 0.814$, automated assessment had $R^2 = 0.797$, educational data analysis had $R^2 = 0.792$, and intelligent support had $R^2 = 0.748$. The dissertation abstract also reports an overall explanatory coefficient of 0.712 for the model summary. Taken together, these values indicate a highly explanatory structure with strong endogenous prediction.

Table 5. Model adequacy indicators

Indicator	Reported values
VIF range	1.453 to 4.080
Q^2 for e-learning quality	0.547
Q^2 for blended learning	0.514
Q^2 for infrastructure/access	0.587
Q^2 for personalization	0.561
Q^2 for intelligent support	0.491
R^2 for e-learning quality	0.985
R^2 for blended learning	0.857
R^2 for flexibility	0.879
R^2 for learning effectiveness	0.858
R^2 for educational interaction	0.851
R^2 for learner satisfaction	0.845
R^2 for infrastructure/access	0.844
R^2 for interaction	0.841
Dissertation summary coefficient	0.712

ANN-based prioritization of key indicators

To complement the structural model, the dissertation used an artificial neural network to optimize the weighting of the main indicators connected to blended learning and e-learning quality. The ANN showed excellent performance, with a normalized mean squared error of 0.00597407 and a normalized R^2 of 0.95799499. These values indicate high predictive fit for the ANN stage of the analysis.

The ANN results identified learner satisfaction as the most influential indicator (0.2771647), followed by learning effectiveness (0.17803555), flexibility (0.15017014), interaction (0.12808615), educational interaction (0.12635323), infrastructure/access (0.099792), and personalization (0.04039824). These findings show that the most influential variables are closely tied to the student experience and the practical usability of the learning system rather than to abstract technological novelty alone.

Table 6. ANN performance and optimal weights

Metric / variable	Value
MSE (normalized)	0.00597407
R^2 (normalized)	0.95799499
Learner satisfaction	0.2771647
Learning effectiveness	0.17803555
Flexibility	0.15017014

Interaction	0.12808615
Educational interaction	0.12635323
Infrastructure/access	0.099792
Personalization	0.04039824

MABAC ranking of AI capabilities

The MABAC multi-criteria decision-making analysis was used to rank the AI capabilities identified in the qualitative phase. The final Q values indicate that intelligent support ranked first (Q = 0.2373), intelligent recommendation ranked second (Q = 0.2343), automated assessment ranked third (Q = -0.1234), and educational data analysis ranked fourth (Q = -0.1399). The small distance between the first and second ranked options suggests that both support-oriented and recommendation-oriented AI functions are strategically important, but the higher placement of intelligent support indicates that respondent judgments favored direct learner assistance over more back-end or analytic AI roles. filecite turn15file0

Table 7. MABAC ranking of AI capabilities

Option	AI capability	Q value	Rank
A3	Intelligent support	0.2373	1
A2	Intelligent recommendation	0.2343	2
A4	Automated assessment	-0.1234	3
A1	Educational data analysis	-0.1399	4

Integrated interpretation of the results

The combined evidence from PLS-SEM, ANN, and MABAC points to a consistent conclusion. First, blended learning is the strongest direct determinant of e-learning quality, whereas AI capabilities reinforce blended learning very strongly and also contribute directly to quality. Second, learner-centered outcomes—especially satisfaction and effectiveness—are the most influential indicators in the ANN model. Third, among AI functions, those most closely tied to practical learner support and guidance were prioritized over data-heavy or automation-heavy functions. In other words, the dissertation results support a pedagogy-first and support-oriented model of digital transformation in higher education.

Discussion

The purpose of this article was not to generate a new dataset, but to derive a distinct scholarly contribution from an existing dissertation by changing the interpretive frame. That shift proves meaningful. When the findings are read through the lens of governance rather than mere technological enhancement, a clearer institutional logic emerges. The first major insight is that blended learning, not AI, is the principal pedagogical driver of digital education quality. This does not diminish the importance of AI. On the contrary, AI exerted an exceptionally strong effect on blended learning in the model and also contributed directly to e-learning quality. Yet the stronger direct path from blended learning to quality shows that educational health depends first on the architecture of teaching and learning. Flexibility, interaction, personalization, and infrastructure are not optional supports around a technological core; they are the core conditions through which digital learning becomes educationally meaningful (Alamri et al., 2021; Bozkurt, 2022; Kohnke et al., 2024; Lazarinis et al., 2024; Liu, 2024; Mariam et al., 2023; McCarthy & Palmer, 2023; Means et al.; Min & Yu, 2023; Nirmala et al., 2025; Pimdee et al., 2024; Rashidi, 2023; Stöhr & Färnevik, 2020). This finding aligns with wider literature showing that digital tools are most effective when embedded in coherent pedagogical design and accompanied by institutional support (Al-Fraihat et al., 2020; Alhabeeb & Rowley, 2018; Anwar et al., 2020; McCarthy & Palmer, 2023; McGill et al., 2014; Min & Yu, 2023). The second insight is that AI is most valuable when it functions as a support-oriented governance layer. The MABAC results are especially revealing in this regard. Intelligent support and intelligent recommendation were ranked above automated assessment and educational data analysis. This pattern suggests that respondents valued AI most when it helped students act, decide, persist, and navigate. In other words, the preferred form of intelligence in the learning system was not primarily classificatory or surveillance-oriented, but assistive and facilitative. This interpretation resonates with critical scholarship warning that higher education should avoid allowing predictive systems and opaque analytics to dominate educational practice without clear benefit to learners (Annamalai et al., 2025; Bearman et al., 2023; Bond et al., 2024; Chu et al., 2022; Kuleto et al., 2021; Mao et al., 2024; Wang et al., 2023; Wang et al., 2024). A healthy digital learning system is therefore not the system with the most data extraction; it is the system in which AI visibly improves the learner's pathway through education. The third insight concerns how quality should be governed. The ANN results placed learner satisfaction above all other indicators, followed by learning effectiveness. This is significant because universities often interpret digital transformation primarily through operational metrics such as platform adoption, usage counts, or cost efficiency. The results point in a different direction. A system can be technologically advanced yet educationally unhealthy if learners experience confusion, low motivation, weak interaction, or perceived irrelevance. Satisfaction in this context should not be trivialized as a consumerist measure. It reflects the cumulative effect of usability, support, meaningful engagement, and pedagogical fit. When satisfaction is low, the health of the system is at risk even if the technology appears sophisticated (Al-Fraihat et al., 2020; Alhabeeb & Rowley, 2018; Liu, 2024; Sui & Yang, 2023; Wang et al., 2023). A fourth insight concerns the governance meaning of infrastructure. In the qualitative and quantitative model, infrastructure/access appeared as a strong component of blended learning. This suggests that healthy digital learning systems require a broader conception of infrastructure than mere connectivity. Infrastructure includes reliable platforms, equitable access, functional support services, staff capability, responsive design, and organizational arrangements that allow students and teachers to move productively between physical and digital spaces. This is particularly important in large university systems and in contexts where digital inequality remains a concern. Governance frameworks that overlook these infrastructural conditions may overestimate the capacity of AI tools to compensate for systemic weakness. The study also contributes to current debates on AI ethics in higher education. Much of the literature emphasizes privacy, fairness, and transparency (Bearman et al., 2023; Bond et al., 2024; Chu et al., 2022; Kuleto et al., 2021; Mao et al., 2024; Wang et al., 2023; Wang et al., 2024). The findings add an implementation-oriented insight: ethical governance is not only about controlling harm after deployment; it is also about choosing the right order of priorities before deployment. If intelligent support and recommendation are the most valuable capabilities for healthy digital learning systems, then institutions should privilege these functions when piloting AI. By sequencing AI adoption around clear learner benefit, universities can reduce ethical risk while building trust and capability. This is especially relevant in settings where institutional legitimacy and user confidence are still fragile. At the same time, the article should be read with appropriate caution. The present study is a reinterpretation of one dissertation dataset in one university system. Its governance claims are theoretically reasoned from robust empirical results, but they still require further testing across institutions and national contexts. In addition, the article reported some internal complexity in model-level statistics, including different presentations of explanatory power across chapters and tables. For that reason, this article relies conservatively on clearly stated summary values, path coefficients, predictive relevance indices, and ranking outputs. Even with that caution, the overall pattern remains highly consistent: pedagogy-first blended learning, AI as enabler, learner-centered outcomes as the measure of system health. This pattern has broader relevance. As universities increasingly integrate AI into teaching, advising, assessment, and student services, they risk treating digital transformation as a stack of technical acquisitions. The findings imply a different path. Transformation should be governed as the cultivation of healthy digital learning systems—systems in which technology serves educational continuity, interaction, fairness, and growth rather than replacing them. In that sense, the future orientation of the present model lies not in forecasting ever more automation, but in designing institutions that can adopt AI without surrendering pedagogical judgment.

The findings support several practical implications for university leaders, instructional designers, and policy makers. First, pedagogy should lead technology. Institutional strategies for AI adoption should begin with the architecture of blended learning rather than with the procurement of AI tools. This means clarifying where flexibility is needed, what kinds of interaction matter most, how personalization should be defined pedagogically, and what infrastructural weaknesses constrain quality. AI can then be selected to reinforce these priorities instead of forcing pedagogy to adapt to available tools. Second, support-centered AI should be prioritized. Because intelligent support and intelligent recommendation were the highest-ranked AI capabilities, universities should begin with applications that directly help learners navigate courses, receive timely guidance, identify relevant resources, and remain engaged. Examples might include recommendation systems for course content, intelligent FAQs, adaptive learning pathways, and structured support dashboards with human oversight. Such uses are more likely to deliver visible educational value and build institutional trust than analytics-first deployments. Third, learner satisfaction should be treated as a strategic governance metric. Institutions often collect satisfaction data after implementation, but the ANN results suggest that satisfaction is central to system health. Universities should therefore monitor satisfaction continuously and connect it to design decisions about platform usability, communication quality, assessment burden, and access conditions. Satisfaction data should not stand alone; it should be interpreted alongside learning effectiveness and educational interaction. Fourth, infrastructure must be understood as socio-technical capacity. Investment in servers and platforms is necessary, but not sufficient. Institutions also need faculty development, responsive technical support, clear communication channels, digital accessibility standards, and mechanisms for iterative course redesign. Governance frameworks should specify who is responsible for each of these layers and how improvements will be evaluated over time. Fifth, AI governance should be iterative and proportionate. Rather than adopting comprehensive AI systems across all functions simultaneously, universities should pilot specific capabilities, evaluate their impact on quality indicators, and revise implementation based on evidence. This approach is particularly important for ethically sensitive functions such as predictive analytics and automated assessment. Proportionality means matching the sophistication and intrusiveness of AI tools to demonstrable educational need and institutional readiness.

Finally, the model has value for higher education systems beyond the specific case of Islamic Azad University. Many universities in the Global South and in large distributed systems face similar challenges: uneven infrastructure, varied staff readiness, growing demand for flexibility, and pressure to modernize. The present governance model offers a practical principle for such contexts: strengthen the pedagogical backbone first, use AI to enhance support, and judge success through the health of the learning system rather than the novelty of the technology.

Conclusion

This article reinterpreted a doctoral dissertation on AI-supported blended learning at Islamic Azad University through the lens of intelligent governance. Instead of asking how AI and blended learning enhance digital education quality in general terms, the present study asked how universities should govern those relationships if their aim is to build healthy digital learning systems. The answer is clear. Blended learning is the main pedagogical driver of quality. AI is powerful, but its role is primarily enabling and amplifying rather than foundational. Learner satisfaction, learning effectiveness, and educational interaction are the most meaningful indicators of whether the system is healthy. Among AI capabilities, intelligent support and intelligent recommendation should be prioritized over more extractive or automation-heavy functions. The future-oriented implication is that successful universities will not be those that adopt the most AI, but those that govern AI most wisely. By grounding this interpretation in mixed-methods evidence, the article provides a practical framework for higher education institutions seeking to align innovation with pedagogy, ethics, and institutional capacity. Healthy digital learning systems do not emerge from technology alone. They emerge when universities govern technology in ways that sustain educational purpose, human support, and adaptive resilience over time.

Acknowledgments

We would like to express our appreciation and gratitude to all those who cooperated in carrying out this study.

Authors' Contributions

Fatemeh Akbari Markhali contributed to the original dissertation research, data collection framework, and primary conceptual development. Mehdi Keramatpour supervised the dissertation, contributed to methodological guidance, and served as corresponding author. Both authors contributed to the present article's framing, interpretation, revision, and final approval.

Declaration of Interest

The authors of this article declared no conflict of interest.

AI use statement

Generative AI tools were used only for English language refinement, structural reorganization, and journal-style presentation of material derived from the dissertation. All empirical results, analytical decisions, and final verification of accuracy were the responsibility of the authors.

Ethical Considerations

According to the doctoral dissertation on which this article is based, participation in the qualitative interviews and quantitative survey was voluntary, and respondent confidentiality was protected throughout data collection and analysis. The accessible dissertation text includes the institutional research ethics charter of Islamic Azad University.

Transparency of Data

The article is derived from a doctoral dissertation and the dataset is not deposited in a public repository in the accessible source file. Reasonable requests for research materials should be directed to the corresponding author, subject to university policies and participant confidentiality.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

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