PREDICTIVE LEARNING ANALYTICS IN AI-BASED ADAPTIVE DIGITAL EDUCATION: A METHODOLOGICAL FRAMEWORK FOR EARLY SUPPORT

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Abstract. This article develops a methodological framework for applying predictive learning analytics in AI-based adaptive digital education. The study focuses on early identification of learning difficulties, individualized support, and data-informed teacher decision-making. In digital learning environments, students generate continuous traces of activity, including assessment results, task completion time, error patterns, forum participation, video viewing behavior, and self-regulation indicators. When these data are interpreted pedagogically, they can help prevent academic failure before it becomes visible in final assessment. The article proposes a predictive adaptive methodology consisting of diagnostic data collection, learner risk modeling, intelligent recommendation, differentiated intervention, teacher dashboard interpretation, and continuous profile updating. Mathematical models are presented for calculating a Learner Risk Probability, an Intervention Priority Score, and a Predictive Methodological Effectiveness Index. The research results demonstrate that predictive analytics strengthens adaptive learning by transforming digital education from a reactive assessment model into a preventive pedagogical support system. The proposed framework emphasizes that artificial intelligence should assist, not replace, the teacher: AI detects patterns, while the teacher validates recommendations, organizes meaningful support, and ensures ethical use of learner data.

Keywords: predictive learning analytics, artificial intelligence, adaptive digital education, learner risk model, personalized support, formative assessment, teacher dashboard, competency development.

Introduction

The rapid growth of digital education has changed the methodological structure of teaching and learning. Modern learning management systems, online courses, electronic assessment platforms, virtual laboratories and multimedia resources create a large amount of educational data. These data are not only technical records of learner activity; they also contain valuable pedagogical information about students' readiness, engagement, difficulties and progress. Therefore, the effective use of digital education increasingly depends on the ability to interpret learning data and transform it into individualized instructional decisions.

The scientific problem addressed in this article is connected with the improvement of adaptive teaching methodology through artificial intelligence technologies. In many digital learning environments, assessment is still used mainly at the end of a module or course. As a result, the teacher often identifies a student's learning difficulty only after the student has already accumulated a serious knowledge gap. Predictive learning analytics offers a preventive alternative: it uses patterns in learner data to forecast possible difficulties and recommend timely support.

Adaptive learning is usually understood as the adjustment of content, tasks, feedback and learning trajectory according to the learner's individual characteristics. However, adaptation becomes truly effective when it is not limited to responding to current performance, but also anticipates future learning risks. For example, a student may pass an online quiz but still demonstrate low engagement, long task completion time, repeated conceptual errors and irregular platform participation.

Predictive analytics can reveal such hidden risk signals and help the teacher intervene earlier.

The relevance of this research is determined by the need to develop a clear methodological model for using predictive learning analytics in AI-supported adaptive digital education. Such a model should connect data analysis with pedagogical goals, competency-based assessment, ethical requirements and teacher decision-making. The purpose of this article is to design a methodological framework that identifies at-risk learners, recommends individualized interventions and supports continuous improvement of adaptive instruction.

Literature Review

The concept of learning analytics emerged as a scientific direction aimed at measuring, collecting, analyzing and reporting data about learners and their contexts for the purpose of understanding and optimizing learning. Siemens defined learning analytics as an educational data-based approach that allows institutions and teachers to make more informed decisions. In this framework, data are not valuable by themselves; their value appears when they are interpreted through pedagogical theory and used to improve learning outcomes.

Adaptive learning theory is closely related to individualized instruction, mastery learning, formative assessment and intelligent tutoring systems. Bloom's mastery learning approach emphasized the importance of corrective feedback and sufficient learning time. Hattie and Timperley demonstrated that feedback has a strong influence on learning when it answers three questions: where the learner is going, how the learner is progressing and what should be done next. These ideas provide a strong pedagogical foundation for AI-supported adaptive feedback.

Research on intelligent tutoring systems shows that digital environments can model learner knowledge, provide hints, select appropriate problems and guide students through complex tasks. Brusilovsky's adaptive hypermedia research demonstrated that digital systems can personalize content presentation and navigation according to the user model. Woolf emphasized that intelligent tutors should support both cognitive and affective dimensions of learning, because motivation and persistence influence academic success.

Predictive learning analytics extends adaptive learning by introducing early warning mechanisms. Instead of waiting for final grades, predictive systems use continuous data such as login frequency, assessment attempts, reading behavior, time on task, forum activity and previous achievement. These indicators are used to identify learners who may need additional support. However, the literature also warns that predictive models must be transparent, fair and pedagogically meaningful. A purely algorithmic decision without teacher interpretation can lead to incorrect labeling or biased support.

The reviewed literature shows that the integration of artificial intelligence, adaptive learning and predictive analytics requires a methodological system. This system should include diagnostic indicators, learner profiles, risk levels, intervention strategies and teacher validation. The present article develops such a system for the context of digital education and competency development.

Research Methodology

The study uses theoretical analysis, structural modeling and algorithmic interpretation as its main research methods. The methodological framework was developed through analysis of artificial intelligence in education, adaptive learning models, learning analytics and formative assessment principles. The proposed model is designed for use in digital education platforms where learner data are continuously collected and can be interpreted by teachers through an analytical dashboard.

The research methodology consists of five stages. The first stage is diagnostic data collection, which includes academic, behavioral and engagement indicators. The second stage is learner profile construction, where the system creates a dynamic profile for each learner. The third stage is risk prediction, where AI algorithms estimate the probability of learning difficulty. The fourth stage is adaptive intervention, where the system recommends corrective or enrichment activities. The fifth stage is pedagogical validation, where the teacher reviews the recommendation and adjusts it according to the educational context.

Learner Risk Probability Model

To calculate the probability that learner i may experience difficulty in the next learning unit, the following Learner Risk Probability model is proposed:

$$\mathbf{LRP_i(t) = \sigma(\beta_0 + \beta_1 E_i + \beta_2 T_i + \beta_3 Q_i + \beta_4 R_i + \beta_5 S_i) \qquad (1)}$$

Where $LRP_i(t)$ is the predicted risk probability of learner i at time t; σ is the logistic activation function; E_i represents engagement level; T_i represents task completion time deviation; Q_i represents quiz or task performance; R_i represents repeated error frequency; S_i represents self-regulation behavior; and β_0 ... β_5 are model coefficients. This formula allows the system to classify learners into low, moderate and high-risk groups.

Intervention Priority Score

After identifying learner risk, the system must determine which intervention should be prioritized. For this purpose, the Intervention Priority Score is formulated as follows:

$$\mathbf{IPS_{ij} = \alpha LRP_i + \gamma G_{ij} + \mu U_j - \delta L_j \qquad (2)}$$

Where IPS_{ij} is the priority score for assigning intervention j to learner i; LRP_i is the learner's risk probability; G_{ij} is the relevance of intervention j to the learner's knowledge gap; U_j is the expected usefulness of the intervention; L_j is the cognitive load of the intervention; and α, γ, μ, δ are weighting coefficients. The most appropriate intervention is selected using the following rule:

$$\mathbf{I_i^* = arg\ max_j(IPS_{ij})} \qquad \mathbf{(3)}$$

This rule means that the digital system recommends the intervention with the highest priority score, while the teacher maintains the right to confirm, modify or reject the recommendation.

Predictive Methodological Effectiveness Index

To evaluate the effectiveness of the proposed methodology during pedagogical implementation, the Predictive Methodological Effectiveness Index is introduced:

$$\mathbf{PMEI = (0.30A + 0.25P + 0.20F + 0.15M + 0.10S) \times 100} \qquad \mathbf{(4)}$$

Where A represents academic achievement growth, P represents prediction accuracy, F represents feedback effectiveness, M represents learner motivation, and S represents self-regulation improvement. The PMEI can be used to compare traditional digital teaching, general adaptive teaching and predictive adaptive teaching.

Results

The structural modeling of predictive adaptive instruction resulted in a methodological system that connects educational data, artificial intelligence and teacher-led pedagogical support. The main result is the design of a preventive adaptive cycle in which the system continuously analyzes learner behavior and helps teachers organize differentiated interventions before major academic failure occurs.

Table 1: Core Components of Predictive Adaptive Learning Methodology

Component	Data Source	AI Function	Pedagogical Purpose
Diagnostic monitoring	Tests, assignments, LMS logs	Pattern recognition	Identify current learning state
Learner profile	Achievement, time, errors, engagement	Dynamic modeling	Create individualized learning map
Risk prediction	Historical and current learning traces	Predictive analytics	Detect possible future difficulties
Intervention selection	Risk level and knowledge gap	Recommendation algorithm	Select corrective or enrichment task
Teacher dashboard	Visualized analytics and alerts	Decision support	Help teacher plan targeted support
Profile updating	Post-intervention results	Continuous recalculation	Improve next recommendation

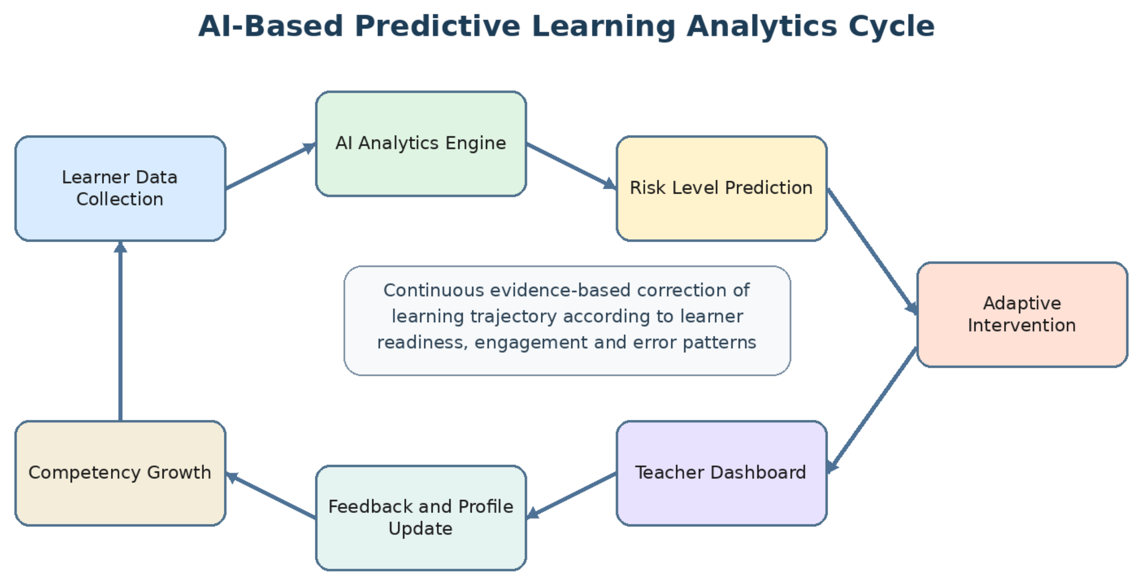

Figure 1: AI-Based Predictive Learning Analytics Cycle

Figure 1 Academic Caption: The diagram illustrates a continuous cycle in which learner data are collected, analyzed by artificial intelligence, transformed into risk predictions, interpreted by the teacher and updated through feedback after adaptive intervention.

The model demonstrates that predictive adaptive learning is not a single automated action. It is a cyclical methodological process. The learner's profile is updated after every significant educational activity, which allows the system to respond to changes in motivation, performance and self-regulation. This feature is especially important in competency-based education because competency development requires repeated practice, reflection and progressive task complexity.

Table 2: Risk Levels and Recommended Pedagogical Interventions

Risk Level	LRP Range	Typical Signs	Recommended Intervention	Teacher Action
Low	0.00-0.30	Stable results, regular participation	Enrichment tasks, independent projects	Encourage autonomy
Moderate	0.31-0.60	Irregular activity, minor gaps	Guided practice, short feedback, peer support	Monitor progress weekly
High	0.61-1.00	Repeated errors, low engagement, slow progress	Remedial module, tutor consultation, simplified scaffolding	Provide direct support

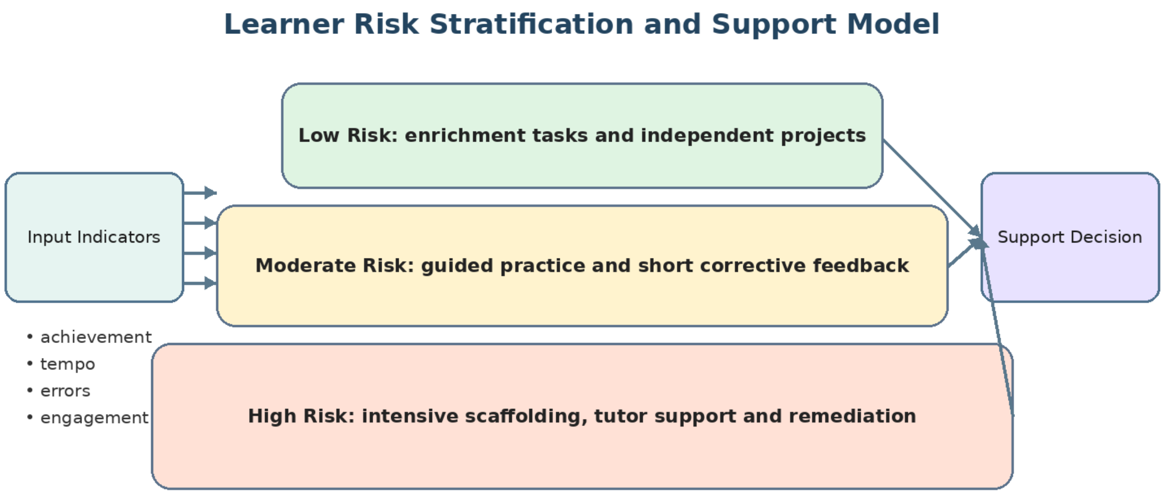

Figure 2: Learner Risk Stratification and Support Model

Figure 2 Academic Caption: The model shows how learners are grouped into low, moderate and high-risk categories according to predictive indicators. Each risk level requires a different level of pedagogical support and teacher involvement.

The risk stratification model is useful because it prevents a one-size-fits-all approach in digital education. Learners with low risk do not need repetitive remedial tasks; they need challenging projects and opportunities for independent exploration. Moderate-risk learners need short corrective feedback and guided practice. High-risk learners require direct teacher support, simplified scaffolding and structured remediation. Thus, prediction becomes meaningful only when it is connected with appropriate pedagogical action.

Table 3: Comparative Analysis of Digital Teaching Models

Parameter	Traditional Digital Teaching	Adaptive Digital Teaching	Predictive Adaptive Teaching
Main logic	Content delivery	Adjustment to current level	Early prevention of future difficulty

Parameter	Traditional Digital Teaching	Adaptive Digital Teaching	Predictive Adaptive Teaching
Assessment role	Mostly summative	Formative and continuous	Predictive and preventive
Teacher decision	Based on visible results	Supported by analytics	Supported by risk forecasts and alerts
Feedback	Delayed or general	Individualized	Individualized and prioritized
Learner support	Same tasks for all	Personalized tasks	Targeted intervention by risk level
Main limitation	Low personalization	Requires quality learner data	Requires ethics, transparency and teacher validation

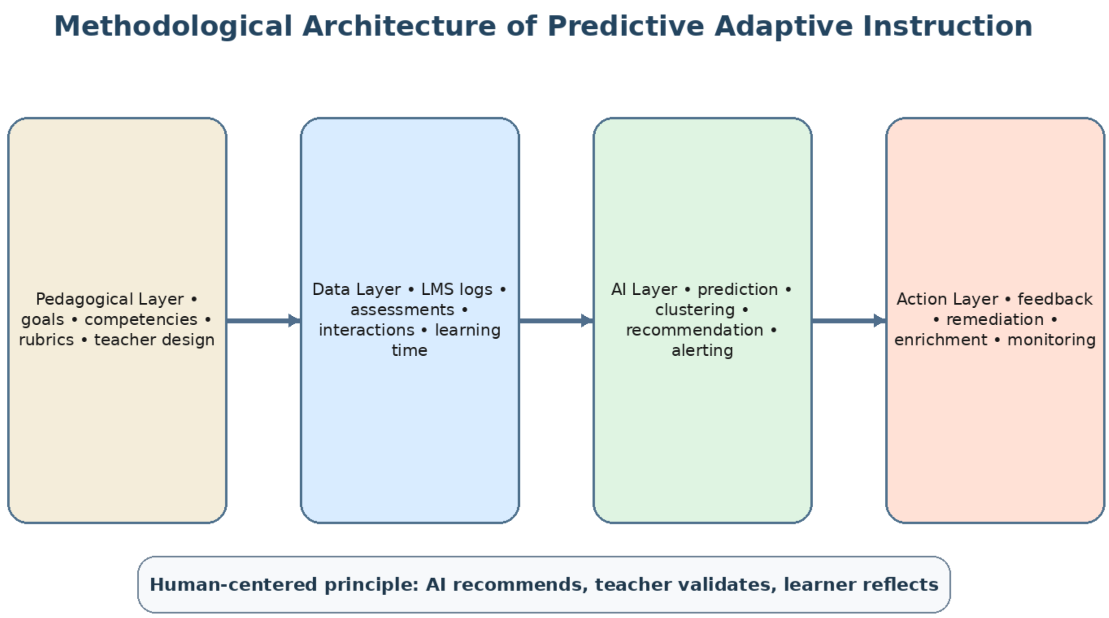

Figure 3: Methodological Architecture of Predictive Adaptive Instruction

Figure 3 Academic Caption: The architecture integrates pedagogical, data, AI and action layers. The final decision is human-centered: artificial intelligence provides analytical recommendations, while the teacher validates them according to learning objectives and learner context.

Discussion

The proposed framework shows that predictive learning analytics can significantly improve the methodology of adaptive digital education. The key difference between ordinary adaptive learning and predictive adaptive learning is the time of pedagogical response. Ordinary adaptivity usually responds to what has already happened: a student fails a task, then the system recommends easier material. Predictive adaptivity tries to identify the probability of difficulty before failure occurs. This preventive logic is important for improving learning quality and reducing academic disengagement.

Another important result is the transformation of the teacher's role. In a predictive adaptive environment, the teacher becomes not only a content provider but also an analyst, mentor and designer of intervention strategies. The teacher uses the dashboard to understand why the system has classified a learner as at risk, what type of difficulty is expected and what kind of support may be effective. Therefore, the teacher's professional competence in interpreting learning analytics becomes a necessary condition for successful implementation.

The mathematical models proposed in the article have methodological significance. The Learner Risk Probability model helps to combine several indicators instead of relying on a single test score. This is important because a learner's educational situation is multidimensional. Low motivation, unstable attendance, repeated conceptual errors and long task completion time can be more informative than one isolated grade. The Intervention Priority Score connects risk prediction with didactic action and helps avoid random or excessive intervention.

At the same time, predictive learning analytics must be implemented carefully. The system should not label students permanently or create psychological pressure. Risk prediction should be understood as a temporary pedagogical signal, not as a fixed judgment about learner ability. Data privacy, algorithmic fairness, transparency of recommendation logic and teacher supervision are essential principles. Learners should also receive explanations and opportunities for reflection so that predictive analytics supports self-regulation rather than passive dependence on the system.

The discussion confirms that artificial intelligence is most effective when it strengthens the human side of education. AI can process large amounts of data, detect hidden patterns and generate timely recommendations. However, it cannot replace the teacher's empathy, contextual understanding, moral responsibility and communication with learners. Therefore, the proposed methodology is based on the principle: AI predicts and recommends, the teacher interprets and guides, the learner reflects and acts.

Conclusion

This article proposed a methodological framework for applying predictive learning analytics in AI-based adaptive digital education. The study demonstrated that predictive analytics can transform digital learning from a reactive model of assessment into a preventive model of pedagogical support. By analyzing learner activity, performance, time management, error patterns and engagement, artificial intelligence can help identify students who may need support before their learning difficulties become severe.

The developed framework includes diagnostic data collection, learner profile construction, risk prediction, adaptive intervention selection, teacher dashboard interpretation and continuous profile updating. The Learner Risk Probability model, Intervention Priority Score and Predictive Methodological Effectiveness Index provide a structured basis for implementing and evaluating predictive adaptive teaching.

The main scientific conclusion is that predictive learning analytics should be considered not only a technical instrument but also a methodological component of modern digital education. Its effectiveness depends on the integration of artificial intelligence algorithms with didactic goals, competency-based assessment, formative feedback, ethical data use and teacher decision-making. When these conditions are met, predictive adaptive learning can improve academic achievement, learner motivation, self-regulation and the quality of professional competency development.

Practical Recommendations

1. Digital education platforms should include predictive analytics modules that identify early signs of learner difficulty based on achievement, engagement, errors and learning tempo.

2. Teachers should be trained to interpret analytical dashboards and use risk predictions for constructive, supportive and non-discriminatory intervention.

3. Learning materials should be classified by difficulty level, competency orientation, cognitive load and intervention type so that recommendations are pedagogically meaningful.

4. Institutions should develop ethical regulations for learner data privacy, algorithmic transparency, consent and responsible use of artificial intelligence in education.

5. Predictive adaptive learning should be evaluated through pedagogical experiments using academic achievement, prediction accuracy, feedback effectiveness, motivation and self-regulation indicators.

6. The teacher must remain the final methodological decision-maker, while AI should function as a decision-support tool rather than an autonomous controller of the learning process.

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