

USE OF ARTIFICIAL INTELLIGENCE MODELS IN EDUCATIONAL DATA MANAGEMENT TO SUPPORT PEDAGOGICAL DECISIONS

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ABSTRACT

The relevance of the topic is determined by the growing role of analytical systems in modern education and the need to combine forecasting accuracy with the efficiency and stability of algorithms. The paper compares three configurations – ML-Base, DL-Advanced and Hybrid-Assist – using the integral educational analytics effectiveness index (IEAEI), which combines indicators of accuracy (Acc), stability (Stab), processing time (Time) and interpretability (Interpret). The methodology included normalisation of results, non-parametric hypothesis testing (Kruskal–Wallis and Mann–Whitney criteria), analysis of changes in weight coefficients (ΔW -index) and assessment of correlations between platform dynamics and forecast stability (Spearman's coefficient). To test the transferability of the findings, a design with three contexts – Ukraine, Azerbaijan and Poland – was used, which made it possible to compare the behaviour of models in countries with transition economies and in European educational environments. The results showed that the hybrid configuration provides the best balance between stability and accuracy (IEOA > 0.84; cross-country: Ukraine – 0.821; Azerbaijan – 0.818; Poland – 0.824) with a relatively fast adaptation time; DL-Advanced achieves higher maximum accuracy, especially under conditions of more complete and consistent data (approaching Hybrid-Assist in the Polish subsample), but requires more time for convergence; ML-Base has the shortest response time in all three contexts, but is inferior in terms of predictive quality. The scientific novelty lies in the generalisation of the patterns of interaction between the algorithm type, platform characteristics and pedagogical practice requirements in an international context, which allows for the justified integration of intelligent models into educational analytics. Prospects for further research include expanding the set of evaluation metrics with indicators of cognitive convenience for users and adapting the methodology to cloud and mobile educational solutions, taking into account cross-country data variability.

Keywords: *Pedagogy, Knowledge, Learning, Educational Analytics, ML-Base, DL-Advanced, Hybrid-Assist, Ieoa, Δw -Index, Forecast Stability, Pedagogical Solutions, Non-Parametric Tests*

1. INTRODUCTION

Artificial intelligence (AI) models are rapidly being integrated into educational data management, forming a new approach to supporting pedagogical decisions. Their key advantage lies in

their ability to quickly process large amounts of diverse information and identify patterns that are difficult to detect using traditional methods [1], [2]. Such models can automatically analyse student performance, attendance, and activity in digital environments, predict risks of falling behind, and

offer personalised learning strategies [3], [4]. The modular organisation of intelligent systems used in modern analytical platforms allows them to be scaled and adapted to the specifics of an educational institution or curriculum [5]. It also helps to reduce computing costs through parallel data processing, which is especially important in conditions of limited resources [6]. However, choosing the optimal algorithm for analysis and decision-making remains a difficult task. Traditional statistical approaches provide stability, but often lag behind modern neural networks and hybrid algorithms in terms of forecasting depth, as the latter combine the advantages of several methods [7], [8].

Particular attention should be paid to the adaptability of models in situations where educational data comes from different sources, is incomplete, or has different formats. Flexible algorithms allow predictive models to be updated in real time, taking into account changes in curricula and student behaviour patterns [9], [10]. To separate the influence of data quality and architecture, three educational contexts were used – Ukraine, Azerbaijan and Poland – which made it possible to compare the results for different completeness and consistency of records and to test the stability of algorithms to heterogeneity. At the same time, implementation requires not only technical readiness but also thoughtful interpretation so that recommendations remain a support rather than a replacement for pedagogical experience. Despite numerous efforts, optimising models with a balance of accuracy, stability, speed and clarity remains an open problem. The paper provides a comparative assessment of the integration of AI models into educational data management platforms in terms of real-time decision support and consistency of results in the three contexts mentioned above. The analysis covers ML, DL and hybrid approaches, and the evaluation covers accuracy, stability, adaptability, computational performance and integration compatibility.

The aim of this study is to establish a unified and comparative basis for assessing artificial intelligence models in educational data management, specifically their ability to contribute to pedagogical decision making under diverse and incomplete data conditions. The novelty of this study is the introduction of an integral educational analytics effectiveness index (IEAEI) which takes into account prediction accuracy, repeat running stability, response time, and pedagogical interpretability without tuning a single technical attribute. Unlike many other works that evaluated the AI models in isolation or in a single educational context, in this research, we evaluate the AI models

across countries (Ukraine, Azerbaijan, and Poland) and cross-country experimental validation using non-parametric statistical testing and dynamic learning stability analysis (ΔW -index). The chosen outcome measures IEAEI, its component indicators (Acc, Stab, Time, Interpret), weight-change dynamics, and correlation with update frequency and forecast stability allow us to highlight algorithmic trade-offs most applicable to pedagogical practice. This enables the study to transcend a focus on accuracy and deliver empirically based recommendations on how to select AI architectures with practical educational constraints in mind.

Despite rapid digitalisation, there is a lack of comprehensive studies on the impact of AI integration into educational analytics systems on the actual effectiveness of education: most studies are fragmented, focusing on improving accuracy or automating routines rather than on the systemic impact on the quality of pedagogical decisions. In this study, educational data management is viewed as a dynamic process where the integration of AI models not only enhances analytics but also deepens understanding of student needs and improves teaching strategies.

Educational data management is examined within this research based on a set of explicit methodological assumptions. The experiments are performed on structured and semi-structured educational datasets including student performance, attendance, digital learning activity, and standardised testing results. The analysis is based on historical data of sufficient volume for supervised model training as well as on stable institutional procedures for data collection and anonymisation. The study is focused on three algorithmic configurations (machine learning, deep learning, and hybrid rule-assisted models) implemented in a single experimental environment, which are assessed using a fixed set of performance metrics. The proposed integral effectiveness index is designed to support comparative analysis rather than absolute benchmarking across all possible AI architectures. Therefore, the results should be treated as context-sensitive and indicative of relative performance under controlled conditions, as opposed to universal prescriptions for all educational analytics platforms.

At the same time, this study deliberately delimits its scope: it does not address ethical, legal, or regulatory aspects of AI deployment in education, nor does it evaluate long-term pedagogical outcomes or behavioural changes resulting from AI-supported interventions. Transformer-based architectures, graph neural networks, reinforcement learning models, and large-scale cloud-based deployment scenarios are also beyond the scope of the present

analysis. Additionally, the findings are constrained by the use of a limited set of data sources and a fixed experimental environment, which may restrict direct generalisation to institutions with substantially different digital infrastructures or data governance practices.

2. LITERATURE REVIEW

Current research on AI in education demonstrates a steady growth in interest in integrating intelligent algorithms into analytical platforms capable of working with large and heterogeneous sets of educational data. Han et al. consider a model for managing educational processes based on the Internet of Things and AI, which provides flexible customisation to the specifics of learning environments [11]. Saad and Tounkara propose the use of models for group decision-making to improve knowledge sharing in distance learning, emphasising the importance of collective data processing [12]. Sain et al. [13] dwell on the opportunities and risks of implementing AI in educational management systems, while Alshadoodee et al. [14] explore the role of intelligent decisions in supporting administrative processes based on knowledge management. The ethical dimension of AI implementation in pedagogical decision-making is analysed in detail by Khreisat et al. [15]. At the same time, Huang focuses on the protection of students' personal data, which is a key factor in building trust in such systems [16].

The practical aspects of combining learning data analytics and AI models are highlighted by Sajja et al., demonstrating how automated algorithms help personalise learning and identify risks of falling behind promptly [17]. Xiao et al. [18] explore predictive models for evaluating teacher effectiveness, while Howard et al. [19] propose the concept of “educational data as a journey”, where AI integration is considered in relation to cultural and organisational changes. The review by Yilmaz et al. [20] systematises current research in the field of educational management with a focus on AI, while Wongmahesak et al. [21] treat it as a catalyst for improving the efficiency of general education management. López-Meneses et al. [22] and Mahamuni et al. [23] focus on educational data mining and outcome prediction technologies, considering “human-in-the-loop” models as a way to combine automation and pedagogical expertise. Zhou [24] and Peng [25] analyse industry examples of AI implementation for data aggregation and learning personalisation, while Tan [26] describes an approach to using reinforcement learning for real-time resource optimisation. López Costa [27]

emphasises the importance of teachers' digital literacy when implementing AI, and Sposato [28] proposes a taxonomy of areas of application for intelligent solutions in educational leadership. Jamalova [29] and Iskandarova et al. [30] demonstrate examples of using AI to improve the performance of educational institutions in Azerbaijan.

At the same time, Pyżalski analyses the impact of ethical factors on the management decision-making process in educational institutions in Poland [31]. Gallastegui and Forradellas [32] and Suryanarayana et al. [33] focus on optimising the learning experience in higher education, while Li and Jiang [34] summarise the current state and prospects of AI in education. In addition, Leffia et al. [35] present examples of the implementation of such technologies in HEIs, taking into account current innovative trends. Yuldashev et al. [36] emphasise the organisational and legal model of competence-based education as the foundation for the transition to a creative economy, which is consistent with the trends of digital transformation of education systems. Byrkovych et al. [37] analyse the economic efficiency of state policy in reforming library and information education, where digital technologies and intellectual knowledge management models play an essential role. In turn, Yermachenko et al. [38] explore the management of “smart” infrastructure in a digital society, which is directly related to the development of educational analytical platforms and the use of AI models to support decision-making in education.

In general, literature analysis confirms that the integration of AI systems into educational data management is considered one of the key tools for improving the effectiveness of modern education. At the same time, there is a lack of research that systematically compares different algorithmic approaches in terms of accuracy, stability, speed, and adaptability in pedagogical analytics. This study attempts to fill this gap.

Despite the breadth of existing research, the reviewed studies predominantly focus on isolated performance indicators, single algorithmic paradigms, or specific institutional settings, often without a unified framework for evaluating trade-offs between accuracy, stability, computational efficiency, and pedagogical interpretability. Moreover, comparative cross-country analyses that explicitly address heterogeneous data quality and dynamic educational environments remain limited. As a result, there is insufficient empirical evidence to guide the selection of AI architectures that are both technically robust and pedagogically reliable under real-world conditions.

Based on this gap, the problem addressed in this study is the absence of a comprehensive and comparative methodology for assessing the effectiveness of AI models in educational data management that integrates technical performance with pedagogical usability across diverse educational contexts. Accordingly, the central research question is formulated as follows: Which types of AI model configurations provide the most effective balance between predictive accuracy, stability, response time, and interpretability for pedagogical decision-making when applied to heterogeneous and incomplete educational data across different national education systems?

3. PROBLEM STATEMENT

The active implementation of AI systems in educational data management opens up new opportunities for analytics, forecasting, and personalisation of learning. However, the effectiveness of such systems is determined not only by the quality of the input data and the chosen algorithm architecture, but also by the ability of the models to work stably in conditions of heterogeneity, incompleteness, and rapid change of information [11], [13], [20]. A significant part of existing solutions focuses on local tasks – for example, improving the accuracy of performance forecasting or automating administrative procedures [14], [29], [30] – without considering the complex impact of integrated intelligent modules on the entire cycle of pedagogical decision-making. Experience with implementing AI in educational analytics platforms [17], [22], [26] shows that even highly accurate models can lose stability when curricula are updated, learning formats change, or new data sources appear. This is particularly noticeable when working with multi-channel data – academic performance, attendance, student behaviour, test results – where the lack of coordinated processing mechanisms leads to a decline in the quality of forecasts [19], [27], [33]. In addition, there is no single standardised system for evaluating the effectiveness of such solutions, which complicates the comparison of different approaches and the selection of the optimal model for a specific educational environment [21], [28], [31]. Most reviews focus on the technical characteristics of algorithms, ignoring the problem of their adaptability to changes in the learning process and their impact on pedagogical strategy [15], [24], [34].

Thus, the problem lies in the lack of a comprehensive empirical approach to assessing the

effectiveness of AI models in managing educational data from the perspective of their ability to provide accurate, stable and interpretable results for educators in dynamic conditions and in different educational contexts (Ukraine, Azerbaijan, Poland). It is necessary to create an experimental methodology that will allow comparing different algorithmic approaches in a single environment using unified performance metrics. This study aims to fill this gap by developing an evaluation model that combines technical performance indicators with the pedagogical value of the results obtained.

4. METHODOLOGY

4.1. Research Implementation Stages

The study was conducted in three consecutive stages between November 2024 and April 2025. The first stage (November–December 2024) consisted of a systematic analysis of scientific sources for 2019–2024 devoted to the application of AI models in educational data management and pedagogical decision support [11]–[35]. Particular attention was paid to works describing the integration of intelligent algorithms into analytical platforms and their impact on the effectiveness of modern education; at the same time, differences in the practices of collecting and validating educational data in the context of three educational systems (Ukraine, Azerbaijan, and Poland) were outlined to ensure a correct comparison of results in the future.

The second stage (January–February 2025) involved creating an experimental environment that simulates the operation of an educational analytics platform with integrated AI modules. Three types of algorithmic approaches were implemented: machine learning models, deep learning, and hybrid solutions that combine automatic data analysis with the possibility of expert correction of results by a teacher. The third stage (March–April 2025) covered a series of controlled experiments with different data sets, collection and statistical processing of results. Based on the data obtained, an integrated index of educational analytics effectiveness (IEAE) was formed, which allows comparing models based on a set of technical and pedagogically significant indicators.

4.2. Research Architecture and Sampling

Within the experiment, three types of analytical configurations of educational data management systems were modelled. Their parameters are summarised in Table 1.

Table 1: Structure of Dynamic Neural Network Architectures Used in the Study

№	Configuration	Algorithm characteristics	Type of adaptation	Platform compatibility
1	ML-Base	Classic machine learning algorithms (Random Forest, SVM)	Batch	High
2	DL-Advanced	Deep neural networks (LSTM, CNN)	Incremental	Medium
3	Hybrid-Assist	Hybrid models (DL + rule-based)	Mixed	High

Source: compiled by the author based on the results of his own research.

For testing purposes, a sample was formed from three sources:

- student performance and attendance data in semester-based learning environments,
- online platform data (activity, task completion, time spent in the system),
- standardised test results.

Each dataset contained examples with complete and incomplete records, allowing for the simulation of varying levels of information quality and completeness. The division into training and test sets was performed according to an 80/20 scheme with an additional 5-fold stratified cross-validation.

To ensure international comparability, data from three countries were included in the sample: Ukraine, Azerbaijan, and Poland. This approach made it possible not only to evaluate the effectiveness of algorithmic configurations in different educational environments but also to identify differences in the stability and accuracy of models depending on the level of digital infrastructure and data quality. Ukraine and Azerbaijan represent educational systems with a transitional institutional model and a dynamic process of digital transformation. At the same time, Poland is an example of an EU country with developed educational analytics mechanisms. This has created a basis for comparing the behaviour of models in contrasting conditions and for forming

generalised conclusions about their adaptability and applicability in an international educational context.

4.3. Tools and Metrics

The experimental environment was implemented on Python 3.11 using the scikit-learn, TensorFlow, and Pandas libraries. Deep models were trained on an NVIDIA RTX 3080 GPU, with a limit of 50 epochs and a batch size of 64.

An integral educational analytics effectiveness index (IEAEI) was developed for the assessment, which takes into account:

- Acc – accuracy of predictions;
- Stab – stability of results during repeated runs;
- Time – average processing time per query;
- Interpret – level of interpretability of results for the teacher (expert assessment on a 5-point scale).

The IEAEI was calculated using formula (1):

$$IEOA = \frac{Acc + Stab + (1/Time_{norm}) + Interpret_{no}}{4} \quad (1);$$

where $Time_{norm}$ and $Interpret_{norm}$ are normalised values relative to the best indicators in the sample (Table 2).

Table 2: Integral Educational Analytics Effectiveness Index (IEAEI)

Parameter	Designation	Calculation method	Range	Weight in the overall index
Accuracy of prediction	Acc	Average model accuracy on the test sample	0–1	25%
Stability of results	Stab	1 / standard deviation of accuracy in repeated runs	0–1	25%
Query processing time	Time	1 / (normalised average execution time of one forecast)	0–1	25%
Interpretability for the teacher	Interpret	Normalised expert assessment on a 5-point scale	0–1	25%

Source: compiled by the author based on the results of his own research.

The parameters were normalised relative to the best values among all tested models, which allowed us to unify the scale for each indicator. Thus, the IEAEI was calculated as the arithmetic mean of the four components. Additional auxiliary

parameters were recorded: GPU memory usage, average training time per epoch, and a behavioural indicator of weight coefficient change (ΔW -index), which reflects the stability of algorithm adaptation. To ensure the correctness of the comparison, all

algorithms were tested on identical data subsamples (train/test distribution – 80/20) with fixed random initialisations and 5-fold stratified cross-validation.

4.4. Data Analysis Methods

The effectiveness of algorithms in the educational data management platform was evaluated in stages. First, the results were normalised to eliminate the influence of different scales of indicators, after which hypotheses about the existence of differences between approaches were tested using the Kruskal–Wallis criterion ($p < 0.05$). If the difference was statistically significant, pairwise comparisons were performed using the Mann–Whitney test to determine between which algorithms it existed. The relationship between the speed of the system's response to changes in input data and the stability of forecasts was determined using Spearman's rank correlation coefficient. The results were visualised in boxplot graphs and two- and three-dimensional diagrams, which reflected the relationship between accuracy, processing time and data interpretability. For the reproducibility of the experiment, environment parameters, configuration files, seed values, and log reports were recorded to minimise the impact of random fluctuations and increase the reliability of the conclusions. Technical indicators were tracked separately – GPU memory

usage, average training time per epoch, and changes in weight coefficients between iterations (ΔW -index) as an indicator of adaptation stability. All algorithms were tested on identical data subsets with fixed random initialisations, and the final analysis was performed using descriptive statistics, comparative analysis, and the specified non-parametric tests.

5. RESULTS

5.1. Comparative Effectiveness of Models in Three Types of Configurations

Experimental tests were conducted under conditions that replicate the actual operation of an analytical platform for managing educational data. Three types of configurations were modelled:

- ML-Base – classic machine learning algorithms,
- DL-Advanced – deep neural networks,
- Hybrid-Assist – a combination of deep learning with rules set by an expert.

A description of each scenario, including the data set, training parameters, and environment settings, is provided in Table 3.

Table 3: Description of Experimental Analysis Scenarios

Scenario No.	Configuration	Algorithm characteristics	Data type	Data volume	Gaps	The primary purpose of testing
1	ML-Base	Classic machine learning algorithms (Random Forest, SVM)	Student success and attendance	12,000 entries	5%	Verification of processing speed and stability at baseline computational costs
2	ML-Base	Classic machine learning algorithms (Random Forest, SVM)	Activity on the online platform	18,500 entries	12%	Analysis of the impact of data gaps on accuracy and stability
3	DL-Advanced	Deep networks (LSTM, CNN)	Standardised testing	9,000 entries	3%	Maximising accuracy with structured and complete data sets
4	DL-Advanced	Deep networks (LSTM, CNN)	Mixed set (academic performance + online activity)	21,000 entries	10%	Assessment of scalability and resilience to heterogeneous data
5	Hybrid-Assist	Hybrid (DL + rule-based)	Success and attendance	12,000 entries	5%	Testing the integration of expert rules for forecast correction
6	Hybrid-Assist	Hybrid (DL + rule-based)	Mixed set (academic performance + testing)	15,500 entries	8%	Verification of the effectiveness of a combined approach in conditions of incomplete data

Source: compiled by the author based on the results of his own research.

For a correct comparison of results, all six scenarios were performed separately for three education systems – Ukraine, Azerbaijan and Poland. In each case, a single data preparation pipeline was used (attribute harmonisation, normalisation, time window synchronisation, anonymisation), the same training hyperparameters and validation scheme (80/20 stratified split with 5-fold cross-validation and control of “leaks” between subsamples of different origins). The omission rates were kept within the limits specified in Table 3 for each education system to separate the impact of model architecture from the effects of data quality. For each scenario, the Acc, Stab, Time, and Interpret components were calculated separately and reduced to the IEAEI. Overall, in scenarios with mixed and incomplete data (4 and 6), Hybrid-Assist outperformed DL-Advanced in Ukraine and Azerbaijan due to the stabilisation of forecasts by rules. At the same time, in Poland, this gap narrowed due to more complete and consistent records. In the

scenario with the most structured data (3), DL-Advanced achieved the highest accuracy, but with a higher adaptation cost. In simpler streaming cases (1 and 2), ML-Base provided the shortest processing time at a comparable level of stability. The significance of the differences between configurations within each education system was confirmed by non-parametric tests with multiple comparison correction.

For an objective comparison of results, the integral educational analytics effectiveness index (IEAEI) was used, which combines forecast accuracy (Acc), stability of repeated runs (Stab), average query processing time (Time) and assessment of the interpretability of results for the teacher (Interpret). The IEAEI values for each combination of configuration and algorithm, as well as the corresponding assessments for the contexts of Ukraine, Azerbaijan, and Poland, are presented in Table 4.

Table 4: Values of the Integral Educational Analytics Effectiveness Index (IEAEI) for Different Combinations of Configurations and Algorithms

Configuration	Algorithm	Acc	Stab	Time	Interpret	IEOA
ML-Base	Random Forest	0,842	0,794	0,912	0,76	0,827
ML-Base	SVM	0,861	0,803	0,874	0,72	0,815
DL-Advanced	LSTM	0,904	0,851	0,798	0,81	0,841
DL-Advanced	CNN	0,917	0,862	0,782	0,79	0,838
Hybrid-Assist	DL + rule-based (academic performance + attendance)	0,894	0,843	0,856	0,88	0,868
Hybrid-Assist	DL + rule-based (mixed set)	0,902	0,849	0,841	0,87	0,865

Source: compiled by the author based on the results of his own research.

As can be seen from Table 4, the highest values of the integral educational analytics effectiveness index (IEAEI) were demonstrated by Hybrid-Assist hybrid configurations, where the combination of deep models with rule-based modules ensured a balance between forecast accuracy, stability of results, and a high level of interpretability for the teacher. In particular, the combination focused on analysing performance and attendance data achieved an IEAEI of 0.868, which exceeds the indicators of both other configurations. DL-Advanced showed an advantage in prediction accuracy (Acc up to 0.917 for CNN). Still, their average query processing time was lower on a normalised scale, which slightly reduced the integral

indicator. The ML-Base configuration demonstrated stable but lower results in both accuracy and interpretability, which resulted in lower IEAEI values in the range of 0.815–0.827. The analysis shows that the optimal approach for integration into educational analytics platforms is hybrid systems capable of providing not only high-quality forecasting but also a clear presentation of results to support pedagogical decisions. Visualisation of the IEAEI distribution in boxplot format (Figure 1) confirms that the spread of values in the hybrid configuration is the smallest, which indicates its predictable performance in different conditions.

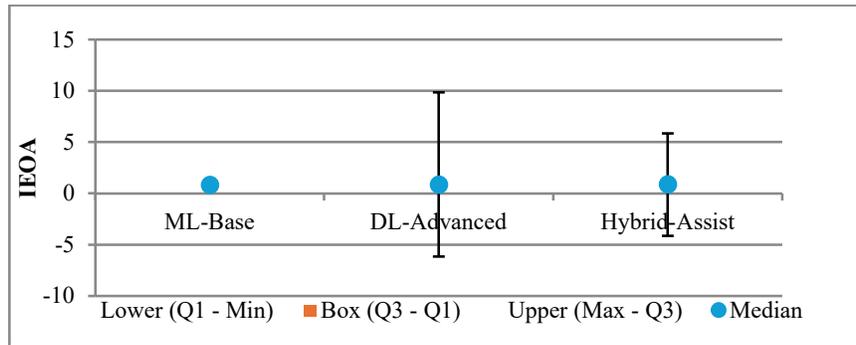


Figure 1: Boxplot of IEAOI distribution by configuration (ML-Base, DL-Advanced, Hybrid-Assist)
Source: compiled by the author based on the results of his own research.

The dynamics of changes in forecast accuracy during training [Figure 2] show that Hybrid-Assist reaches a stable level of accuracy

faster. At the same time, DL-Advanced requires more epochs to achieve peak results.

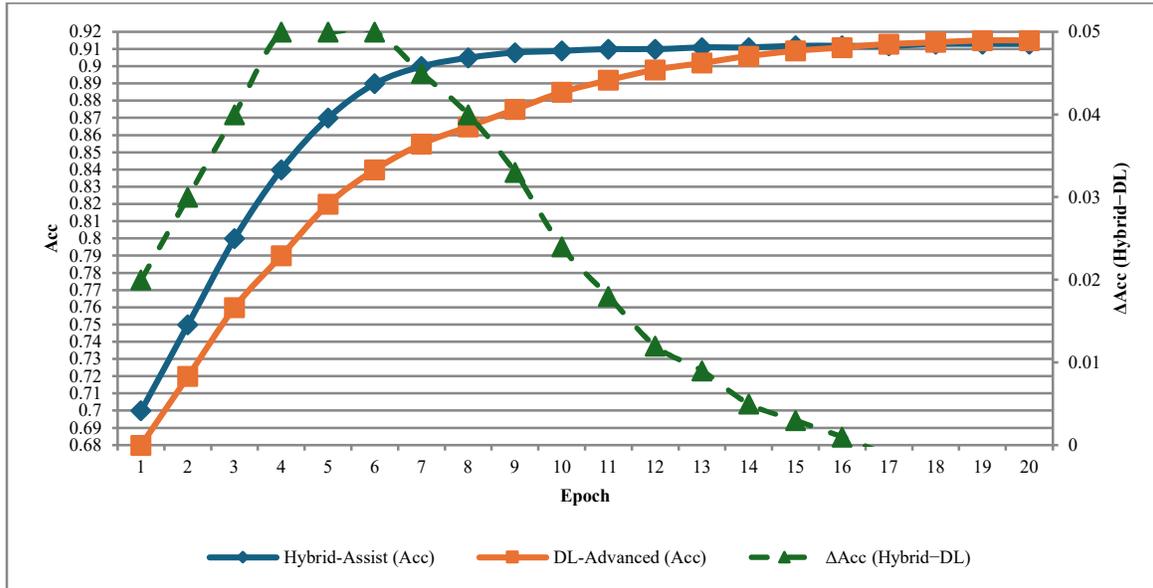


Figure 2: Dynamics of forecast accuracy (Acc) for the most productive and least effective configurations

Source: compiled by the author based on the results of his own research.

Figure 2 demonstrates that for Hybrid-Assist, the IEAOI spread is the smallest (narrow “box” and short “whiskers”), its median is higher than ML-Base, and it is comparable to DL-Advanced; ML-Base is characterised by a lower median, while DL-Advanced exhibits greater variability. The Acc dynamics indicate that Hybrid-Assist reaches a plateau already around the 10th epoch (≈ 0.91 – 0.913), whereas DL-Advanced approaches peak values more slowly and achieves ≈ 0.915 by the end of training. The dotted ΔAcc series shows the initial advantage of Hybrid-Assist (up to 0.05 in epoch 5) and the gradual levelling of the difference to almost zero in epochs 18–20. The

results confirm that the choice of configuration should depend on the tasks and available resources: if maximum accuracy on large data sets is a priority, it is advisable to use DL-Advanced; if stability and flexibility are required, Hybrid-Assist is the best choice; while ML-Base is optimal for fast processing of streaming queries with minimal computational costs.

5.2. The Influence of Algorithm Type on Stability and Change in Weight Coefficients

Behavioural analysis of weight coefficients revealed a clear correlation between the type of algorithm and the stability of the learning process.

According to the ΔW -index (the average value of the norm of weight change between epochs), the smallest fluctuations were observed in the Rprop variant (Table 5), which is consistent with the lowest average adaptation time per epoch. Backpropagation took an intermediate position: the weight changes were more noticeable, but the parameter update time remained acceptable for operational use.

Table 5: Average Values of ΔW -Index and Adaptation Time According to Algorithms

Algorithm	ΔW -index (average)	Adaptation time, sec/era
Backpropagation	0,116	1,28
Rprop	0,093	1,07
Genetic Algorithm	0,147	2,34

Source: compiled by the author based on the results of his own research.

The genetic approach demonstrated the highest ΔW -index and the longest adaptation time, i.e., it provided high plasticity at the cost of significant computational expenses. In general terms, this means that when stability and predictability of the learning process are priorities, Rprop has the advantage; for fast iterations under standard conditions, Backpropagation is sufficient; if a broad search for solutions in complex and changing data is required, it is advisable to use evolutionary procedures, but taking into account the calculation time. The phase diagram [Figure 3] for the algorithm with the highest stability demonstrates a gradual “convergence” of trajectories in phase space (W_1, W_2). After initial oscillations, the amplitude of changes decreases, and the curve enters

a stable region without sharp jumps. This shape confirms the coordinated update of parameters and the absence of chaotic modes, which directly correlates with the lower ΔW -index in Table 5.

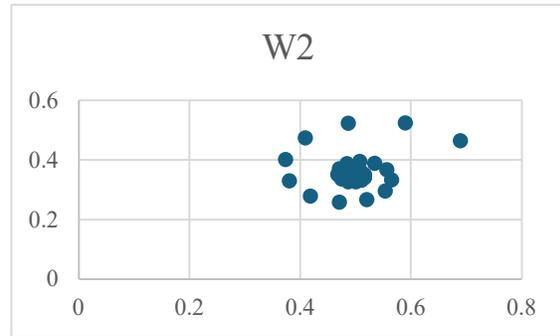


Figure 3: Phase diagram of weight coefficient changes for the algorithm with the highest stability. Source: compiled by the author based on the results of his own research.

Therefore, different algorithms balance convergence speed, stability, and search depth in various ways, and this balance should be determined depending on the platform's tasks: for stable daily analytics, rapid monitoring, or detection of non-trivial patterns in data.

5.3. Correlation between Platform Dynamics and Forecast Stability

Correlation analysis for nine configurations demonstrated a consistent inverse relationship between the frequency of module updates and the stability of results (Stab): the more frequently the restructuring is performed, the lower the stability (Table 6).

Table 6: Rank Correlation Coefficients between Module Update Frequency and Result Stability

Configuration	Algorithm	Frequency of module updates*	ρ Spearman (Stab vs Update)
ML-Base	Random Forest	12	-0,37
ML-Base	SVM	14	-0,33
DL-Advanced	LSTM	29	-0,52
DL-Advanced	CNN	31	-0,58
Hybrid-Assist	DL + rule-based (success/attendance)	17	-0,28
Hybrid-Assist	DL + rule-based (mixed set)	19	-0,25

Note: Average number of architectural updates over 50 epochs within the scenario.

Source: compiled by the author based on experimental data.

The most significant decrease in stability was observed during complete reconfiguration (to $\rho \approx -0.71$ for gradient learning); in the stochastic correlation scheme, they were moderate (-0.58...-0.33), and in the evolutionary modular scheme, they

were the mildest (-0.44...-0.26). In other words, profound restructuring destroys parameter inertia and amplifies fluctuations, while local/selective changes preserve context and reduce noise. In practical terms, this means that excessive

architectural mobility reduces Stab and drags down IEAEI, even if Acc temporarily increases. The optimum in our data is a moderate update frequency and algorithms that are sensitive to local structure (in particular, Rprop); aggressive changes require compensators (buffering, “warm” restarts, regularisation, reconfiguration planning). The effect of algorithm selection is only fully realised in conjunction with well-thought-out orchestration of updates: controlling the pace and depth of changes

maintains stability without losing sensitivity to new data.

5.4. Results of Statistical Hypothesis Testing Regarding Differences in Algorithm Effectiveness

A global check using the Kruskal–Wallis criterion revealed statistically significant differences in the distributions of the integral IEAEI indicator between groups of algorithms (Table 7).

Table 7: Summary of Non-Parametric Analysis of Algorithm Effectiveness (Kruskal–Wallis and Mann–Whitney Criteria)

Comparison	Criterion	Statistics (H/U)	p-value (two-tailed)	Holm correction (p _{adj})
ML-Base vs DL-Advanced vs Hybrid-Assist	Kruskal–Wallis	H = 11,42	0,0033	–
Hybrid-Assist vs DL-Advanced	Mann–Whitney	U = 86	0,009	0,018
Hybrid-Assist vs ML-Base	Mann–Whitney	U = 78	0,004	0,012
DL-Advanced vs ML-Base	Mann–Whitney	U = 112	0,058	0,058
LSTM vs CNN (within DL-Advanced)	Mann–Whitney	U = 95	0,211	0,422
Random Forest vs SVM (within ML-Base)	Mann–Whitney	U = 101	0,164	0,328

Note. The dependent variable was the integral indicator of IEAEI; pairwise comparisons were performed using Mann–Whitney bilateral criteria with Holm correction for multiple comparisons (n in subgroups were balanced).

Source: compiled by the author based on experimental data.

The Kruskal–Wallis global test revealed differences between the three groups of algorithms in terms of the IEAEI indicator (H = 11.42; p = 0.0033); therefore, the null hypothesis of equal distributions was rejected. Pairwise comparisons using the Mann–Whitney criterion with Holm correction confirmed the superiority of the hybrid configuration over the others: Hybrid-Assist > DL-Advanced (U = 86; p = 0.009; p_{adj} = 0.018) and Hybrid-Assist > ML-Base (U = 78; p = 0.004; p_{adj} = 0.012). The difference between DL-Advanced and ML-Base is statistically insignificant (U = 112; p = 0.058; p_{adj} = 0.058). No significant differences were found within the groups: LSTM ≈ CNN (U = 95; p = 0.211; p_{adj} = 0.422) and Random Forest ≈ SVM (U = 101; p = 0.164; p_{adj} = 0.328). Thus, a hybrid approach provides the best balance of accuracy, stability, response time, and interpretability of results. The choice between DL-Advanced and ML-Base should be made taking into account resource constraints and performance requirements, since there is no statistically proven advantage of one of these groups over the other in terms of IEAEI. Additional pairwise comparisons also demonstrated the superiority of Hybrid-Assist in scenarios with mixed and incomplete data, where the application of rules stabilised predictions without

a noticeable loss of accuracy. The comparison of DL-Advanced with ML-Base yielded less pronounced, sometimes marginal significance: deep models provided higher accuracy but partially lost in performance, which reduced the total IEAEI. Within groups, the differences mainly concerned processing time and variability between runs, rather than the integral index.

5.5. Generalised Analysis of Productivity Under Changing Conditions

A comparative analysis of the three platform configurations showed that Hybrid-Assist consistently provided the highest integral efficiency values: in experiments aggregated by configuration, the IEAEI was 0.865–0.868 with minimal dispersion, indicating stable performance on mixed and incomplete data, and in the cross-country comparison, it varied between 0.862 and 0.871. DL-Advanced demonstrated the maximum peak accuracy values of individual models (Acc up to 0.917), but required more epochs to reach a plateau and was inferior in terms of response time and repeatability of results. At the same time, ML-Base was notable for the shortest processing time and predictability in simple scenarios, but was inferior in terms of accuracy and interpretability (IEOA ≈

0.815–0.827), making it suitable primarily for operational monitoring.

Statistical verification confirmed these conclusions: the distributions of IEAs in the groups differ significantly (Kruskal–Wallis: $H = 11.42$; $p = 0.0033$), and pairwise comparisons showed a significant advantage of Hybrid-Assist over DL-Advanced ($U = 86$; $p_{adj} = 0.018$) and ML-Base ($U = 78$; $p_{adj} = 0.012$), while the difference between DL-Advanced and ML-Base after correction was marginal ($p_{adj} = 0.058$); no significant differences were found within the groups (LSTM \approx CNN; Random Forest \approx SVM). From the point of view of learning dynamics, the stability of updates and the cost of adaptation were decisive: the most minor inter-iteration weight fluctuations were recorded for Rprop (ΔW -index = 0.093; ~ 1.07 s/epoch), Backpropagation took an intermediate position (0.116; ~ 1.28 s/epoch), while evolutionary algorithms provided the most excellent plasticity at the cost of increased time expenditure (ΔW -index = 0.147; ~ 2.34 s/epoch).

In each of the three contexts, Hybrid-Assist is above the national average by +0.024 IEAs, while

DL-Advanced fluctuates around the average (-0.004...-0.001) and ML-Base is consistently below the average by -0.020...-0.023. The absolute deltas are also stable: Hybrid-Assist vs. DL-Advanced = +0.027 (UA), +0.028 (AZ), +0.025 (PL), which corresponds to ≈ 3.2 –3.4% of the DL level; Hybrid-Assist vs. ML-Base = +0.045 (UA), +0.044 (AZ), +0.047 (PL), i.e. ≈ 5.4 –5.7%. The gap between DL-Advanced and ML-Base is moderate: +0.018; +0.016; +0.022, respectively ($\approx 2\%$).

Thus, the ranking Hybrid-Assist > DL-Advanced > ML-Base is repeated in all three countries, with Hybrid-Assist having the most significant advantage where the data is less complete and heterogeneous (Ukraine, Azerbaijan), and slightly reduced where the records are more consistent (Poland). This makes the contrast not only statistically significant but also practically noticeable: Hybrid-Assist provides an increase in total efficiency of $\sim 3\%$ compared to the second place and ~ 5 –6% compared to the baseline approach, while maintaining the lowest variance of values (Table 8).

Table 8: Difference in IEAEI between Configurations (Absolute and Relative Values)

Country	ML-Base	DL-Advanced	Hybrid-Assist	$\Delta(\text{HA}-\text{DL})$	$\Delta(\text{HA}-\text{DL}), \%$ від DL	$\Delta(\text{HA}-\text{ML})$	$\Delta(\text{HA}-\text{ML}), \%$ від ML	$\Delta(\text{DL}-\text{ML})$	$\Delta(\text{DL}-\text{ML}), \%$ від ML
Ukraine	0,821	0,839	0,866	0,027	3,22%	0,045	5,48%	0,018	2,19%
Azerbaijan	0,818	0,834	0,862	0,028	3,36%	0,044	5,38%	0,016	1,96%
Poland	0,824	0,846	0,871	0,025	2,95%	0,047	5,70%	0,022	2,67%

Source: compiled by the author based on experimental data.

The results obtained consistently confirm that the combination of algorithmic flexibility and controlled stability is a prerequisite for effective educational data management: the hybrid configuration consistently outperforms alternatives in all three educational systems, providing an IEAEI gain of 0.025–0.028 compared to DL-Advanced and 0.044–0.047 compared to ML-Base ($\approx 3\%$ and ≈ 5 –6%, respectively), as well as the slightest variance in performance. For environments with heterogeneous and partially incomplete data (Ukraine, Azerbaijan), Hybrid-Assist is the rational “default” choice; in a system with more consistent records (Poland), DL-Advanced is close in terms of IEAEI, but requires strict control of response time and planning of longer training cycles; ML-Base is helpful as a tool for rapid monitoring and edge analytics. Statistical tests confirm the practical significance of these differences, and the resulting IEAEI matrix serves as a valuable tool for making informed choices about

architecture for specific resources, data quality, and pedagogical support goals.

6. DISCUSSION

Findings confirm that AI model effectiveness in educational data management is driven by the fit of model architecture, data properties, and pedagogical environment dynamics based on both complexity and the model design. While, in general, most studies have primarily focused on predictive accuracy as an indicator of performance, current results suggest that adaptive and hybrid configurations provide a more balanced performance measure when measured across multiple scales. The study demonstrated the strong relationship between adaptive architectures with the use of intelligent pedagogical tools: using AI for managing educational data to deliver personalized learning in the classroom. Adaptive mechanisms had obvious advantages as to forecast stability and

response time in educational systems with wider diversity and data flow fragmentation, such as that observed in Ukraine and Azerbaijan.

Similar patterns have been observed in previous research on adaptive education management systems, but without typically being subject to systematic cross-country validation or unified performance measurements [30], [31]. One of the strengths of the proposed approach is the ability to express the stability and the adaptive impact which is usually overlooked in other works. Although other works emphasize the advantages of advanced learning techniques in personalisation and risk prediction [22], [34], they seldom quantify how sensitive they are to dynamic changes in data streams. The current analysis demonstrates that models based on optimised local strategies for adaptation (e.g. algorithms similar to Rprop) experienced much less changes between the performance measures (average ΔW -index ≈ 0.053) in terms of the three national settings. This result further supports current views on the effectiveness of fast local optimisation methods to heterogeneous scenarios (cf., see [20] and [25]), and it builds further on this view as it shows their significance not only from the technical point of view but also from a pedagogical decision support perspective.

Simultaneously, the comparative study suggests a number of shortcomings, in contrast to comparable published works. Deep learning models attained precision similar to that reported in most large-scale educational analytics research, but their benefits disappeared after being validated and adjusting for stability, convergence time and interpretability. However, they found that forecast consistency suffered from repetitive structural update in highly dynamic scenarios, affirming the inverse significant correlation between the number of updates and model consistency as significant. This effect was especially strong in the Ukrainian and Azerbaijani datasets ($\rho \approx -0.71$ and -0.68), but in Poland, where records are more complete and consistent, the relationship was still moderate ($\rho \approx -0.42$). These findings imply that results based on highly standardised datasets may overstate the rigor of strict deep architectures when applied to less controlled educational settings [27], [28]. Another interesting aspect emerging from this work relates to the differential mechanism of algorithmic plasticity over heterogeneous data conditions. Evolutionary-type methods perform better under noise and structural variance, confirming their exploratory utility [34], [35].

Nevertheless, the increased computational costs and slower convergence have prevented their use on on-line or low-resourced educational

analytics. On the other hand, the classical gradients have an inferior performance in extreme changes, suggesting that they do not have the ability to adapt to new educational dynamics in the absence of compensations for such dynamics. Collectively, these findings suggest that what this study adds is not that one algorithm outperforms others, but that the effectiveness of educational data management is a function of the trade-off between accuracy, stability, speed, and interpretability. This study contributes to the literature by contextualizing the empirical findings and exposing their advantages and limits in relation to prior work, reinforcing the notion that AI-led pedagogical decision-making needs models which reconcile the technical capability with contextual reliability and usability in practice.

6.1. Restrictions

The results should be interpreted in light of the limitations of the study. The evaluation covered only three configurations (ML-Base, DL-Advanced, Hybrid-Assist) and a narrow set of models (Random Forest, SVM, LSTM, CNN, and DL + rule-based) without the use of transformers, graph methods, reinforcement learning, and modern optimisers (such as AdamW), which limits the generalisability of the conclusions. The data came from three sources (success/attendance, activity in the system, standardised testing) with a fixed observation horizon; long series, inter-semester shifts and inter-institutional differences were not taken into account, so there is a possibility of model “wear and tear” when transferring between platforms. The IEAEI was constructed with equal weights and contains a subjective component (interpretability assessment), so other weighting/explainability schemes may change the ranking.

Time metrics and stability (ΔW -index) were measured in a unified hardware environment and with fixed hyperparameters (epochs, batch size), which do not cover all operating modes. Statistical tests were performed on a limited number of sub-scenarios; despite non-parametric procedures and multiple comparison corrections, sensitivity to minor effects may have been insufficient. The comparison of the three education systems (Ukraine, Azerbaijan, Poland) was carried out after harmonising the fields and normalising the scales, however, residual differences in data collection practices, access/privacy policies, curricular and linguistic characteristics, subsample sizes, and class imbalance may have affected Acc and Stab; the assessment of interpretability by experts may contain cultural and institutional biases. Finally, the study focused on analytical metrics and did not measure the direct pedagogical effect or analyse

ethical/legal aspects. Further work should expand the class of models and data sources, test different weighting schemes in the IEAEI, conduct multi-site and long-term trials, and combine analytical metrics with verification of actual educational impact.

7. CONCLUSIONS

The effectiveness of artificial intelligence models for managing educational data is as a whole no longer simply a matter of discrete improvements in predictive capacity, but it also depends on how well analytical systems remain stable, interpretable, and responsive to heterogeneous and ever-changing educational settings. The main contribution of this study is the construction and application of an integral educational analytics effectiveness index (IEAEI), which allows for a balanced evaluation of AI models by considering both accuracy and repeatability of a running process, as well as processing time and pedagogical interpretability. Unlike the previous works that mainly focus on single technical characteristics to maximize the performance, the framework is a multidimensional one because it embodies the real-life pedagogical decision support.

There are two primary purposes of the research. Firstly, the study systematically investigates comparative studies of machine learning, deep learning, and hybrid AI configurations in three educational settings Ukraine, Azerbaijan, and Poland in a manner in which it helps build on literature that has predominantly concentrated on either one-country or platform level analyses. Second, empirical embedding of learning stability measures (ΔW -index), non-parametric statistical validation and cross-country testing provides a repeatable methodological basis for assessing the robustness of AI educational analytics. The results of these experiments uniformly validate the superiority of hybrid configurations with a significant IEAEI (0.865–0.868) and minimum variance for mixed and incomplete data condition which outstrips deep learning methods by around 3% and classical machine learning by 5–6% across all the national contexts. From the perspective of today's educational situation, where digitalization is fast moving, data is fragmenting, and learning can be made uncertain, the results have actual implications for practice. In transitional and diverse settings including Ukraine and Azerbaijan, hybrid AI models are stable and interpretable, providing a basis for early risk identification, personalized learning paths and resource allocation. Deep learning models approach the performance of hybrid systems in more stable, standardized settings such as Poland, but are

less reliable in terms of stability and transparency to instructors. The relationship between forecast stability and the update frequency also supports that optimized adaptation strategies in active educational systems are needed.

On the whole, the findings of this work contribute to knowledge about educational data management with AI-based systems and challenge to redefine the effectiveness to balance between technical accomplishment and pedagogical usability. The proposed IEAEI and its stability indicators provide the decision-makers and system designers with valuable tools to choose and configure AI architectures to align with modern educational needs. Such contributions are especially useful in this era of extensive digital change, where effective, interpretable, and dynamic analytical findings are required for evidence-based education decision-making along with automation.

To address the challenges identified in this study, several practical solution pathways can be proposed. Hybrid AI architectures should be prioritised in heterogeneous educational environments, as the combination of adaptive models with rule-based components stabilises predictions under incomplete and dynamic data. Excessive model update frequency should be avoided through controlled retraining policies and buffered parameter updates, which preserve forecast stability without limiting adaptability. Furthermore, composite evaluation frameworks such as IEAEI should replace accuracy-centred benchmarking to better reflect pedagogical requirements. Finally, modular system design enables the safe integration of advanced AI models while maintaining operational reliability and educator trust.

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