IMPROVING ARTIFICIAL INTELLIGENCE-BASED DECISION SUPPORT SYSTEMS IN THE QUALITY CONTROL OF EDUCATION AT HIGHER EDUCATION INSTITUTIONS

Abduganiyeva Mavjuda Asatullayevna
Senior Lecturer, Department of Digital Economy
Tashkent State University of Economics
ORCID: 0009-0005-0256-236X
E-mail: mavjudaabduganiyeva02.27@gmail.com

ARTICLE INFO

Received: 27th August 2026
Accepted: 29th August 2026
Online: 31st August 2026

KEYWORDS

artificial intelligence, education quality, decision support, explainability, monitoring, higher education, data quality

ABSTRACT

This thesis scientifically developed an artificial intelligence-based decision support architecture for higher education quality control. The study integrated data, analytical, explanation, decision, and feedback layers into a unified governance cycle. International standards, educational legislation, and recent scientific literature were used to define the function of each layer. The findings showed that explainability, human oversight, data quality, and institutional readiness were essential for effective quality management and responsible use of artificial intelligence in higher education.

Introduction

Quality control in higher education has moved from a periodic administrative verification exercise towards a continuous, evidence-driven management function. The Standards and Guidelines for Quality Assurance in the European Higher Education Area treat internal quality assurance as a cyclical process in which study programmes are designed, approved, monitored, periodically reviewed and improved on the basis of systematically collected information [1]. A comparable logic is embedded in the international standard for management systems of educational organisations, which organises institutional activity around a plan-do-check-act sequence and requires that decisions affecting learners and other beneficiaries rest on verifiable evidence [2]. Both frameworks share one theoretical premise: educational quality is never observed directly, but reconstructed from indirect signals that an institution must be able to collect, interpret and convert into action.

The theoretical difficulty arises from an asymmetry between the two halves of that premise. Digital administration of the academic process - learning management platforms, electronic assessment records, graduate and employer surveys, institutional information systems - has multiplied the volume and frequency of available signals. Interpretation, by contrast, has remained bound to committee cycles, retrospective reporting and expert judgement exercised at long intervals. The outcome is a system rich in measurement and comparatively poor in timely inference: a deviation frequently becomes visible only after the academic period in which it could have been corrected has already closed.

Decision support systems built on artificial intelligence constitute a conceptual response to that asymmetry. Their function is not to displace institutional judgement but to compress the interval between the appearance of a signal and its transformation into an interpretable statement about quality. International guidance on artificial intelligence in education anchors the distinction in a humanistic position: algorithmic output is admissible as an input to human deliberation provided that data protection, transparency and human agency remain intact [3]. Read in this way, a decision support system is a mediating architecture between a measurement layer and a governance layer, and its scientific value depends on how faithfully that mediation has been designed.

The higher education system of Uzbekistan offers a favourable institutional setting for such architectures. The Concept for the Development of the Higher Education System of the Republic of Uzbekistan until 2030 defines the introduction of digital technologies into the educational process and the improvement of specialist training quality as connected priorities [4]. Educational legislation establishes state requirements for the quality of education together with the supervisory arrangements that accompany them [5]. The scale of the system reinforces the practical relevance of analytical instrumentation: according to official statistics, admission to higher education organisations of the republic in the 2024/2025 academic year amounted to 381.7 thousand persons [6]. Governing quality signals for a student body of that magnitude through exclusively manual review procedures constrains both the depth and the frequency of institutional analysis, which makes the architectural question a substantive one rather than a technical detail.

The purpose of the article is to substantiate a layered architecture for artificial intelligence-based decision support in the quality control of education, and to establish the correspondence between each layer and the normative and methodological sources that legitimise it. The contribution is conceptual: instead of advocating a particular algorithm, the article specifies the structural conditions under which an algorithmic result becomes admissible evidence inside an institutional quality assurance system.

LITERATURE REVIEW

Research on learning analytics forms the empirical foundation on which decision support for educational quality has been constructed. A systematic review of adoption in higher education institutions established that the factors governing institutional uptake are distributed across several dimensions simultaneously - stakeholder configurations, institutional and pedagogical processes, technical limitations and ethical considerations - and that a large share of developments remains at pilot stage without reaching institution-wide adoption [7]. Complementary evidence on study success indicated that broader deployment presupposes standardised measures, visualisations and interventions capable of integration into any digital learning environment [8]. A review of learning outcome evaluation through analytics systems drew attention to the limited standardisation of outcome measures, which complicates comparison between programmes and between institutions [9]. Synthesis of interventions embedded in learning management systems confirmed that analytical capacity improves practice only where an analytical result has been connected to a defined pedagogical action [10].

A second stream examines decision support at the level of institutional management. An empirical investigation of an artificial intelligence-enabled decision support system in the information and communication technology department of a South African university reported considerable improvement potential in operational decision-making while underlining the ethical and societal implications of integration [11]. A policy-to-practice analysis of the national quality assurance framework of Qatar demonstrated how artificial intelligence tools can be embedded into accreditation and institutional accountability arrangements, and proposed a structured model covering readiness assessment, policy development and responsible integration [12]. Both contributions locate the value of such systems in governance quality rather than in predictive accuracy taken in isolation.

A third stream concerns the admissibility of algorithmic output. A framework for explainable artificial intelligence in education identified six design aspects - stakeholders, benefits, modes of presenting explanations, model classes, human-centred interface design and the pitfalls of explanation - as conditions for trustworthy educational applications [13]. A five-dimensional trust framework covering privacy, safety, fairness, explainability and accountability was applied to representative educational systems and disclosed recurring governance vulnerabilities, among them insufficient oversight and an unclear allocation of responsibility [14]. A systematic review of ethical concerns seen from the perspective of users established that guidelines for trustworthy artificial intelligence operate as the principal reference point in educational applications [15]. A further review of explainability definitions in education showed that terminological heterogeneity by itself impedes the formulation of clear institutional requirements [16].

A fourth stream addresses institutionalisation. A systematic review of human-centred learning analytics and artificial intelligence in education positioned stakeholder participation in design as a determinant of sustained use [17]. Empirical work on the critical determinants of learning analytics adoption identified organisational readiness, data quality and perceived usefulness among the decisive conditions [18]. A cross-national comparative study of university policies on the governance of generative artificial intelligence showed that institutional rules, rather than technical capability, delimit the space within which algorithmic tools may legitimately be used [19].

Considered together, these strands describe a mature analytical literature alongside a comparatively underdeveloped architectural one. Studies of predictive quality, of explanation techniques and of adoption barriers exist in abundance; explicit specifications of how an analytical result travels from a data source to a formally recorded quality decision, and of which normative instrument authorises each transition, remain scarce. The architecture proposed below is addressed to that specific gap.

METHODOLOGY

The work follows a conceptual-analytical design. Three categories of material were used. Normative instruments supplied the requirements that any quality control mechanism has to satisfy: the European standards and guidelines for internal quality assurance [1], the international standard for management systems of educational organisations [2], international guidance on artificial intelligence in education [3], the national strategic framework for higher education development [4] and the requirements of educational legislation [5]. Peer-reviewed and open-access scholarship provided the state of knowledge on analytical instruments and their institutional reception. Official statistics on the higher education system supplied the contextual parameters within which the architecture is intended to operate [6].

Construction of the architecture followed methodological principles established for composite measurement. The handbook on constructing composite indicators formulates a sequence - theoretical framework, variable selection, treatment of missing data, normalisation, weighting and aggregation, robustness testing, interpretation - that fixes the order in which methodological choices have to be justified and documented [20]. The multidimensional assessment approach adopted by U-Multirank contributed a second principle: performance across distinct dimensions is displayed separately rather than compressed into a single weighted score, because weighting schemes have proven insufficiently robust to support such compression [21]. A comparative reconstruction of the computational pipelines of major international ranking systems confirmed that normalisation and aggregation decisions encode normative assumptions and produce divergent results across systems [22].

Four criteria were applied to every element of the proposed architecture. Normative traceability requires that the function performed by a layer be attributable to an identifiable requirement in a quality assurance instrument. Analytical validity requires that the transformation carried out within a layer preserve the measurement properties of its input. Interpretability requires that the output of a layer be expressible in terms intelligible to the academic staff and administrators who will act upon it. Decision usability requires that the output be connectable to a specific institutional action with a defined owner and a defined time horizon. A layer satisfying fewer than all four criteria was treated as incompletely specified and returned for redesign.

The design carries a deliberate limitation. Empirical estimation of predictive performance falls outside its scope, since such estimation is institution-specific and depends on the data actually available within a particular information environment. The article accordingly establishes the structural conditions for valid application rather than the numerical performance of any single implementation.

ANALYSIS AND RESULTS

Application of the four criteria produced an architecture of five layers connected by a single directed flow and closed by a return path. Figure 1 presents the resulting structure.

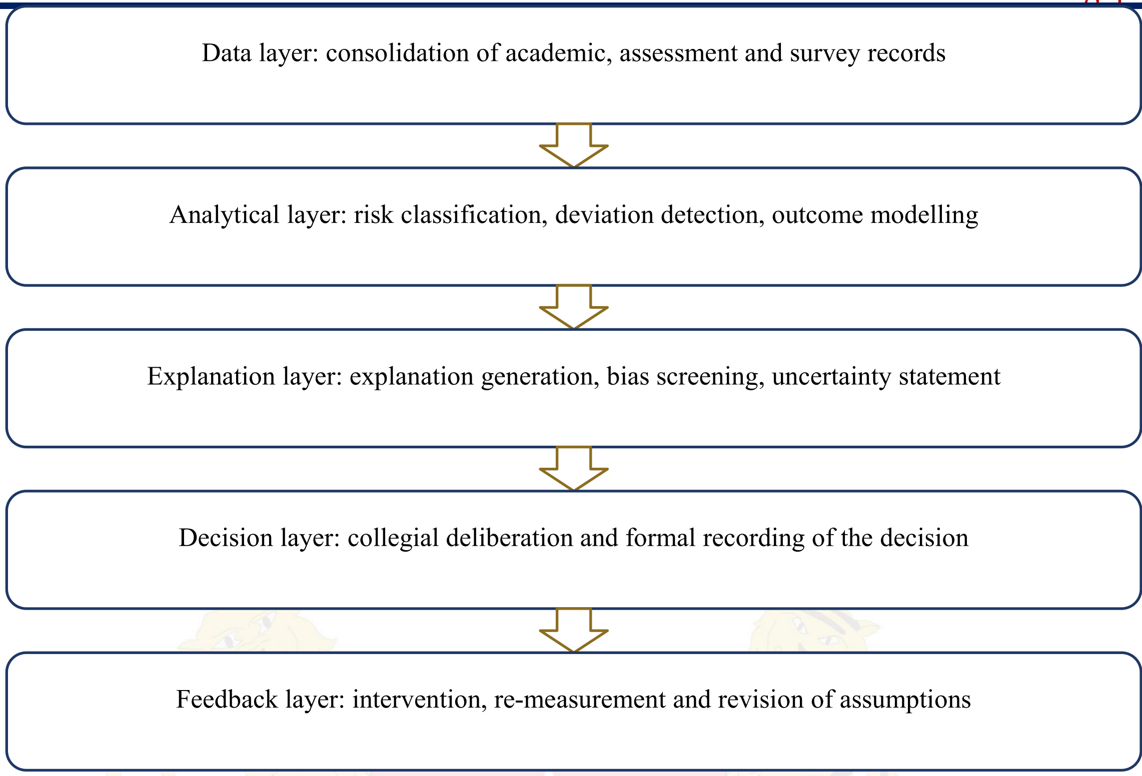

Figure 1. Layered architecture of an artificial intelligence-based decision support system for the quality control of education[1]

The data layer performs consolidation. Records generated by different subsystems - enrolment and progression files, assessment results, attendance and engagement traces, satisfaction surveys, employer feedback - are brought to a common identification scheme, a common temporal granularity and a documented level of completeness. Normative traceability is direct: the European standards require institutions to collect, analyse and use information for the effective management of programmes [1], and the international management standard places documented information among the mandatory elements of the system [2]. The layer is complete only when the provenance of every field can be reconstructed, since an analytical result inherits the defects of its inputs and organisational data quality has been identified as one of the decisive conditions of adoption [18].

The analytical layer converts consolidated records into structured statements. Its typical operations are the classification of academic risk, the detection of deviation from expected trajectories, the identification of programme components with atypical outcome distributions and the estimation of relationships between teaching conditions and learning results. Analytical validity is the governing criterion here: transformations must preserve the measurement properties of the inputs, and outcome measures whose comparability is limited require explicit qualification [9]. The layer acquires practical meaning only when each analytical output has been mapped in advance to a category of institutional response, since analytical capacity detached from a defined action does not modify practice [10].

The explanation layer is the element most frequently omitted in institutional practice and the one on which the admissibility of the whole architecture depends. Three operations

[1] Source: compiled by the author on the basis of [1], [2], [3], [13] and [20].

belong to it: generation of an explanation that identifies the factors driving a particular output, screening for systematic bias across student groups, and explicit statement of uncertainty. The design aspects formulated for explainable artificial intelligence in education define the content of this layer [13], while the five-dimensional trust framework supplies its verification agenda across privacy, safety, fairness, explainability and accountability [14]. The terminological heterogeneity documented in the literature makes it necessary for an institution to fix its own operational definition of an acceptable explanation and to record that definition in its quality regulations [16]. Ethical requirements recognised by users of educational systems are satisfied at this layer rather than at the analytical one [15].

The decision layer restores authority to the collegial bodies that hold it. An explained and qualified analytical statement enters the agenda of a department council, a faculty quality commission or a rectorate committee, where it is weighed against contextual knowledge unavailable to any model. Human agency is preserved by design, in accordance with international guidance on artificial intelligence in education [3]. The boundaries of permissible use are set by institutional policy rather than by technical possibility [19], and the readiness-policy-integration sequence proposed for national quality assurance frameworks offers a workable template for establishing those boundaries [12]. Governance value, rather than model accuracy alone, is what distinguishes a functioning system from an experimental one [11].

The feedback layer closes the cycle. A decision taken at the previous layer generates an intervention, the intervention generates new records, and the new records re-enter the data layer, where the effect of the intervention becomes measurable. The plan-do-check-act logic of the management standard is realised precisely at this point [2], and the requirement for ongoing monitoring and periodic review of programmes acquires an operational form [1]. Without the return path, the architecture degenerates into a reporting instrument; with it, the architecture becomes a learning system in the organisational sense.

Table 1 summarises the correspondence between the layers, their core functions and the normative or methodological sources that authorise them.

Table 1

Functional layers of an artificial intelligence-based decision support system for education quality control and their normative anchors[2]

Layer	Core function	Governing criterion	Normative or methodological anchor
Data layer	Consolidation of academic, assessment and survey records into a documented common scheme	Normative traceability	Information management in internal quality assurance [1]; documented information [2]; data quality as an adoption condition [18]
Analytical layer	Risk classification, deviation detection, estimation of relations between conditions and	Analytical validity	Limits of outcome-measure standardisation [9]; action-linked analytics [10]; methodological sequence for composite

[2] Source: compiled by the author on the basis of the cited normative documents and open-access scholarly sources.

Layer	Core function	Governing criterion	Normative or methodological anchor
	outcomes		measurement [20]
Explanation layer	Explanation generation, bias screening, explicit statement of uncertainty	Interpretability	Design aspects of explainable artificial intelligence in education [13]; trust dimensions [14]; ethical requirements of users [15]
Decision layer	Collegial deliberation, recording of the decision and of its justification	Decision usability	Preservation of human agency [3]; institutional policy boundaries [19]; readiness-policy-integration model [12]
Feedback layer	Intervention, re-measurement and revision of the analytical assumptions	Normative traceability and decision usability	Plan-do-check-act cycle [2]; ongoing monitoring and periodic review [1]

Two conditions govern whether the architecture operates as designed. The first is organisational readiness. Adoption research consistently identifies readiness, data quality and perceived usefulness as the conditions that separate durable implementations from pilot projects [18], and participation of academic staff in the design of analytical interfaces has been shown to sustain use over time [17]. Institutions that introduce the analytical layer before the data layer has been stabilised accumulate outputs that no committee is willing to act upon. The second condition is the functional separation of the explanation layer from the analytical layer. Where explanation is produced by the same component that produced the prediction, and by the same team, the verification function is weakened; assigning explanation and bias screening to a distinct methodological unit preserves the independence that the trust dimensions presuppose [14].

A third design decision concerns aggregation. The architecture deliberately refrains from reducing institutional quality to a single composite value. The multidimensional principle requires that results be reported dimension by dimension, since composite scores respond sharply to small changes in weights [21], and comparative work on ranking pipelines has shown that normalisation and aggregation choices carry normative content of their own [22]. Where aggregation is nevertheless required for reporting purposes, the weighting rule is declared in advance, documented, and accompanied by a sensitivity check, in line with the sequence prescribed for composite indicators [20].

The Uzbek institutional context supports each of these conditions. The strategic priority given to the introduction of digital technologies into the educational process creates a legitimate basis for investment in the data and analytical layers [4], while the state requirements for educational quality provide the external reference against which internal decisions are calibrated [5]. The scale of enrolment recorded in official statistics [6] makes the marginal value of automation in the data and analytical layers substantial, and the existence of a national strategic horizon to 2030 allows institutions to sequence the layers over successive planning cycles rather than attempting simultaneous deployment. The architecture is therefore compatible both with the international quality assurance framework [1] and with the domestic governance environment in which Uzbek institutions operate.

CONCLUSIONS AND SUGGESTIONS

The analysis supports several conclusions. First, the contribution of artificial intelligence to the quality control of education is architectural rather than algorithmic: value emerges from the ordered transition of a signal through consolidation, analysis, explanation, decision and re-measurement, and not from the accuracy of an isolated model. Second, every layer of that transition can be anchored to an existing normative requirement, which means that such systems extend established quality assurance practice instead of competing with it [1], [2]. Third, the explanation layer performs the decisive function, since it converts a statistical output into evidence that a collegial body is entitled to act upon [13], [14]. Fourth, the boundaries of legitimate use are established by institutional policy, and the drafting of that policy precedes technical deployment [19]. Fifth, restraint in aggregation preserves the informational content of a multidimensional quality picture [21].

Several practical suggestions follow for higher education institutions of Uzbekistan. It is advisable to begin with a documented audit of the data layer, establishing the provenance, completeness and temporal granularity of every field before any analytical component is commissioned. It is expedient to adopt an internal regulation defining what constitutes an acceptable explanation of an analytical output, which academic body receives it, and within what period a response is required. It is reasonable to assign explanation and bias screening to a methodological unit organisationally distinct from the developers of the analytical component. It is useful to report quality results dimension by dimension, reserving aggregation for cases where a documented and tested weighting rule exists. It is productive to include academic staff in the design of analytical interfaces from the outset, since sustained use depends on the perceived usefulness of the instrument to those who operate it [17], [18]. Implementation of these measures allows an institution to convert its accumulated digital records into a consistent and transparent instrument of quality governance, in full accordance with the strategic direction of the national higher education system [4].

References:

1.Standards and Guidelines for Quality Assurance in the European Higher Education Area (ESG). Yerevan: EHEA Ministerial Conference, 2015. URL: https://ehea.info/media.ehea.info/file/2015_Yerevan/72/7/European_Standards_and_Guidelines_for_Quality_Assurance_in_the_EHEA_2015_MC_613727.pdf

2.ISO 21001:2018. Educational organizations - Management systems for educational organizations - Requirements with guidance for use. Geneva: International Organization for Standardization, 2018. URL: https://www.iso.org/standard/66266.html

3.Miao F., Holmes W. Guidance for generative AI in education and research. Paris: UNESCO, 2023. URL: https://unesdoc.unesco.org/ark:/48223/pf0000386693

4.Decree of the President of the Republic of Uzbekistan No. PF-5847 of 8 October 2019 “On approval of the Concept for the development of the higher education system of the Republic of Uzbekistan until 2030”. URL: https://lex.uz/ru/docs/-4545884

5.Law of the Republic of Uzbekistan “On Education” of 23 September 2020, No. OʻRQ-637. URL: https://lex.uz/docs/5013007

6.Higher education in the Republic of Uzbekistan. Tashkent: National Statistics Committee of the Republic of Uzbekistan. URL: https://stat.uz/img/higher-education_p64577.pdf
7.Márquez L., Henríquez V., Chevreux H., Scheihing E., Guerra J. Adoption of learning analytics in higher education institutions: A systematic literature review // British Journal of Educational Technology, 2024. URL: https://doi.org/10.1111/bjet.13385
8.Ifenthaler D., Yau J. Y.-K. Utilising learning analytics to support study success in higher education: a systematic review // Educational Technology Research and Development, 2020, Vol. 68. URL: https://doi.org/10.1007/s11423-020-09788-z
9.Hernández-Campos M., Gonzalez-Torres A., García-Peñalvo F. J. Learning Outcomes Evaluation Through Learning Analytics Systems in Higher Education: A Systematic Literature Review // SAGE Open, 2025. URL: https://doi.org/10.1177/21582440251347374
10.A Systematic Review of Learning Analytics // Journal of Learning Analytics, 2024. URL: https://learning-analytics.info/index.php/JLA/article/view/8093
11.Artificial intelligence-powered decision support system for operational decision-making in the ICT department of a selected African university // African Journal of Science, Technology, Innovation and Development, 2024. URL: https://doi.org/10.1080/20421338.2024.2376916
12.Artificial intelligence for quality assurance in higher education: a policy-to-practice model from Qatar with global relevance // Quality in Higher Education, 2025. URL: https://doi.org/10.1080/13538322.2025.2576326
13.Khosravi H., Buckingham Shum S., Chen G., Conati C., Tsai Y.-S., Kay J., Knight S., Martínez-Maldonado R., Sadiq S., Gašević D. Explainable Artificial Intelligence in education // Computers and Education: Artificial Intelligence, 2022, Vol. 3. URL: https://doi.org/10.1016/j.caeai.2022.100074
14.Trustworthy AI in education: Framework, cases, and governance strategies // Innovation and Emerging Technologies, 2025. URL: https://www.worldscientific.com/doi/10.1142/S2737599425500264
15.Decoding AI ethics from users' lens in education: A systematic review // Heliyon, 2024. URL: https://pmc.ncbi.nlm.nih.gov/articles/PMC11620203/
16.Systematic Literature Review: Explainable AI Definitions and Challenges in Education. arXiv preprint 2504.02910, 2025. URL: https://arxiv.org/pdf/2504.02910
17.Human-Centred Learning Analytics and AI in Education: A Systematic Literature Review. arXiv preprint 2312.12751, 2023. URL: https://arxiv.org/pdf/2312.12751
18.Critical determinants for learning analytics adoption in higher education. ERIC document ED639842. URL: https://files.eric.ed.gov/fulltext/ED639842.pdf
19.A Framework for Developing University Policies on Generative AI Governance: A Cross-national Comparative Study. arXiv preprint 2504.02636, 2025. URL: https://arxiv.org/pdf/2504.02636
20.OECD, European Union, EC-JRC. Handbook on Constructing Composite Indicators: Methodology and User Guide. Paris: OECD Publishing, 2008. URL: https://doi.org/10.1787/9789264043466-en
21.U-Multirank. Our approach to university rankings. URL: https://www.umultirank.org/about/methodology/our-approach/

22.International university rankings: composite indicators and methodological approaches //Frontiers in Research Metrics and Analytics, 2026. URL: https://www.frontiersin.org/journals/research-metrics-and-analytics/articles/10.3389/frma.2026.1828850/full