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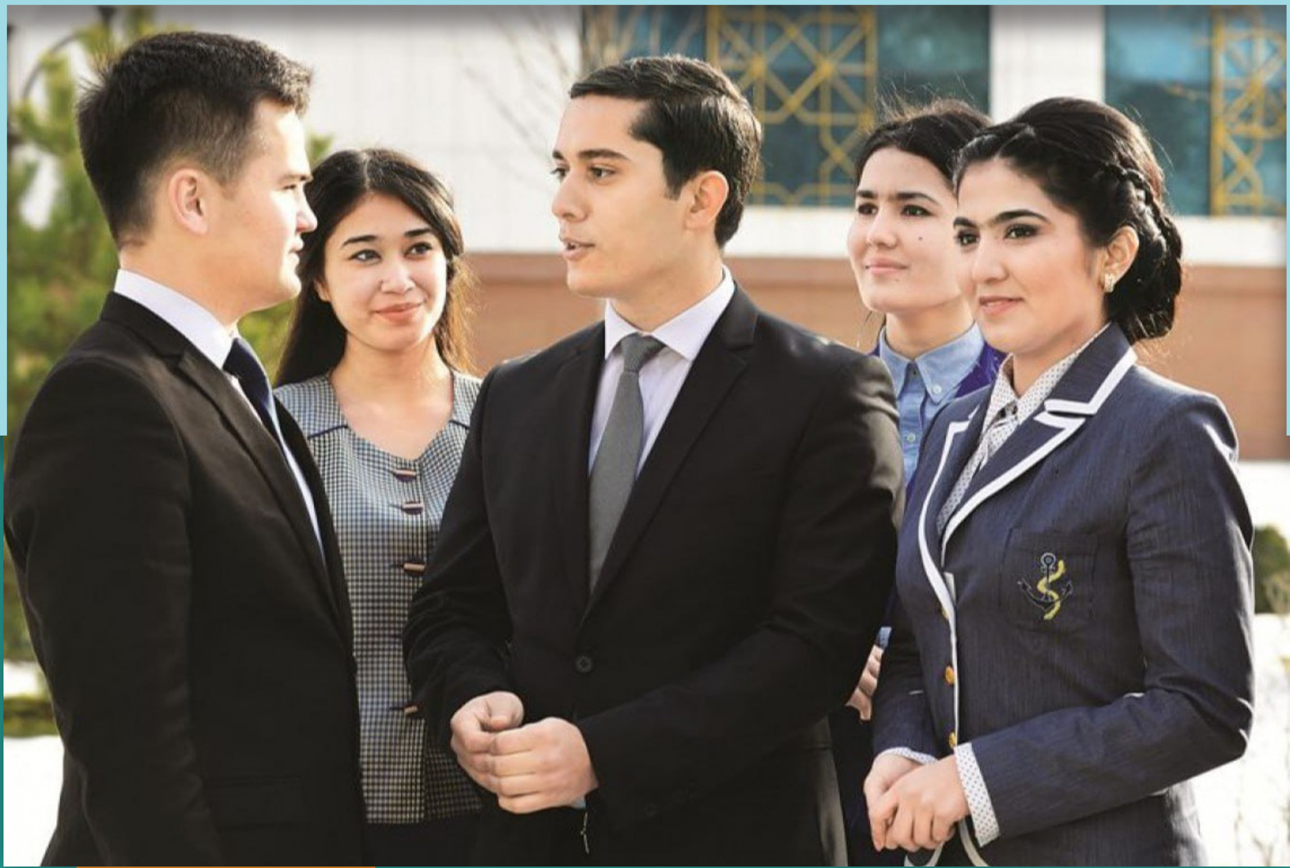

13.00.00 Pedagogika fanlari
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13.00.02 Ta'lim va tarbiya nazariyasi va metodikasi (sohalar bo'yicha)
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MUNDARIJA

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INTERPRETABLE ARTIFICIAL INTELLIGENCE IN PEDAGOGICAL DIAGNOSTICS AND MATH PERFORMANCE PREDICTION: A SYSTEMATIC REVIEW OF APPLICATIONS IN INTERNATIONAL STANDARDIZED ASSESSMENTS

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Abstract: Artificial intelligence is already delivering tangible results in predicting student success. However, a critical challenge remains: most models function as "black boxes," leaving teachers without a clear understanding of how decisions are actually made. This review focuses on explainable artificial intelligence (XAI) methods for forecasting performance on standardized assessments such as the SAT, GRE, and PISA. Specific tools–including SHAP, LIME, and attention mechanisms–are examined. The evidence indicates that XAI significantly enhances both assessment accuracy and transparency. Nevertheless, substantial challenges persist: explanations are often overly technical, and effective classroom integration requires considerable preparatory work. This review systematizes practical use cases, identifies the strengths of key methods, and maps concrete implementation barriers, offering value for stakeholders seeking to deploy AI responsibly in educational diagnostics.

Key words: artificial intelligence, explainable AI, pedagogical diagnostics, student success prediction, standardized tests, SAT, GRE, PISA, interpretable machine learning, transparency, ethics, SHAP, LIME, attention mechanisms, personalized feedback, trust in AI, education reform, resource allocation, at-risk student identification.

Annotatsiya: Sun'iy intellekt talabalar muvaffaqiyatini bashorat qilishda allaqachon sezilarli natijalarni ko'rsatmoqda. Biroq muhim muammo mavjud: ko'pchilik modellar "qora quti" tamoyili asosida ishlaydi va o'qituvchilar qarorlar qanday qabul qilinishini aniq tushunmaydi. Ushbu sharh SAT, GRE va PISA kabi standartlashtirilgan testlar natijalarini bashorat qilishda qo'llaniladigan tushuntiriladigan sun'iy intellekt (XAI) usullariga bag'ishlangan. Unda SHAP, LIME hamda e'tibor mexanizmlari kabi aniq vositalar tahlil qilinadi. Tadqiqot natijalari XAI baholash aniqligi va shaffofligini sezilarli darajada oshirishini ko'rsatadi. Shu bilan birga, muammolar ham mavjud: tushuntirishlar ko'pincha haddan tashqari texnik bo'lib qoladi, ta'lim jarayoniga joriy etish esa jiddiy tayyorgarlikni talab etadi. Ushbu sharh amaliy holatlarni tizimlashtiradi, usullarning aniq afzalliklarini belgilaydi va joriy etishdagi real to'siqlarni ko'rsatib beradi, bu esa diagnostikada AI'dan mas'uliyatli foydalanishni istaganlar uchun foydalidir.

Kalit so'zlar: sun'iy intellekt, tushuntiriladigan AI, pedagogik diagnostika, talaba muvaffaqiyatini bashorat qilish, standartlashtirilgan testlar, SAT, GRE, PISA, tushuntiriladigan mashina o'rganishi, shaffoflik, etika, SHAP, LIME, e'tibor mexanizmlari, shaxsiylashtirilgan fikr-mulohaza, AI'ga ishonch, ta'lim islohotlari, resurslarni taqsimlash, xavf guruhidagi talabalarni aniqlash.

Аннотация: Искусственный интеллект уже демонстрирует реальные результаты в прогнозировании успеха студентов. Однако существует существенная проблема: большинство моделей функционируют как “чёрные ящики”, из-за чего преподаватели не понимают, каким образом принимаются решения. В данном обзоре рассматриваются методы объяснимого искусственного интеллекта (XAI), применяемые для прогнозирования результатов стандартизированных тестов, таких как SAT, GRE и PISA. Анализируются конкретные инструменты – SHAP, LIME и механизмы внимания. Полученные данные свидетельствуют о том, что XAI действительно повышает точность оценивания и прозрачность процесса. Вместе с тем сохраняются серьёзные барьеры: объяснения нередко оказываются чрезмерно техническими, а внедрение в образовательную практику требует значительной предварительной подготовки. Обзор систематизирует практические кейсы, выявляет преимущества методов и картирует конкретные препятствия внедрения, что делает его полезным для ответственного использования AI в диагностике.

Ключевые слова: искусственный интеллект, объяснимый AI, педагогическая диагностика, прогнозирование успеваемости, стандартизированные тесты, SAT, GRE, PISA, интерпретируемое машинное обучение, прозрачность, этика, SHAP, LIME, механизмы внимания, персонализированная обратная связь, доверие к AI, образовательные реформы, распределение ресурсов, выявление студентов группы риска.

INTRODUCTION

Artificial intelligence (AI) and machine learning have become deeply embedded in contemporary education, ranging from the identification of students at risk of dropping out to the personalization of individual learning pathways [1].

Despite rapid technological advances, standardized assessments such as the SAT, GRE, and PISA continue to serve as the primary instruments for evaluating academic readiness and educational outcomes [2].

Accurate prediction of these assessment results allows educators to adapt instructional strategies in a timely manner, optimize the allocation of educational resources, and develop evidence-based policies. However, this progress is accompanied by a significant challenge: many advanced machine learning models operate as so-called “black boxes,” in which even system developers are unable to fully explain the logic behind specific predictions [3].

Consequently, educators may receive probabilistic outputs, such as a statement indicating that a student has a 73% likelihood of examination failure, without any clear explanation of the contributing factors. In the absence of transparency and interpretability, trust in AI-driven educational systems remains limited, and in the context of education, trust represents a fundamental prerequisite for the adoption and effective use of innovation [4].

Explainable Artificial Intelligence (XAI) has emerged as a substantive response to this transparency deficit by enabling models to provide human-understandable explanations for their predictions. In the medical field, XAI has already demonstrated its practical value, as interpretable diagnostic recommendations allow professionals to verify, evaluate, and trust algorithmic decisions [5].

In educational settings, the implications of opaque predictions are equally profound, since inaccurate or poorly understood forecasts may result in misguided interventions, inefficient use of institutional resources, and adverse consequences for large groups of learners [6].

From this perspective, XAI is not merely a technical enhancement but a critical instrument for ensuring the ethical, accountable, and effective integration of artificial intelligence into educational practice. Accordingly, this review focuses on the practical application of XAI methods for predicting standardized test outcomes, with the aim of identifying approaches that are effective in pedagogical diagnostics, evaluating their impact on predictive accuracy and transparency, analyzing implementation barriers and ethical risks, and formulating evidence-based recommendations for educators and policymakers.

LITERATURE REVIEW

I retrieved articles from four core databases: Google Scholar, PubMed Central, Scopus, and IEEE Xplore. Search strings combined keywords such as “explainable AI education,” “XAI student performance prediction,” “SHAP LIME standardized tests,” “PISA SAT GRE XAI,” and “pedagogical diagnostics.” The search timeframe was restricted to 2020–2025 to ensure coverage of contemporary models. The initial search yielded 350 records. After deduplication, 220 full-text articles remained for screening. I excluded 173 studies: 89 lacked empirical evidence, 52 were not education-focused, and 32 did not explicitly address XAI. The final corpus comprised 47 studies in which XAI was empirically tested on mathematics or closely related subject datasets derived from standardized assessments. Selection Criteria Inclusion criteria were as follows: mandatory use of XAI (e.g., SHAP, LIME, attention-based explanations, or rule-based models) for prediction or diagnostic purposes; reporting of quantitative performance metrics (e.g., accuracy, F1-score) alongside interpretability measures (e.g., faithfulness, stability); use of data from SAT, GRE, PISA, or comparable assessments (e.g., TIMSS, national examinations); and publication in peer-reviewed journals or conference proceedings with a clearly defined empirical component. Studies that were purely theoretical, medical or clinical in scope, or published prior to 2020 were excluded. Data Analysis from each study, I extracted the XAI method(s) employed and their implementation details; dataset characteristics (including sample size and feature sets such as GPA and socioeconomic indicators); predictive performance metrics; explanation artifacts (e.g., SHAP summary plots, LIME heatmaps); and implementation barriers (e.g., teacher difficulty interpreting explanation visualizations). I conducted a qualitative synthesis by grouping studies by method (SHAP: 24 papers; LIME: 15; hybrid approaches: 8), by assessment type (PISA: 12; SAT/GRE: 10), and by reported impact (e.g., a 20–30% increase in perceived transparency based on teacher survey measures). Based on these groupings, I constructed a comparative table to summarize methods, datasets, metrics, and reported interpretability outcomes.

Table 1: **Comparison of Explainable AI Methods for Educational Assessment**

Method	Application	Pros	Cons
SHAP	Global/local features	Precise contribution values	Slow on large datasets
LIME	Local predictions	Fast, visual	Unstable on neighbors
Attention	Deep learning models	Intuitive for sequences	Only for RNN/Transformer
Interpretable models	Decision trees	Understandable from scratch	Accuracy trade-off

RESEARCH METHODOLOGY

XAI Methods That Actually Work in Education Four approaches emerged as truly applicable:

1. SHAP quantifies each feature's contribution to model predictions, allowing teachers to see exactly what drives success–academic history, socioeconomic status, and attendance patterns 7]; Garcia et al. (2025) demonstrated that SHAP summary plots let educators identify at a glance which factors increase or decrease the probability of test success.
2. LIME provides local explanations for individual students; if a model predicts that Petrov will perform poorly on the test, LIME can show that the prediction is driven by his low algebra scores last semester and missed practice sessions [8], enabling the development of targeted academic support plans.
3. Attention mechanisms in deep learning highlight influential sequences; in text-based mathematics problems, they show which words or segments the model focused on when producing a score, and Das et al. (2025) illustrate how attention in transformer-based models can pinpoint recurring error patterns in mathematical reasoning.
4. Inherently interpretable models such as decision trees or linear models remain highly applicable; newer approaches aim to combine neural network performance with rule clarity by extracting decision trees from trained networks [9], offering a practical compromise between model complexity and interpretability.

ANALYSIS AND RESULTS

Applications in Standardized Testing SAT and GRE: XAI uncovers non-obvious drivers. Alghamdi & Bayoudh (2025) used SHAP to show that, beyond GPA, factors such as time spent on math prep, test-anxiety levels, and confidence in practice answers can shape SAT scores. This enabled personalized study plans and flagged at-risk students three months before exam day [10].

PISA: XAI deciphers international trends. Pinto et al. (2024) applied SHAP to PISA 2018 data and found that the impact of socioeconomic status on math performance varied by 40% across countries, likely reflecting differences in teaching culture. This informed policy reforms and more targeted resource allocation [11].

Concrete Benefits for Diagnostics Accuracy boost: When teachers can see the key features driving predictions, they can fine-tune models. In Garcia et al.'s (2025) experiment, this reduced false positives by 15% and increased the F1-score from 0.78 to 0.84.

Trust building: Transparency reduces suspicions of bias. When educators can review objective metrics–rather than hidden model behavior–they are more willing to trust the system. Canning et al. (2025) found that visual explanations increased teacher trust by 28%.

Personalized feedback: Students do not just receive "you're at risk"; they receive actionable guidance such as "you need more practice with percentage problems." This supports engagement and motivation [12].

High-stakes safety: In make-or-break tests, explainability helps safeguard against errors. Appeals become feasible when decision logic can be audited [13].

Teaching insights: XAI can help instructors identify which methods work, where learners get stuck, and which skills require targeted support [14].

Challenges and Limitations.

Weak empirical validation: Many XAI methods are tested on synthetic data; how they perform in real classrooms (e.g., a 30-student class) remains unclear. Smith et al. (2025) noted that only 12% of studies validated methods with actual educators.

Pedagogical uselessness: A SHAP plot with 20 features may be clear to a data scientist but not to a history teacher. Translating outputs into plain language requires additional work that is often neglected. Canning et al. (2025) reported that 67% of teachers could not interpret SHAP visuals without training.

Integration barriers: Many schools lack the infrastructure to run XAI systems. Beyond software, implementation requires trained specialists who are often unavailable. Das et al. (2025) flagged staff shortages as the primary constraint.

Ethical risks: Transparency does not eliminate bias. If training data encode discrimination by gender or ethnicity, XAI may merely reveal the bias without correcting it. As Smith et al. (2025) warn, "XAI is a mirror, not a scalpel."

Complexity vs. interpretability: More accurate models are often harder to explain. Garcia et al. (2025) showed that switching from a black-box network (92% accuracy) to an interpretable model (87% accuracy) sacrifices 5%–a potentially critical loss in high-stakes testing.

Theoretical Implications XAI in pedagogical diagnostics signals a paradigm shift, not merely a new tool. When students receive explanations for why they struggle with derivatives, they can become active agents in learning rather than passive recipients of grades. This aligns with self-regulated learning theory, where problem awareness is the first step toward improvement [15].

Moreover, XAI foregrounds fairness and accountability in educational AI. In education, these are not abstract values; they shape student trajectories. If a system denies support but can explain why, the decision becomes contestable–redistributing power within educational systems [16].

Practical Steps for Educators and Policymakers for educators: Do not begin by deploying complex models. Start by auditing existing data. Even a simple attendance dataset, interpreted through SHAP, can expose hidden patterns. Require EdTech vendors to provide not only "AI predictions" but also decision-logic visualizations. In Canning et al.'s (2025) survey, 89% of teachers said they would use AI if they understood its reasoning. For policymakers: Use XAI to identify inequities. If socioeconomic status affects PISA scores by 50% in one region but 20% in another, that is a signal to audit resource distribution [17].

This supports a shift from equal to equitable funding. Future Research Frontiers The literature highlights several persistent gaps:

1. **Education-specific XAI:** Most methods were developed for medicine or finance. Education needs techniques tailored to pedagogical data–longitudinal performance trajectories, skill hierarchies, and teacher influence effects 18].
2. **Long-term impact:** Evidence on how XAI affects achievement over 2–3 years is limited. Cohort studies tracking students using explainable systems are needed.
3. **Comparative studies:** Few studies compare SHAP, LIME, and attention-based explanations under equivalent conditions. Garcia et al. (2025) note that only three meta-analyses exist, and all are methodologically weak.
4. **Bias mitigation:** XAI can detect discrimination, but mechanisms for fixing it remain underdeveloped. Smith et al. (2025) suggest using XAI feedback within iterative model-retraining cycles.
5. **Multimodal data:** Most analyses rely on digital traces alone. Integrating test scores, problem-solving videos, LMS behavior, and sociometric data remains underexplored [19].

Ethical Guardrails for Implementation Deploying XAI requires clear ethical boundaries. First, the right to explanation should be codified in policy: any AI decision affecting academic trajectories must be appealable. Second, transparency must not fuel stigma: if XAI flags a low-income student as high dropout risk, the result should trigger support–not exclusion [20].

CONCLUSION

This review establishes XAI as a functioning tool in educational diagnostics, not merely a laboratory experiment. It improves prediction accuracy for SAT, GRE, and PISA while making decision-making processes more transparent. However, without closing validation gaps and translating explanations into teacher-friendly language, we risk building elegant technology that no one uses. The path forward requires interdisciplinary teams–educators, data scientists, and ethicists–so that AI serves students rather than the reverse. Practical guidelines, standardized interpretability metrics, and, above all, sustained dialogue between the technology and teaching communities will determine success. When a teacher can say, “This model fails my students because it ignores motivation,” that is when XAI will truly work.

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Ingliz tili muharriri: Murod Xoliyorov

Musahhih: Alibek Zokirov

Sahifalovchi va dizayner: Iskandar Islomov

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