



To cite this article: Radkevych, O. (2026). THE POTENTIAL OF ARTIFICIAL INTELLIGENCE IN EDUCATIONAL ANALYTICS AND MANAGERIAL DECISION-MAKING. *Professional Pedagogics*, 2(33), 168-184.
<https://doi.org/10.32835/2707-3092.2026.33.168-184>

THE POTENTIAL OF ARTIFICIAL INTELLIGENCE IN EDUCATIONAL ANALYTICS AND MANAGERIAL DECISION-MAKING

Oleksandr Radkevych

Doctor of Sciences in Education, Professor, Chief Research Fellow, Department for Monitoring and Assessment of the Quality of General Secondary Education, Institute of Pedagogy of the National Academy of Educational Sciences of Ukraine, <https://orcid.org/0000-0002-2648-5726>, e-mail: mr.radkevych@gmail.com

Abstract

Relevance. Large-scale national and international assessments generate substantial volumes of performance, contextual, and administrative data; however, their use in education governance is often confined to a retrospective description of mean scores and between-group gaps. The need to move from descriptive reporting to anticipatory, differentiated, and evidence-based governance brings to the fore the application of artificial intelligence (hereinafter – AI) technologies in educational analytics. At the same time, the high legal and social stakes of educational decisions call for overcoming technological determinism, preventing discriminatory profiling, strictly complying with personal data protection legislation, and guaranteeing human primacy and accountability.

Purpose. To substantiate a conceptual model for transforming the results of national and international assessments into managerial decisions using AI tools, and to determine the organisational, managerial, methodological, ethical, and legal conditions for its responsible implementation.

Methods. The study employs: *conceptual analysis* to distinguish educational analytics from static data visualisation, to differentiate four levels of analytics (descriptive, diagnostic, predictive, and prescriptive (recommendation-oriented)), and to clarify the essence of the concepts of “algorithmic fairness”, “differentiated explainability”, and “socio-technical system”; *comparative analysis* to juxtapose the purposes, scales, target populations, and limits of normative interpretation of assessment data (PISA, TIMSS, the National Multi-Subject Test (NMT), nationwide monitoring studies, and digital traces from educational platforms), and to weigh the performance of complex algorithmic models against interpretable baseline statistical models; *thematic coding* to systematise the provisions of international framework documents (OECD, UNESCO, EU legal acts) and scholarly works in order to identify key risks (sampling bias, temporal degradation of predictive models, bias against particular groups of learners, and over-reliance on automated decisions) and the potential of algorithmic methods in education quality assessment; *critical synthesis* to reconcile the standards of educational measurement (test measurement error, equivalence of test booklet forms, and the probabilistic nature of scores) with the analytical potential of machine learning methods and language models and with the legal norms governing the protection of confidential information; and *structural-functional modelling* to design a closed cycle of managerial decision support (data – algorithmic model – expert verification – managerial decision – impact monitoring), to substantiate the component structure of evidence-based education quality governance, and to formalise a composite criterion of the fitness of analytical models (Q).

Results. A fourteen-component model for transforming the results of national and international assessments (PISA, NMT, monitoring studies) into managerial actions is substantiated. The model is built as a closed cycle: from specifying the educational construct (a construct passport) and ensuring the interoperability of heterogeneous registers

and reference directories to expert verification of signals and evaluation of the actual consequences of managerial actions. A multi-criteria composite index of model fitness (Q) is developed, which weighs validity with respect to the educational construct, robustness of algorithms on new samples, algorithmic fairness, intelligibility for users, and the aggregate cost of possible errors. Scenarios of AI application are systematised according to the levels of education governance (national, regional, institutional, and the level of the individual learning trajectory), and information security requirements are defined to preclude direct access of generative models to learners' personal data.

Conclusions. It is demonstrated that AI in educational analytics serves to augment expert judgement rather than to act as an autonomous decision-maker; an automated output is a probabilistic signal for a professional, not an imperative directive. The transition from prediction to action requires an independent evidence base on the effectiveness of pedagogical interventions and pre-agreed criteria for evaluating possible errors, where the unconditional priority is to prevent discriminatory profiling of students and to protect comprehensively the rights of all participants in the educational process. For the education system of Ukraine, a phased transition to AI-supported decision-making is essential: from ensuring the interoperability of the core classifiers and reference directories of state information systems (in particular, AIKOM and EDEBO) and implementing low-risk pilot projects (automated processing of response datasets, data validity checks, and error detection) to legally regulated predictive modelling subject to mandatory interdisciplinary audit, guaranteed transparency of conclusions, and the right to appeal and to mandatory human review.

Keywords: *artificial intelligence, educational analytics, quality of general secondary education, managerial decisions, PISA, National Multi-Subject Test, forecasting, differentiated explainability of algorithms, algorithmic fairness, evidence-based education policy, personal data protection.*

Introduction. Education quality assessment systems perform not only a measurement function but also a direct public governance function: they make it possible to identify systemic trends, compare the results of different categories of learners, diagnose equity of access to quality education, and provide a scientific basis for the strategic priorities of state policy. In practice, however, a tangible gap has long persisted between the generation of primary datasets and the implementation of managerial decisions. Analytical reports are often published with a considerable time lag, operate with highly aggregated indicators, and lack the granularity needed to determine which specific measures will be effective and at what level. Consequently, the information collected is largely recorded as a formality rather than being transformed into a dynamic instrument for the early detection of learning losses, the targeted provision of resource support, and the ongoing verification of the effectiveness of the programmes introduced (Ferguson, 2012; OECD, 2026a). Contemporary educational analytics extends beyond traditional descriptive analysis through the comprehensive integration of educational measurement results, contextual questionnaires, state education statistics, and digital learning traces in information and communication systems. AI algorithms are capable of analysing non-linear multifactor dependencies,

identifying latent structures, classifying textual corpora of open-ended responses, performing predictive modelling, and consolidating multidimensional indicators to facilitate interpretation. The *OECD Digital Education Outlook 2026* regards advanced machine learning methods and language models not merely as a didactic tool but as a systemic foundation for modelling individual learning trajectories and optimising the functioning of educational institutions and education authorities. At the same time, extensive computational capabilities do not override the basic requirements of measurement reliability, sample representativeness, validity, and sound interpretation of conclusions (Ferguson, 2012; OECD, 2026b; UNESCO, 2023).

Literature Review. The empirical and documentary base of the study comprises Ukrainian legislative and regulatory acts in the fields of education and information protection, the Concept for the Development of Artificial Intelligence in Ukraine, international framework documents of UNESCO and the OECD on the regulation of AI in education, official reports and databases of the PISA and TIMSS studies, and analytical materials of the Ukrainian Center for Educational Quality Assessment. Sources were selected according to the criteria of relevance to the research purpose, methodological rigour, institutional authority, and

practical significance for educational measurement. Preference was given to regulatory documents, official analytical reports, and publications in peer-reviewed scholarly journals (OECD, 2026a, 2026b; UNESCO, 2023).

The published results of the PISA 2025 international study constitute a representative, internationally comparable empirical platform for assessing the state of basic and upper secondary general education in Ukraine. The study involved 8,962 adolescents from 17 regions of the country; mean scores were 448 points in scientific literacy, 431 points in mathematics, and 418 points in reading. Compared with 2022, no statistically significant decline or increase was recorded, which indicates a stage of stabilisation of results amid ongoing security challenges (Hryvko & Zhuk, 2026). The territorial coverage achieved allows valid direct comparisons between the 2022 and 2025 cycles; however, the generalisations made cannot be automatically extrapolated to all regions of the country owing to objective geographical constraints on sampling. Alongside PISA data, the Ukrainian information space accumulates datasets from the National Multi-Subject Test (NMT), the state final attestation of certain periods, nationwide monitoring of school graduates' learning outcomes, local regional studies, and data from state information systems, primarily the Automated Information Complex of Educational Management (AIKOM) and the Unified State Electronic Database on Education (EDEBO). Their comprehensive juxtaposition opens up the potential for a transition to an advanced system of data-driven governance. However, fundamental differences in measurement purposes, original scales, sampling designs, and data-collection regulations preclude their mechanical aggregation without prior scientific, methodological, and regulatory harmonisation (OECD, 2026a; Ukrainian Center for Educational Quality Assessment, 2026).

Ukrainian scholarship has produced a substantial theoretical body of work on the digitalisation of education. In particular, O. Spirin (2025) substantiates the human-centred, ethical, and normatively balanced foundations of the digital transformation of the educational environment; S. Lytvynova et al. (2026) analyse the transformation

of the information and digital competence of participants in the educational process under the influence of generative AI; I. Vorotnykova et al. (2025) examine adaptive learning environments, the digital maturity of educational institutions, and institutional barriers to the adoption of emerging technologies; M. Pryhodii and O. Radkevych (2026) substantiate models of personalised learning and automated test-based assessment and propose approaches to building intelligent systems that support effective pedagogical and managerial decision-making; O. Ovcharuk, O. Hrytsenchuk, and O. Kravchyna (2026) investigate the needs, professional readiness, and practices of Ukrainian teachers with regard to the use of digital tools. These contributions attest to the progress of Ukrainian educational science from describing applied software to a comprehensive analysis of institutional policies, information security standards, algorithmic ethics, and mechanisms that guarantee human oversight. Nevertheless, the direct methodological integration of the results of large-scale education quality assessments, the algorithmic systems for processing them, and the subsequent steps towards effective managerial decisions remains insufficiently addressed. Other Ukrainian authors regard AI as a key instrument for transforming the educational space, focusing on the construction of flexible individual trajectories, accessibility principles, and support for teachers' work. At the same time, they highlight challenges related to academic integrity, uneven digital literacy, insufficient transparency of automated algorithms, and potential user distrust of generated analytical outputs. These findings lay the groundwork for the present study, but the specific mechanism for transforming external assessment data into legally sound managerial actions with the involvement of AI requires holistic conceptualisation (Luchaninova, 2025; Oleksiuk et al., 2025; Pinchuk & Kokhan, 2024; V. O. Radkevych et al., 2025; Yatsyshyn, 2025).

International experience demonstrates that algorithmic methods can successfully streamline the review of test materials for alignment with framework specifications, ensure standardised coding of open-ended responses, detect early signs of educational disadvantage, and model the

differential effects of interventions. At the same time, IEA analytical reports based on TIMSS indicate high agreement between language-model classifications of items and content domains, but considerably lower quality in differentiating items by cognitive domain and in estimating the empirical difficulty of items. Hence, even in formalised subject domains, algorithmisation has limited reliability and requires mandatory expert review (Bezirhan & von Davier, 2026; Holmes et al., 2019). The scientific contradiction lies in the fact that education governance actors at all levels need prompt, detailed analytical conclusions to make timely decisions, whereas ensuring the validity of educational measurement results requires in-depth contextualisation, estimation of statistical error, and time for expert verification. A further contradiction arises between the aspiration to individualise targeted support for learners and the imperative of preventing their discriminatory profiling, the restriction of their rights, or their unjustified automated allocation to categories of educational risk. The research gap lies in the absence of a theoretically grounded model that comprehensively integrates a contemporary analytical toolkit, psychometric reliability, legal and ethical safeguards, and a regulated decision-making cycle.

Purpose: to provide a theoretical substantiation of a conceptual model for transforming the results of national and international education quality assessments into evidence-based managerial decisions using AI tools, and to determine the organisational, managerial, methodological, and legal conditions for its safe and responsible use.

Methods: The study employs: *conceptual analysis* to distinguish educational analytics from static data visualisation, to differentiate four levels of analytics (descriptive, diagnostic, predictive, and prescriptive (recommendation-oriented)), and to clarify the essence of the concepts of “algorithmic fairness”, “differentiated explainability”, and “socio-technical system”; *comparative analysis* to juxtapose the purposes, scales, target populations, and limits of normative interpretation of assessment data (PISA, TIMSS, the National Multi-Subject Test (NMT), nationwide monitoring studies, and digital traces from educational platforms), and to weigh the

performance of complex algorithmic models against interpretable baseline statistical models; *thematic coding* to systematise the provisions of international framework documents (OECD, UNESCO, EU legal acts) and scholarly works in order to identify key risks (sampling bias, temporal degradation of predictive models, bias against particular groups of learners, and over-reliance on automated decisions) and the potential of algorithmic methods in education quality assessment; *critical synthesis* to reconcile the standards of educational measurement (test measurement error, equivalence of test booklet forms, and the probabilistic nature of scores) with the analytical potential of machine learning methods and language models and with the legal norms governing the protection of confidential information; and *structural-functional modelling* to design a closed cycle of managerial decision support (data – algorithmic model – expert verification – managerial decision – impact monitoring), to substantiate the component structure of evidence-based education quality governance, and to formalise a composite criterion of the fitness of analytical models (Q).

Results and Discussion. To address the challenges outlined above systematically, the use of AI tools should be regarded not as the local deployment of a stand-alone algorithm but as a component of a comprehensive socio-technical system. In such a system, source data are accumulated through clearly regulated measurement procedures, the algorithmic output is interpreted by qualified professionals, and the resulting managerial decision directly affects educational institutions, teachers, and learners. Under this approach, the key emphasis shifts from the purely technological question “Which model should be chosen?” to methodological and managerial questions: which specific managerial task requires analytical support; whether the data collected are representative and valid for addressing it; which types of algorithmic error pose a critical threat to the rights of participants in the educational process; and who bears personal responsibility for the practical consequences of the decision made. Within evidence-based governance, educational analytics should be defined as a regulated process of collecting, semantically integrating, mathematically and statistically

processing, and substantively interpreting information on learning outcomes, conditions, environment, and dynamics in order to develop and verify decisions. It should not be equated with static data visualisation. A dashboard primarily answers the retrospective question “What happened?”, whereas a complete analytical cycle should identify probable influencing factors, forecast the onset of risks, propose and evaluate scenarios for possible interventions, and track their actual effectiveness (Ferguson, 2012). The analytical cycle clearly distinguishes four functional levels: the first, *descriptive analytics*, systematises and presents empirical distributions of indicators, the state of the educational environment, and retrospective dynamics; the second, *diagnostic analytics*, assesses correlations, performs factorisation, and formulates scientific hypotheses about the probable causes of the observed results; the third, *predictive analytics*, uses historical dependencies and available indicators to estimate the probability of certain educational events in the future (for example, the risk of not attaining a baseline level of literacy); and the fourth, *prescriptive (recommendation-oriented) analytics*, models possible options for managerial action and evaluates their expected consequences against a given set of criteria. The greatest risks to learners’ rights and to the soundness of decisions arise at the transition from the predictive to the prescriptive level. A statistically established high probability of underachievement or educational failure indicates a correlational risk but does not, by itself, establish its root cause or guarantee that a proposed standard intervention will be effective. Any managerial recommendation must rest on a separate evidence base of pedagogical effectiveness (Ferguson, 2012; OECD, 2026b).

In this context, the concept of AI encompasses a set of methods of machine learning, natural language processing, anomaly detection, and generative language models that automate certain

analytical procedures. At the same time, classical methods of educational statistics and psychometrics (item response theory (IRT), structural equation modelling, etc.) remain the priority where direct interpretability of model parameters, work with multistage subsamples, or preservation of the equivalence of measurement scales over time is critical. The choice of a specific tool should be determined not by its technological novelty but by the substance of the managerial task and the structure of the data (Holmes et al., 2019; UNESCO, 2023). Analytical added value arises from the systematic combination of different data sources, yet each of them has its own normative nature and research design. PISA assesses the functional literacy of 15-year-olds and provides a broad contextual snapshot of learning conditions; TIMSS is directly linked to the content of mathematics and science curricula in specified grades; NMT results serve the normative selection purpose of competitive admission; and the nationwide monitoring studies of the Ukrainian Center for Educational Quality Assessment (UCEQA) focus on the level of development of key competences at certain stages of general secondary education. Administrative information from state registers (in particular, AIKOM and EDEBO) characterises the network of institutions, their material and technical condition, staffing, and student mobility, whereas digital distance-learning platforms record process traces of everyday activity. The fundamental differences in the primary purposes of data collection indicate that no indicator may be used outside its defined domain of validity without a dedicated scientific and methodological justification (International Association for the Evaluation of Educational Achievement, 2026; OECD, 2026a; Ukrainian Center for Educational Quality Assessment, 2026). The main data sources and the limits of their use are mapped in Fig. 1.

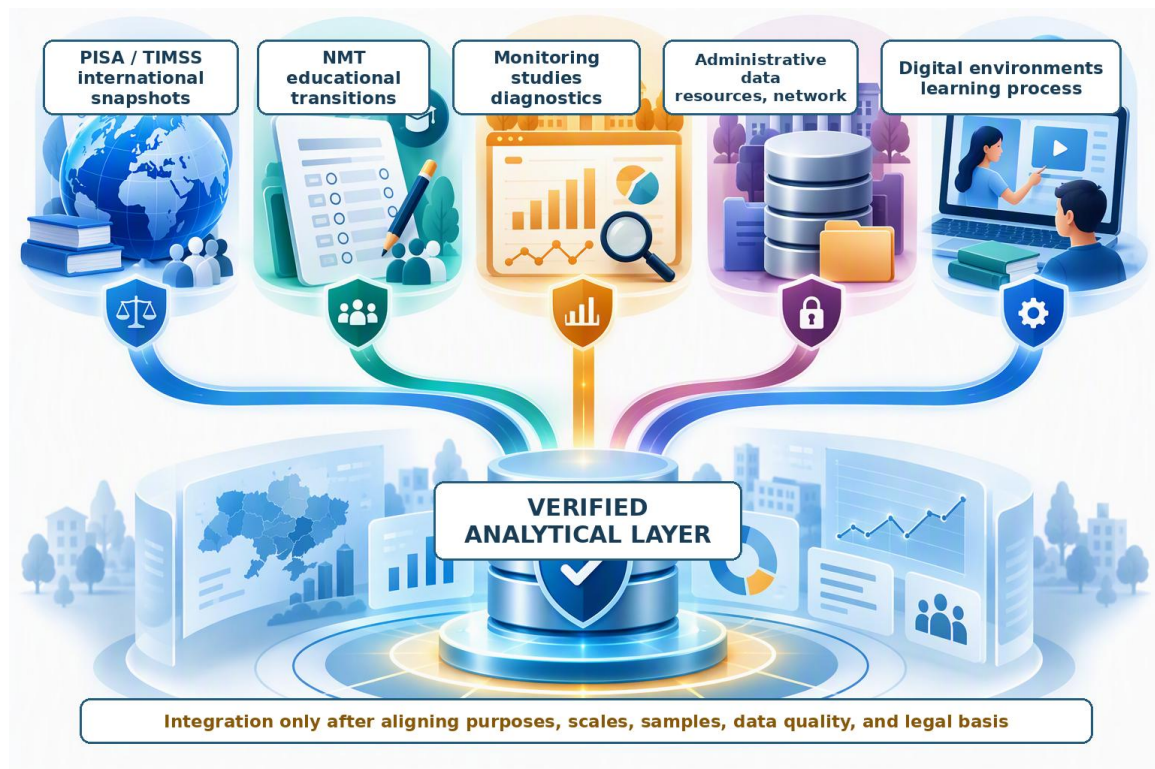


Fig. 1. Analytical map of data sources and the limits of their use
Source: developed by the author.

Integrating data into a single analytical system requires ensuring the interoperability of core classifiers and reference directories, using persistent identifiers, removing duplicates, strictly logging data provenance, and having a legal basis for processing information in accordance with the Law of Ukraine “On Personal Data Protection”. Technical and legal separation of information is of fundamental importance: data suitable for aggregated systemic macro-analysis must be isolated from the pipelines through which individual decisions concerning a specific learner or teacher are made. De-identification substantially reduces the threat of personal data leakage; however, where numerous geographical and contextual attributes are present, the risk of re-identification of small groups

persists. Therefore, user access should be differentiated by roles (role-based access control), and the publication or generation of analytical conclusions concerning small groups of students should be subject to regulatory rules on the minimum permissible group size (European Parliament & Council of the European Union, 2024; UNESCO, 2023). To evaluate the fitness of a particular mathematical model for the needs of education governance, it is insufficient to rely on indicators of its formal statistical accuracy (for example, Accuracy, RMSE, or AUC-ROC). It is proposed to apply a composite model quality criterion formalised as a weighted score (Kizilcec & Lee, 2022; UNESCO, 2023):

$$Q = w_1V + w_2R + w_3F + w_4E - w_5C$$

In this expression, Q denotes the composite index of a model's fitness for managerial decision-making; V is the level of validity with respect to the target educational construct; R is the stability of results on new datasets; F is algorithmic fairness (the absence of discriminatory bias against vulnerable or

specific groups of learners); E is the degree of intelligibility and explainability of the model's logic for a professional; C is the aggregate cost of implementing the model and of potential losses from erroneous decisions; and $w_1...w_5$ are normalised weighting coefficients determined by the normative

priorities of education policy. The practical significance of this relationship is that a model with high formal accuracy must be unconditionally rejected if it shows substantially poorer algorithmic fairness, sampling bias, or complete opacity (a “black box”). The composite index Q should be

interpreted as an internal criterion for comparing alternative solutions within a defined task rather than as a universal scale for rating algorithms. The closed cycle within which such models are applied is shown in Fig. 2.



Fig. 2. Ecosystem for transforming assessment data into managerial decisions
Source: developed by the author.

At the stage of primary data preparation, AI algorithms provide automated detection of technical errors and duplicate records, data verification, harmonisation of discrepancies in reference directories, and structuring of open-ended text responses. This streamlines resource-intensive routine processes. At the same time, systematic errors of algorithmic matching can imperceptibly distort the structure of the primary dataset. Accordingly, all steps of automated data transformation must be logged, reproducible, and regularly verified on control samples by experts in educational measurement (OECD, 2026b; UNESCO, 2023). At the modelling stage proper, AI methods enable early prediction of the risks of learning losses, classification of the needs profiles of educational institutions, and detection of hidden correlations between resource provision and learning outcomes. However, an algorithmically

generated prediction is by no means a statement of a student's fixed “abilities”. It is a conditional probabilistic estimate based on the past state of the environment and a limited set of input parameters. If the historical dataset reflected the consequences of socio-economic inequality or restricted access to in-person learning, the model will inevitably reproduce this inequality in the form of a seemingly “objective” negative prediction (Kizilcec & Lee, 2022; UNESCO, 2023). At the stage of substantive interpretation, explainable AI tools make it possible to quantify the contribution of individual factors to a prediction or to construct counterfactual scenarios. However, the local explainability of an individual prediction does not prove a causal relationship, and the high weight of a certain variable does not guarantee that an artificial change in this parameter will produce the desired improvement in the quality of education. For example, a relationship detected

by the system between the number of missed classes and low learning outcomes provides grounds for a professional examination of the situation, but managerial decisions must take into account the security situation, health status, internal displacement, or the lack of technical devices for learning (Kizilcec & Lee, 2022; Veale & Borgesius, 2021).

Generative AI makes it possible to rapidly transform structured reports into draft analytical briefs tailored to the needs of specific stakeholders. Its advantage lies in the speed of text synthesis, whereas its risk lies in a tendency to produce inaccurate information (hallucinations) and

plausible yet unfounded generalisations. Accordingly, generative tools must under no circumstances be entrusted with calculating official statistical indicators or formulating final managerial conclusions. A secure architecture requires the generative model to operate exclusively on top of a verified table of aggregated indicators as a text interface, with mandatory retention of source references and under the mandatory editorial control of a professional (OECD, 2026b; UNESCO, 2023). The correspondence between analytical approaches, their appropriate applications, and mandatory safeguards is summarised in Fig. 3.

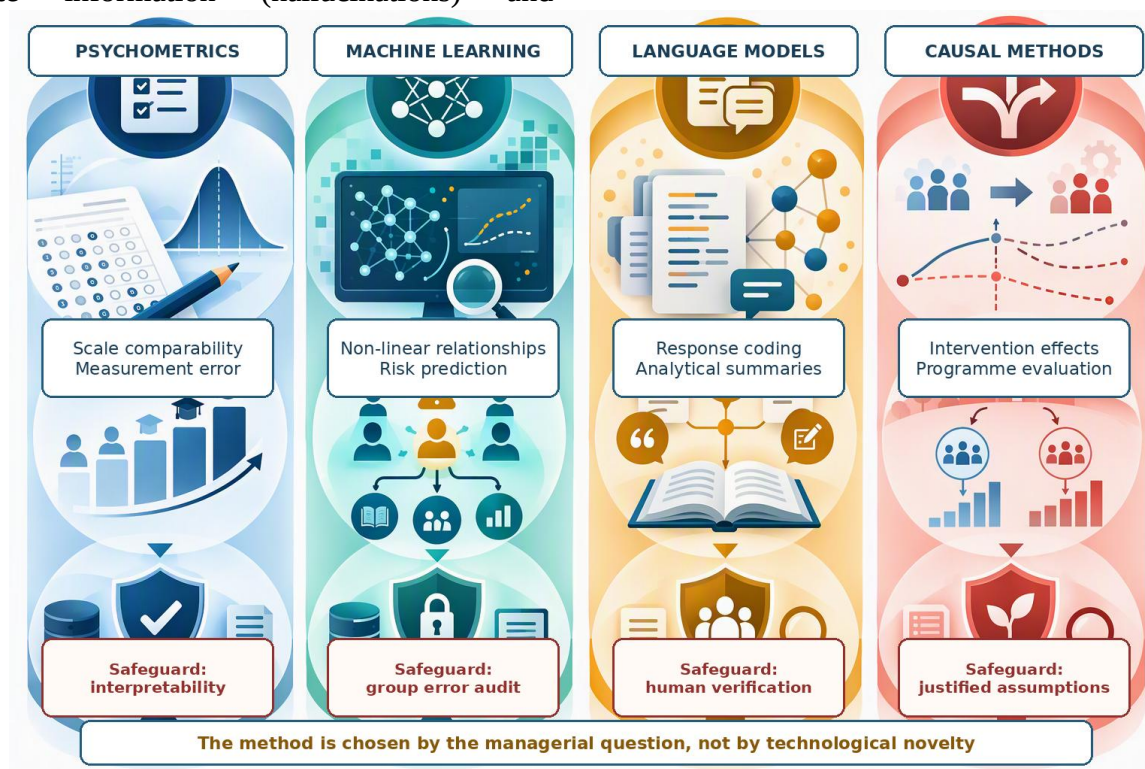


Fig. 3. Matrix for selecting an analytical approach

Source: developed by the author.

The transition to practical managerial action requires a clear delineation of the levels of education governance and of the powers of the actors involved:

at the national level, algorithmic analytics makes it possible to identify systemic inter-regional and socio-economic gaps, forecast the need for capital and learning resources, and substantiate targeted state support programmes;

at the regional level, AI systems are appropriate for analysing the territorial accessibility of the network of general secondary education

institutions, modelling the risks of staff shortages, and planning a safe educational environment;

at the level of the educational institution, analytical tools may alert the leadership and the pedagogical council to typical subject-specific difficulties of student groups so that the educational programme can be adjusted in a timely manner, but they may not be used for the automated ranking of teachers or the segregation of student groups;

at the level of the individual learner, only supportive, recommendation-oriented adaptive

learning materials may be generated; the decision to provide them is made by the teacher, while the learner and their legal representatives have a statutory right to appeal the conclusions and to refuse automated intervention (European Parliament & Council of the European Union, 2024).

The decision threshold of a predictive model is determined not only by a statistical criterion but also by the normative and ethical weight of possible errors. Since an undetected risk deprives a student of timely individualised support, the system is optimised in favour of sensitivity in order to minimise Type II errors. If, however, an automated signal entails mandatory referral to special programmes, which may lead to stigmatisation or an artificial restriction of access to academic programmes, a false-positive error becomes critically dangerous. Hence, the ratio of permissible errors must be formally approved by the education authority before the system is put into practical operation (Kizilcec & Lee, 2022). The practical algorithm for implementing a model consists of seven consecutive steps: *first*, formalising the managerial task and defining the target criteria; *second*, legal verification of the lawfulness of using the selected data and of privacy protection; *third*, building a baseline interpretable model and comparing it with machine learning algorithms; *fourth*, external validation on control samples; *fifth*, an audit of algorithmic fairness across demographic groups; *sixth*, review of the results by an interdisciplinary expert commission; and *seventh*, post-implementation evaluation of the consequences of the decision for the educational process.

A mandatory rule should be the comparison of a complex AI algorithm with a simple interpretable model: if the gain in practical accuracy of the complex solution is statistically insignificant, unconditional preference is given to the transparent and intelligible analytical approach (Veale & Borgesius, 2021). The key risks of algorithmisation include non-representative samples, measurement error of instruments, personal data leakage, entrenchment of discriminatory biases, algorithmic

opacity, automation bias (uncritical acceptance of computer-generated conclusions by officials), and model instability over time. Under martial law and during post-war recovery, the continuous migration of learners, disruptions to the stability of the educational process, and differences in security conditions substantially distort established relationships. A model calibrated on data from previous years rapidly loses validity and requires re-examination (European Parliament & Council of the European Union, 2024; UNESCO, 2023).

Algorithmic fairness cannot be reduced to a single coefficient. The mathematical conditions of equal rates of positive predictions, equal sensitivity, and consistent calibration come into mutual conflict when the base rate of outcomes objectively differs between groups owing to unequal starting conditions. Therefore, the priority understanding of fairness is defined normatively for each individual project. For compensatory support programmes, the principle of equal access to support prevails, whereas decisions with high legal stakes are subject to strict constraints that exclude any form of discrimination (Kizilcec & Lee, 2022). The requirement of explainability should likewise be targeted and differentiated. An analyst needs information on the model structure, parameter weights, confidence intervals, and calibration curves; the head of an education authority needs a clear statement of the problem, the level of uncertainty of the conclusion, the list of verified influencing factors, and the limits of legitimate action; a teacher needs a detailed account of learning difficulties and error types; and learners and parents need a transparent explanation of which information served as the basis for the conclusion, who personally made the decision, and how it can be appealed. The exercise of the right to explanation in education should ensure substantive intelligibility of the process rather than a formal display of mathematical coefficients (Veale & Borgesius, 2021). The multi-level model of responsible AI use, together with its cross-cutting safeguards, is presented in Fig. 4.

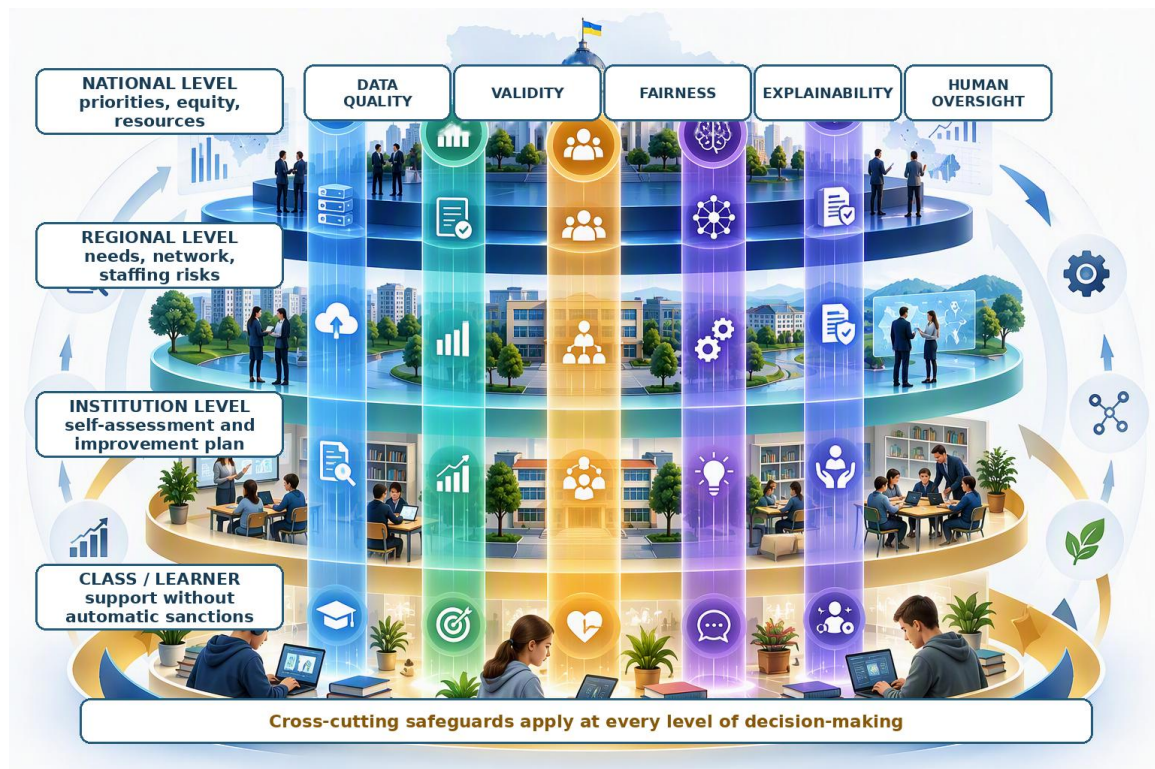


Fig. 4. Multi-level model of responsible AI use in educational analytics

Source: developed by the author.

A holistic concept of applying AI systems to education quality monitoring and governance rests on the recognition that the quality of education is a multidimensional normative and pedagogical construct that can by no means be reduced to an aggregate test score. Quality encompasses the level of learning achievement, equity of access to education, safety, psycho-emotional well-being and inclusiveness of the environment, the sustainability of individual trajectories, the efficient use of material resources, and the adaptability of the educational institution. AI should be applied not to build mechanical school rankings but as a tool for reconciling heterogeneous evidence. Within this paradigm, PISA 2025 data are the most important external international benchmark, capturing the functional literacy of 15-year-olds and the depth of socio-economic gaps; however, they do not substitute for the results of the state final attestation, formative and ongoing assessment, primary-level monitoring, or institutional audit procedures in general secondary education institutions. The conceptual core is an evidence-based quality model in which each analytical indicator has a normatively defined purpose, limits of validity, and a designated

accountable actor (OECD, 2026a). The implementation of this concept encompasses fourteen interrelated components:

1) *model of the educational construct*: before algorithmic data processing begins, it is normatively determined which specific components of educational quality are to be measured, through which indicators they are captured, and which decisions may legitimately be made on their basis. For each model, a “target construct passport” is approved, which records the permissible features, the units of observation, and a prohibition on using simplified digital indicators as proxies for complex pedagogical phenomena (Holmes et al., 2019);

2) *multi-source evidence architecture*: ensures the aggregation and reconciliation of the results of external and internal assessments, sociological surveys, AIKOM and EDEBO register data, and digital traces of interaction with electronic educational resources. Integration is based on a semantically consistent analytical data layer that preserves information on the provenance of each indicator, the date of its recording, the legal basis for processing, and the permissible level of granularity,

without mechanically mixing incompatible datasets (Ferguson, 2012; OECD, 2026b);

3) *data quality and reliability control*: algorithmic models do not correct biased samples; therefore, a data quality profile (completeness, timeliness, representativeness, absence of systematic distortions) is compiled before modelling begins. AI automates the detection of errors and atypical missing values, but data correction procedures must be approved by experts in educational measurement (OECD, 2026a; Ukrainian Center for Educational Quality Assessment, 2026);

4) *psychometrically grounded application of modelling methods*: in large-scale assessments, individual scores are probabilistic in nature (they are estimated through plausible values). AI algorithms must take into account the sampling design, measurement error, and the rotation of test booklet forms. Machine learning combines effectively with classical IRT models: psychometrics ensures the precision and stability of scaling, while machine learning detects non-linear risk factors, with every conclusion accompanied by a confidence interval (OECD, 2026a);

5) *AI-supported review of assessment materials*: language models are involved in the preliminary analysis of item specifications, the initial generation of alternative distractors, and the evaluation of the linguistic accessibility of item stems. At the same time, no automatically generated test item may be used in live assessment without subject-matter, methodological, anti-discrimination, and psychometric review by expert panels, followed by mandatory pilot testing (Bezirhan & von Davier, 2026);

6) *automated processing of constructed-response datasets*: AI algorithms substantially increase the productivity of the initial coding of learners' extended written responses. A scientifically sound procedure relies on an expert-verified sample of responses, mandatory double coding of part of the dataset by a human and by the model, and monitoring of scoring agreement. All non-standard, borderline, low-confidence, and appealed responses are reviewed exclusively by a human expert (Bezirhan & von Davier, 2026; UNESCO, 2023);

7) *analysis of the dynamics of individual and group learning trajectories*: education quality

assessment is reoriented from the discrete recording of static results to the study of the sustainability of learning progress over time. AI makes it possible to model trajectories of recovery from learning losses and to forecast the effectiveness of adaptive programmes. At the same time, a digital profile must not become an instrument of student segregation: it is temporary and is updated in line with current progress (OECD, 2026b);

8) *diagnosis of educational inequality and fairness audit*: AI makes it possible to analyse complex intersecting relationships among factors of educational disadvantage, such as family socio-economic status, type of locality, mode of learning (in-person, distance, blended), and forced displacement. Sensitive demographic data are used exclusively to design targeted support, while the analytical model itself is audited for the uniformity of errors across different categories of students (Kizilcec & Lee, 2022);

9) *causally grounded selection of pedagogical and managerial interventions*: a model's predictive signal indicates the presence of an educational risk but does not determine an unambiguous way to address it. The selection of measures relies on a dedicated scientific evidence base of proven pedagogical technologies and programmes. Every analytical brief must clearly distinguish three positions: the identified risk, the risk factors requiring confirmation by a teacher, and recommended measures with proven effectiveness (Kizilcec & Lee, 2022);

10) *multi-level differentiation of managerial scenarios*: information flows and access rights are strictly distributed in accordance with statutory powers: the national level – macro-analysis of strategic gaps; the regional level – optimisation of the network and resource provision; the institutional level – internal quality assurance and monitoring of subject-specific learning outcomes; the class and learner level – personalised adjustment of the educational process, with priority given to teachers' professional autonomy (OECD, 2026b; UNESCO, 2023);

11) *differentiated explainability of analytical conclusions*: the system must provide a multi-level substantive account of the logic of the models: for analysts – confusion matrices, parameter weights,

and distributional stability; for managers – the logic of recommendations and the degree of uncertainty; for teachers – a characterisation of typical learning gaps; for learners and parents – an accessible explanation of the grounds for the individual support plan and the procedure for its review (UNESCO, 2023; Veale & Borgesius, 2021);

12) *institutional governance and the life cycle of analytical systems*: before a model is put into trial operation, its purpose, legal grounds, composition of input data, and boundary cases in which its use is prohibited are approved. During operation, systematic monitoring of model degradation is ensured, a register of algorithm changes is maintained, and false alarms are recorded. Personal responsibility for managerial actions is legally assigned to the relevant official (European Parliament & Council of the European Union, 2024; UNESCO, 2023);

13) *evaluation of the overall impact of the analytical system*: the effectiveness of AI implementation is measured not by the mathematical accuracy of the code but by practical changes in the educational environment: reduction of learning losses, elimination of inter-regional disparities, speed of access to targeted methodological assistance, teacher satisfaction, and the absence of discriminatory consequences for students (Kizilcec & Lee, 2022; UNESCO, 2023);

14) *human capacity building and the digital culture of participants*: the introduction of AI technologies requires mandatory systematic training of school leaders and teachers in data literacy, the fundamentals of educational measurement, the interpretation of errors, and the legal standards of personal data protection. Analytical tools should be developed with the active participation of educators so that the algorithms correspond to the real operating conditions of educational institutions (Oleksiuk et al., 2025; Ovcharuk et al., 2026; Spirin, 2025).

Thus, the holistic model of AI application in educational analytics is a closed socio-technical system in which, at every stage, technical operations are subordinated to a pedagogical purpose and constrained by legal guarantees of human rights protection. PISA 2025 data provide a systemic comparative baseline, but managerial decisions must

be grounded in a comprehensive, multi-level body of evidence.

For Ukraine, the most rational approach is a phased strategy for implementing this concept:

Stage 1: creating a national catalogue of education data, ensuring the interoperability of the core vocabularies, reference directories, and classifiers of education registers (AIKOM, EDEBO), and developing regulations on data quality and information protection;

Stage 2: launching limited low-risk pilot projects, namely automated coding of open-ended tasks in academic olympiads or monitoring studies, detection of technical errors, and data validity checks;

Stage 3: introducing predictive decision-support systems solely at the level of network planning and targeted assistance, subject to a mandatory external audit, adherence to algorithmic fairness, and a regulated review procedure;

Stage 4: comprehensive institutionalisation of the audit of AI systems in education and regular state monitoring of their actual socio-pedagogical impact (Spirin, 2025; UNESCO, 2023).

The architecture of the state education analytics system should clearly separate the primary protected repository of state registers, a de-identified verified analytical data layer, and user access interfaces. The overwhelming majority of analytical and predictive managerial tasks should be performed using exclusively de-identified or aggregated data. Direct access to identifiable personal data of learners or teachers must be strictly limited by the requirements of current legislation, require a special legal protocol, and be accompanied by comprehensive digital logging of every access request (European Parliament & Council of the European Union, 2024). The organisational core for governing such systems should be a standing Interdisciplinary Expert Council comprising leading experts in educational measurement, specialists in AI and information security, lawyers, representatives of education authorities, heads of educational institutions, and teachers. The Council's remit should consist not in an abstract endorsement of information technologies but in a substantive professional review of each individual analytical algorithm: analysis of its objectives, an audit of data representativeness, estimation of the cost of probable model errors,

assurance of transparency, and verification of decision appeal protocols. Such a mechanism will ensure a transparent allocation of responsibility and guarantee the unconditional primacy of human rights and legitimate interests (UNESCO, 2023).

Conclusions. The study gives grounds to assert that AI technologies open up qualitatively new opportunities for strengthening the analytical capacity of the education governance system on the basis of international and national assessment data. At the same time, the final effect depends not so much on the computational power of algorithms as on the methodological soundness and institutional safety of the entire socio-technical cycle. At the current stage, the most justified functional areas of AI use are automated quality control of primary data, semantic reconciliation of registers, structuring of extended text responses, detection of hidden correlations in the educational environment, modelling of the risks of learning losses, and prompt preparation of draft analytical materials for experts. In each scenario, an algorithmically generated conclusion should be treated exclusively as an advisory analytical signal for a professional rather than as a binding managerial decision.

The scientific novelty of the proposed approach lies in the systematic differentiation of four levels of analytics: descriptive, diagnostic, predictive, and prescriptive. Such structuring prevents a methodological substitution of concepts whereby the statistical probability of an event is mistakenly equated with establishing the cause of difficulties or with a direct prescription for pedagogical action. The conceptual model developed (data – AI modelling – expert verification – managerial decision – impact evaluation) substantiates that managerial validity results not from the autonomous operation of a model but from a balanced combination of the metrological quality of measurement, algorithmic fairness, adaptive explainability, and normative human responsibility. The practical significance of the results for the education sector of Ukraine lies in defining the prerequisites for a transition from fragmented paper-based and digital reports (PISA, NMT, UCEQA monitoring studies, AIKOM and EDEBO registers) to an integrated, regulated

analytical platform. The priority steps should be ensuring full interoperability of state education classifiers and reference directories, approving data quality control protocols, and launching pilot solutions with minimal legal risks for participants in the educational process. The use of predictive models with respect to specific individuals is permissible only subject to their prior external validation, an audit of error fairness across different categories of learners, and statutory guarantees of the right to professional expert review and appeal of conclusions. The use of high-risk automated decision-making systems without human involvement is deemed unacceptable.

The mechanism of explainability of AI decisions in education management functions solely as a multi-level differentiated system: analysts receive technical metrics of model stability, whereas teachers, students, and their legal representatives receive a practical interpretation of the identified learning difficulties together with the legal procedure for appealing or reviewing recommendations. The application of algorithmic fairness in education governance precludes the use of a single mathematical template, making the optimisation criteria (in particular, equalisation of false-positive or false-negative rates) directly dependent on the type of managerial intervention, that is, the provision of compensatory academic support or the making of selective and competitive decisions.

The limitations of the study stem from its theoretical and generalising nature, which did not involve direct computational experiments with training neural networks on primary microdata from Ukrainian assessments. Further research should focus on creating open verified educational datasets for testing domestic models; comparing the accuracy of simple interpretable algorithms and deep neural networks; studying the robustness of algorithmic decisions under war-related distortions of the educational space; developing a sectoral standard for AI audit in education; and empirically testing the effectiveness of implementing evidence-based algorithmic models in the practice of education authorities and general secondary education institutions.

Conflict of Interest

The author certifies that no conflict of interest (financial, professional, or personal) exists that could have influenced the objectivity of the research results or conclusions. The integrity of the double-blind peer review process was ensured through a mandatory declaration of the absence of conflict of interest submitted via the journal's editorial system. This protocol guaranteed complete author anonymity and the independence of the expert evaluation throughout the entire editorial cycle.

Declaration on the Use of Generative Artificial Intelligence.

During the preparation of this manuscript, the author used generative artificial intelligence tools as an auxiliary means for searching for and preliminarily organising information, structuring analytical tables, checking computational relationships, and refining the presentation of formulas. All bibliographic records, numerical values, formulas, and conclusions were verified by the author against primary sources and edited in line with the research purpose. AI was not used to create or substitute primary empirical data or to make research decisions independently. The author takes full responsibility for the content and scientific accuracy of the manuscript. Artificial intelligence is not a co-author of this work.

List of references

- Bezirhan, U., & von Davier, M. (2026). *An AI-driven approach to TIMSS item verification and alignment*. International Association for the Evaluation of Educational Achievement. https://doi.org/10.58150/rd_4_1 [in English].
- European Parliament & Council of the European Union. (2024). *Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence*. Official Journal of the European Union. <http://data.europa.eu/eli/reg/2024/1689/oj> [in English].
- Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, 4(5/6), 304–317. <https://doi.org/10.1504/IJTEL.2012.051816> [in English].
- Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign. <http://bit.ly/AIED-BOOK> [in English].
- Hryvko, A., & Zhuk, Yu. (2026). *The use of educational monitoring research results in the pedagogical practice of secondary school teachers in Ukraine: Analytical materials based on the results of an all-Ukrainian teacher survey*. Zenodo. <https://doi.org/10.5281/zenodo.20749090>
- International Association for the Evaluation of Educational Achievement. (2026). *TIMSS: Trends in International Mathematics and Science Study*. <https://www.iea.nl/studies/iea/timss> [in English].
- Kizilcec, R. F., & Lee, H. (2022). Algorithmic fairness in education. In W. Holmes & K. Porayska-Pomsta (Eds.), *The ethics of artificial intelligence in education* (pp. 174–202). Routledge. <https://doi.org/10.48550/arXiv.2007.05443> [in English].
- Luchaninova, O. P. (2025). Shtuchnyi intelekt yak tekhnolohichnyi trend u vyshchii osviti: psykholoho-etychni aspekty, dosvid ta perspektyvy [Artificial intelligence as a technological trend in higher education: Psychological and ethical aspects, experience and prospects]. *Osvita ta pedahohichna nauka [Education and Pedagogical Sciences]*, 3(190), 80–92. [https://doi.org/10.12958/2227-2747-2025-3\(190\)-80-92](https://doi.org/10.12958/2227-2747-2025-3(190)-80-92) [in Ukrainian].
- Lytvynova, S. H., Nosenko, Yu. H., Osadcha, K. P., Pinchuk, O. P., Rashevskaya, N. V., & Sukhikh, A. S. (2026). *Vykorystannia heneratyvnoho shtuchnoho intelektu dlia rozvytku informatsiino-tsyfrovoi kompetentnosti uchniv rivnia bazovoi serednoi osvity* [The use of generative artificial intelligence for developing information and digital competence of lower secondary education students]. ITsO NAPN Ukrainy [Institute for Digitalisation of Education of the NAES of Ukraine]. <https://doi.org/10.33407/lib.NAES.id/748927> [in Ukrainian].

- OECD. (2026a). *PISA 2025 results (Volume I): Future-ready students*. OECD Publishing. https://www.oecd.org/en/publications/pisa-2025-results-volume-i_73451bc5-en.html [in English].
- OECD. (2026b). *OECD Digital Education Outlook 2026*. OECD Publishing. https://www.oecd.org/en/publications/oecd-digital-education-outlook-2026_062a7394-en.html [in English].
- Oleksiuk, V. P., Spirin, O. M., Balyk, N. R., & Ivanova, S. M. (2025). Rozvytok tsyfrovoy kompetentnosti naukovykh ta naukovo-pedahohichnykh pratsivnykiv zasobamy heneratyvnoho shtuchnoho intelektu [Development of digital competence of researchers and academic staff through generative artificial intelligence]. *Osvita. Innovatyka. Praktyka [Education. Innovation. Practice]*, 13(8), 110–121. <https://doi.org/10.31110/2616-650X-vol13i8-015> [in Ukrainian].
- Ovcharuk, O. V., Hrytsenchuk, O. O., & Kravchyna, O. Ye. (2026). *Vykorystannia heneratyvnoho shtuchnoho intelektu vchyteliamy ZZSO dlia vdoskonalennia pedahohichnykh praktyk* [The use of generative artificial intelligence by general secondary education teachers to improve pedagogical practices]. ITsO NAPN Ukrainy [Institute for Digitalisation of Education of the NAES of Ukraine]. <https://doi.org/10.33407/lib.NAES.id/748926> [in Ukrainian].
- Pinchuk, O. P., & Kokhan, O. V. (2024). Vidpovidalne vykorystannia shtuchnoho intelektu: vyklyk dlia nauky i osvity [Responsible use of artificial intelligence: A challenge for science and education]. In *Shtuchnyi intelekt u nautsi ta osviti (AISE 2024)* [Artificial Intelligence in Science and Education (AISE 2024)]. ITsO NAPN Ukrainy [Institute for Digitalisation of Education of the NAES of Ukraine]. <https://lib.iitta.gov.ua/id/eprint/740813/> [in Ukrainian].
- Pryhodii, M., & Radkevych, O. (2026). Intensification of vocational training for learners via smart technologies. *Professional Pedagogics*, 1(32), 3–17. <https://doi.org/10.32835/2707-3092.2026.32.3-17>
- Radkevych, O. P. (2024). *Vykorystannia shtuchnoho intelektu dlia personalizovanoho otsiniuvannia profesiinoi diialnosti pedahohichnykh pratsivnykiv* [The use of artificial intelligence for personalized assessment of teachers' professional performance]. *Profesiina osvita v umovakh staloho rozvytku suspilstva: monohrafiia* [Vocational Education in the Context of Sustainable Societal Development: Monograph], 6(19), 41–45. <https://lib.iitta.gov.ua/id/eprint/743563/> [in Ukrainian].
- Radkevych, V. O., Pryhodii, M. A., Luparenko, L. A., Kravets, S. H., Herliand, T. M., & Kruchek, V. A. (2025). *Tsyfrova transformatsiia osvity: shtuchnyi intelekt v suchasnomu osvitnomu prostori* [Digital transformation of education: Artificial intelligence in the contemporary educational environment]. Instytut profesiinoi osvity NAPN Ukrainy [Institute of Vocational Education of the NAES of Ukraine]. <https://doi.org/10.5281/zenodo.17164092> [in Ukrainian].
- Spirin, O. M. (2025). *Tsyfrova transformatsiia osvity: shtuchnyi intelekt u suchasnomu osvitnomu prostori* [Digital transformation of education: Artificial intelligence in the contemporary educational environment]. *Visnyk Natsionalnoi akademii pedahohichnykh nauk Ukrainy* [Herald of the National Academy of Educational Sciences of Ukraine], 7(2). <https://doi.org/10.37472/v.naes.2025.7221> [in Ukrainian].
- Ukrainian Center for Educational Quality Assessment. (2026). *Natsionalnyi zvit za rezultatamy mizhnarodnoho doslidzhennia yakosti osvity PISA-2025* [National report on the results of the international educational assessment PISA 2025]. UTsOIaO [Ukrainian Center for Educational Quality Assessment]. <https://testportal.gov.ua/pisa-2025-rezultaty-oprylyudneno/> [in Ukrainian].
- UNESCO. (2023). *Guidance for generative AI in education and research*. UNESCO. <https://unesdoc.unesco.org/ark:/48223/pf0000386693> [in English].
- Veale, M., & Borgesius, F. Z. (2021). Demystifying the Draft EU Artificial Intelligence Act. *Computer Law Review International*, 22(4), 97–112. <https://doi.org/10.9785/cri-2021-220402> [in English].
- Vorotnykova, I. P., Dziabenko, O., & Morze, N. V. (2025). Personalizovane navchannia z vykorystanniam shtuchnoho intelektu u vyshchii osviti: vyklyky ta motyvatsiini chynnyky [Personalized learning using artificial intelligence in higher education: Challenges and motivational factors]. *Informatsiini tekhnolohii i zasoby navchannia* [Information Technologies and Learning Tools], 105(1). <https://doi.org/10.33407/itlt.v105i1.5893> [in Ukrainian].
- Yatsyshyn, A. V. (Ed.). (2025). *Shtuchnyi intelekt v osviti. Chastyna 1* [Artificial intelligence in education. Part 1]. ITsO NAPN Ukrainy [Institute for Digitalisation of Education of the NAES of Ukraine]. <https://doi.org/10.33407/lib.NAES.id/748336> [in Ukrainian].

ПОТЕНЦІАЛ ШТУЧНОГО ІНТЕЛЕКТУ В ОСВІТНІЙ АНАЛІТИЦІ ТА ПРИЙНЯТТІ УПРАВЛІНСЬКИХ РІШЕНЬ

Олександр Радкевич

доктор педагогічних наук, професор, головний науковий співробітник відділу моніторингу та оцінювання якості загальної середньої освіти Інституту педагогіки Національної академії педагогічних наук України, <https://orcid.org/0000-0002-2648-5726>, e-mail: mr.radkevych@gmail.com

Реферат:

Актуальність. Масштабні національні й міжнародні оцінювання генерують значні масиви результативних, контекстних та адміністративних даних, однак їх використання в системі управління освітою нерідко обмежується ретроспективним описом середніх балів і міжгрупових розривів. Потреба переходу від констатувальної звітності до випереджального, диференційованого та доказового управління актуалізує застосування технологій штучного інтелекту (далі – ШІ) в освітній аналітиці. Водночас високі правові й соціальні ставки освітніх рішень вимагають подолання технологічного детермінізму, запобігання дискримінаційним профілюванням, суворого дотримання законодавства про захист персональних даних та гарантування пріоритету і збереження відповідальності людини.

Мета. обґрунтування концептуальної моделі перетворення результатів національних і міжнародних оцінювань на управлінські рішення із застосуванням інструментів ШІ, а також визначення організаційно-управлінських, методичних, етичних і правових умов її відповідального впровадження.

Методи. *концептуального аналізу* – для розмежування понять освітньої аналітики та статичної візуалізації даних, диференціації чотирьох рівнів аналітики (описової, діагностичної, прогнозової, прескриптивної (рекомендаційної)), а також сутнісного розкриття понять «алгоритмічна справедливість», «диференційована пояснюваність» і «соціотехнічна система»; *порівняльного аналізу* – для зіставлення цілей, шкал, генеральних сукупностей і меж нормативної інтерпретації даних оцінювань (PISA, TIMSS, HMT, загальнодержавних моніторингів, цифрових слідів освітніх платформ), а також для оцінювання співвідношення ефективності складних алгоритмічних моделей та інтерпретованих базових статистичних моделей; *тематичного кодування* – для систематизації положень міжнародних рамкових документів (OECD, ЮНЕСКО, правових актів ЄС) та наукових праць щодо виявлення ключових ризиків (спотворення вибірки, застарівання прогнозних моделей у часі, упереджене ставлення до окремих груп здобувачів освіти, наддовіра до автоматизованих рішень) і потенціалу використання алгоритмічних методів в оцінюванні якості освіти; *критичного синтезу* – для методологічного узгодження стандартів педагогічного вимірювання (статистичні похибки тестів, еквівалентність варіантів тестових зошитів, імовірнісний характер балів) з аналітичним потенціалом методів машинного навчання, мовних моделей і нормами законодавства щодо захисту конфіденційної інформації; *структурно-функціонального моделювання* – для розроблення замкненого циклу підтримки управлінських рішень (дані – алгоритмічна модель – експертна верифікація – управлінське рішення – моніторинг наслідків), обґрунтування компонентної структури доказового управління якістю освіти та формалізації комплексного критерію придатності аналітичних моделей (Q).

Результати. Обґрунтовано чотирнадцятикомпонентну модель перетворення результатів національних і міжнародних оцінювань (PISA, HMT, моніторингові дослідження) на управлінські дії, побудовану за замкненим циклом: від паспортизації освітнього конструкта й забезпечення сумісності різнорідних реєстрів і довідників до експертної верифікації сигналів та оцінювання фактичних наслідків управлінських дій. Сформовано багатокритеріальний інтегральний показник придатності моделей (Q), що зважає на валідність щодо освітнього конструкта, стійкість алгоритмів на нових вибірках, алгоритмічну справедливість, зрозумілість для користувачів та сукупну ціну можливих помилок. Систематизовано сценарії застосування ШІ відповідно до рівнів освітнього управління (державного, регіонального, рівня закладу освіти та рівня індивідуальної освітньої траєкторії) і визначено вимоги інформаційної безпеки для унеможливлення прямого доступу генеративних моделей до персональних даних здобувачів освіти.

Висновки. Доведено, що ІІІ в освітній аналітиці виконує функцію підсилення експертного судження, а не автономного суб'єкта ухвалення рішень; автоматизований результат є ймовірнісним сигналом для фахівця, а не імперативною директивою. Перехід від прогнозу до дії потребує незалежної доказової бази ефективності педагогічних втручань і завчасно узгоджених критеріїв оцінювання можливих похибок, де безумовним пріоритетом є недопущення дискримінаційного профілювання учнівства та всебічний захист прав усіх учасників освітнього процесу. Для системи освіти України принциповим є поетапний перехід до прийняття рішень на основі технологій ІІІ: від забезпечення сумісності базових класифікаторів і довідників державних інформаційних систем (зокрема АІКОМ, ЄДЕБО) та реалізації пілотних проєктів із низьким рівнем ризику (автоматизована обробка масивів відповідей, контроль достовірності даних і виявлення помилок) до нормативно регульованого прогностичного моделювання за обов'язкового міждисциплінарного аудиту, гарантування прозорості висновків та забезпечення права на їх оскарження й обов'язковий перегляд людиною.

Ключові слова: *штучний інтелект, освітня аналітика, якість загальної середньої освіти, управлінські рішення, PISA, національний мультипредметний тест, прогнозування, диференційована пояснюваність алгоритмів, алгоритмічна справедливість, доказова освітня політика, захист персональних даних.*

Manuscript received	08.06.2026
Accepted for publication after peer review	14.08.2026
Published	17.09.2026