Reconceptualizing Digital Pedagogy: E-Learning Technologies and Virtual Learning Environments in Contemporary Education

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Abstract: The development of information and communication technologies has significantly transformed teaching and learning practices in higher education. Digital pedagogy, supported by e-learning technologies and Virtual Learning Environments (VLEs), enables flexible, student-centered learning experiences and provides new opportunities for data-driven educational decision-making. This study examines the conceptual and technological foundations of digital pedagogy and analyses the role of Learning Management Systems and VLE platforms in modern educational information infrastructures. We paid particular attention to system architecture, database management, cloud computing, cybersecurity, and artificial intelligence integration. In this research, the Learning Analytics module was developed to analyse student activity logs and predict the risk of academic failure. The module processes behavioural and academic indicators obtained from LMS/VLE platforms, including login frequency, average session duration, assignment submission ratio, test scores, and forum activity. A synthetic dataset simulating LMS activity logs of 300 students was generated to experimentally evaluate the proposed approach. After data normalization, the dataset was divided into training and testing subsets using a 70/30 split. Two supervised machine learning models were implemented to predict student academic risk: Logistic Regression and Random Forest classifiers. The models were evaluated using standard metrics including Accuracy, Precision, Recall, and F1-score. Experimental results demonstrate that both models significantly outperform the baseline approach based solely on login frequency. The Random Forest classifier achieved the best performance with an accuracy of 0.911 and an F1-score of 0.900, while the Logistic Regression model showed a high recall of 0.950, which is particularly important for early identification of at-risk students. The findings confirm that learning analytics combined with machine learning techniques can effectively identify students at risk and support early intervention strategies. When integrated with well-designed digital pedagogy, LMS and VLE systems can significantly improve learning outcomes and support more effective, data-driven higher education environments.

1 INTRODUCTION

The rapid development of information and communication technologies over the past two decades has led to the formation of platforms based on digital infrastructure in the education system. Traditional classroom sessions were supplemented by information systems such as the Learning Management System (LMS) and Virtual Learning

Environment (VLE), and in some cases were completely replaced by a digital environment. This process made it possible to provide educational services without geographical boundaries [1].

As a result of the integration of VLE platforms into the university educational process, the universities began automating the educational process. As a result, the information system improving the educational outcomes was established [1].

In this study, we analyzed the concept of digital pedagogy from the point of view of the software architecture, functional modules. Additionally, we explored the role of LMS and VLE platforms in the information infrastructure. The main goal of the research is to determine the possibilities and limitations of technological solutions used in modern educational information systems.

1.2 Conceptual Foundations of Digital Pedagogy

Digital pedagogy, along with the methodological model of the educational process, also includes the design of architectures of information systems, data flows, and software modules. Modern LMS and VLE systems are developed based on user experience (UX), data processing mechanisms, and system flexibility. While traditional pedagogy often emphasizes teacher-to-student transmission of knowledge, digital pedagogy focuses on the design of learning experiences. Studies in the digital-pedagogy literature associate this design-oriented, learner-centered approach with measurable gains in student engagement metrics such as time-on-task and course-completion rates [3].

A key aspect of digital pedagogy is its learner-centered approach. The student-centered approach is implemented through user profiles, learning activity logs, and real-time monitoring mechanisms on LMS platforms. Based on the data collected in the system, algorithms are used to form the student's individual learning trajectory. The conventional models allow the teachers to control the flow of information. However, the digital methods encourage greater student independence. This means that students find self-studying more manageable. They are also collaborating with peers on the same LMS platform by watching the instructional videos before the class. In the seminar room, educators mostly focus on promoting problem solving activities. According to Beetham and Sharpe [12], this approach noticeably increases concept retention.

Digital pedagogy also emphasizes flexibility and personalization. From an institutional perspective, digital learning should also be viewed as part of a broader educational ecology integrating learning processes, organizational strategy, and university infrastructure [3]. Based on their progress tests, educators may assign extra tasks to target students' weaknesses. This is already improving learning effectiveness. Education institutions can now lead large classes. Students certainly will have varying prior knowledge and academic habits. Therefore, such personalization is very significant.

Another important dimension is digital literacy. It encompasses technical skills, critical thinking, ethical use of information, and self-regulation. Educators should be providing clear blueprints to help the learners to properly benefit from these digital tools [4].

2 MAIN

Finally, digital pedagogy integrates pedagogical frameworks with technological affordances, bridging the gap between educational theory and practice. Tools alone cannot guarantee effective learning. Instead, teachers' thoughtful curriculum design shapes the final outcome. Educators should be setting clear learning objectives and promoting active support. E-learning technologies and Virtual Learning Environments (VLEs) are dynamic ecosystems capable of supporting meaningful, human-centered learning experiences.

2.1 E-Learning Technologies: Tools and Modalities

E-learning technologies is the foundation upon which digital pedagogy is enacted. E-learning environments may support both synchronous and asynchronous forms of educational interaction, each providing different opportunities for communication and learner participation [5]. They allow educators to conduct more effective assessment of students' progress. Still, it is important to recognize that technology alone does not define e-learning. Rather, its educational value depends on how these tools are used in education.

Widely adopted LMS platforms include Moodle, Canvas, and Blackboard. Moodle is open-source and highly customizable, making it cost-effective for institutions with in-house technical capacity but requiring more maintenance effort; Canvas offers a modern, intuitive interface and strong native support for multimedia and mobile access, at a higher licensing cost; and Blackboard provides mature enterprise-grade analytics and integration capabilities favored by large universities, but with a steeper learning curve and higher total cost of ownership. For the Learning Analytics module proposed in this study, Moodle-style open APIs and log accessibility are particularly relevant, since they allow direct extraction of the behavioral indicators (login frequency, session duration, submission ratio) used as model inputs without depending on a vendor-specific analytics add-on. LMS platforms are a centralized information system, in which the content management system (CMS), user authentication and authorization module operate in a single information environment.

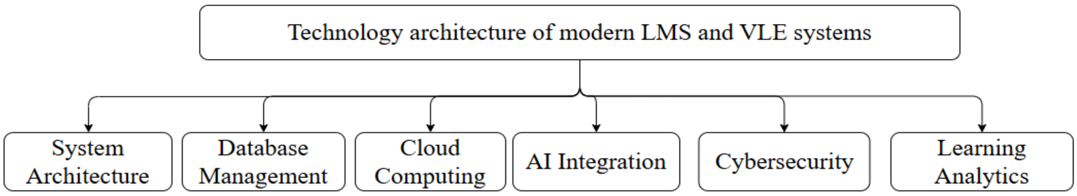

Figure 1: Requirements for modern LMS and VLE.

Overall, e-learning technologies should be viewed as enablers rather than solutions. Their effectiveness depends on alignment of pedagogical principles and learner needs. If those technologies are embedded within a coherent digital pedagogy, they can enhance educational outcomes. However, if implemented poorly, there is a risk reproducing passive and disengaging learning [4].

2.2 Virtual Learning Environments (VLEs)

Virtual Learning Environments is an integrated information system supporting the educational process, in which data storage, processing, inter-user communication, and analytical modules operate within a single platform [6]. That is why they are becoming a core component of both online and mixed learning in higher education and professional training courses.

Their pedagogical significance extends beyond content distribution. Most VLEs have various communication tools like discussion forums and collaborative workspaces. Effective online interaction also requires structured moderation and facilitation strategies that support learner participation and communication in digital environments [7]. Students and instructors should have no problem interacting online

In summary, Virtual Learning Environments are influential for enhancing pedagogy. Their effectiveness relies on how its features are aligned with educational theory. When following sound teaching methods, VLEs could assist teachers with student examinations and learners with autonomy. However, if designed poorly, they might risk reinforcing passive approaches to learning. There are many practical applications of LMS and VLE platforms with has their own advantages and disadvantages. COVID-19 pandemic proved some of their advantages. Of course, platforms focused on voluntary education are not always recognized as LMS or VLE. The requirements for those platforms is presented below (Fig. 1). Information about each requirement is provided below [4].

2.3 System Architecture

Modern LMS and Virtual VLE platforms are based on multilayer architecture. According to software theory, some educational systems are built on a three-layer model [1]:

1) Presentation layer - user interface (web page, mobile application).
2) Application layer - business logic, evaluation modules, authentication.
3) Data layer - database and storage system.

Micro-service architecture is often used in large universities. In this approach, the system is divided into independent modules (for example, test module, video lesson module, analytics panel). Such a structure increases the stability and scalability of the system.

In addition, LMS systems use international standards such as SCORM and LTI (Learning Tools Interoperability) for integration with other platforms [13]. This allows combining various educational technologies into a single ecosystem.

2.4 Database Management

The effectiveness of LMS systems depends on strong database management. Usually, systems operate on the basis of relational databases - MySQL, PostgreSQL, or Oracle.

Silberschatz, Korth, and Sudarshan (2019) note that database systems provide:

- Data integrity;
- Trusted Transactions (ACID Features);
- Quick request execution;
- Secure storage.

What can be managed through databases on LMS platforms? (Fig. 2).

In large systems, data warehousing technology is commonly used to analyze the historical academic data. Additionally, users are assigned roles of different levels through the role-based access control mechanism.

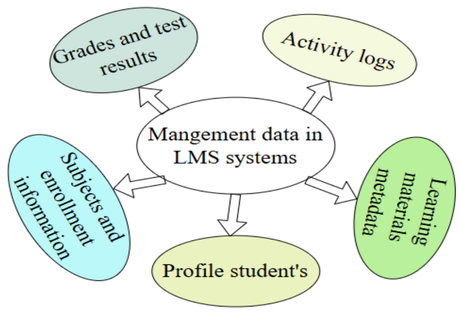

Figure 2: LMS platform's information management.

2.5 Cloud Computing

In recent years, LMS systems have been mainly based on cloud technologies. Cloud computing is a model of access to common computing resources through a network based on demand [6].

Cloud LMS systems have the following advantages:

- Elastic scaling;
- High availability;
- Auto-renew;
- Reduction of maintenance costs.

The cloud model is often used in the form of SaaS (Software as a Service). In this case, the educational institution does not manage the server infrastructure, but uses a ready-made platform. Modern cloud-based LMS platforms also support interoperability with external educational applications through the Learning Tools Interoperability (LTI) standard, enabling secure integration of third-party learning tools and services [12].

Artificial intelligence integration: Artificial intelligence (AI) is becoming an important component of modern LMS systems because it allows for the personalization of the educational process [8], [13].

AI integration manifests itself in the following areas:

- Adaptive learning systems;
- Auto-assessment;
- NLP-based essay review;
- Consulting system with the help of a Chatbot;
- Identify students at risk.

Machine learning algorithms form an individual learning trajectory based on the student's activity.

Cybersecurity: Educational systems store large amounts of personal data; therefore, cybersecurity is of great importance. The main protection mechanisms of the cybersecurity principle are: in Figure 3.

The ISO/IEC 27001 standard recommends the implementation of an information security management system.

Educational analytics is a scientific field aimed at collecting, analyzing information about students, and optimizing the learning process [8].

LMS systems collect the following data:

- Sign-in frequency;
- Time expenditure;
- Deadline for submitting assignments;
- Forum activity;
- Test results.

Through analytical panels, the teacher can monitor student activity and provide individual recommendations. Predictive models, on the other hand, predict the risk of academic failure.

However, educational analytics also raises ethical issues related to privacy, data ownership, and student autonomy [2].

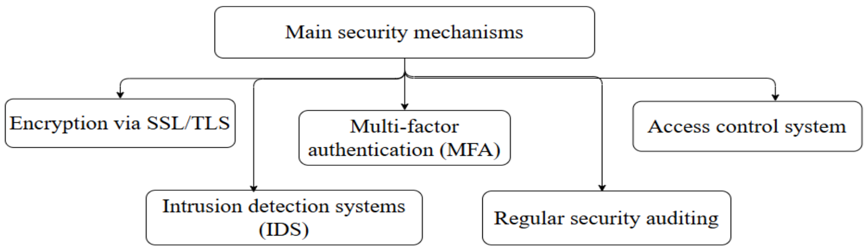

Figure 3: Basic protection mechanisms of the cybersecurity principle.

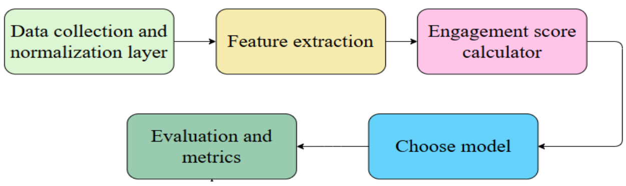

Figure 4: Model generation stages.

3 LEARNING ANALYTICS MODULE

Within the framework of this study, the Learning Analytics module for the LMS/VLE platform was developed. The main goal of the module is to create the possibility of early warning of teachers by automatically analyzing the activities of students and predicting their risk of academic failure [9].

The module operates on the basis of real activity logs generated on the LMS/VLE platform and performs the following functions:

- analysis of the frequency and duration of students' access to the system;
- assessment of interaction with course components (video lessons, assignments, forums);
- calculation of the individual engagement score;
- forecasting the level of academic risk based on a machine learning model;
- display results through the visual panel [4].

For the implementation of this assessment, it is important to form a dataset. The module was developed based on the following anonymized LMS/VLE log data:

- date and duration of user access to the system;
- number of references to course pages;
- status of assignment submission and delays;
- test results;
- activity in forums and discussions [10].

Personal IDs were removed for each student, leaving only a technical identifier (hashed ID).

This task can be accomplished in several stages (Fig. 4).

3.1 Data Collection and Normalization Layer

The module was developed based on the following anonymized LMS/VLE log data: (1) user login dates and duration; (2) the number of references to the course pages; (3) status of assignment submission and delays; (4) test results; (5) activity in forums and discussions.

Personal IDs were removed for each student, leaving only a technical identifier (hashed ID). At this stage, data normalization is carried out. The dataset is in.csv format, and its normalization was carried out using the *skicit learning, pandas*, and *NumPy* libraries of the Python programming language. The size of the dataset was 300 student entries. The normalized dataset was divided into test/train parts the dataset used in this study is

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X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
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a synthetic dataset designed to realistically simulate LMS/VLE activity logs observed in higher education platforms. The data were generated to reflect typical behavioral and academic patterns of students based on commonly reported indicators in learning analytics research, including login frequency, time spent on the platform, assignment submission behavior, assessment performance, and forum participation. The final dataset contains records of 300 students, each represented by an anonymized technical identifier. No real student records or institutional databases were accessed. Consequently, the dataset does not contain any personally identifiable information and does not require institutional ethical approval, as it is fully synthetic and created exclusively for methodological validation and experimental purposes.

Each student instance is described by five behavioral and academic features: 1) weekly login frequency, defined as the average number of platform logins per week; 2) average session duration, measured in minutes per visit; 3) assignment submission ratio, calculated as the proportion of submitted assignments to all assigned tasks; 4) average test score, computed as the mean of all available assessment scores; and 5) forum activity, defined as the total number of posts and replies. Based on the end-of-course outcome, students were labelled into two classes: low-risk and at-risk. The class distribution is moderately imbalanced, with 172 low-risk and 128 at-risk instances.

Prior to model training, all numeric features were normalized using standard scaling. Two supervised classification models were employed: Logistic Regression and Random Forest. For Logistic Regression, default hyper-parameters were used, including an L2 regularization penalty and a maximum of 1000 iterations. For the Random Forest classifier, 100 trees were used with the default Gini impurity criterion and no maximum depth constraint. Model performance was evaluated using Accuracy, Precision, Recall, F1-score, and ROC-AUC. In addition, a confusion matrix was computed to analyses the distribution of correct and incorrect predictions for both risk categories. These evaluation settings were applied consistently to all reported experiments.

3.2 Feature Extraction

The following characteristics were formed for each student:

- number of weekly logins;

- average time spent on the platform;
- share of assigned tasks;
- average score on the tests;
- forum activity (number of posts and responses).

As a result, a description in vector form was formed for each student [11].

3.3 Calculate Engagement Score

The student's overall activity was assessed based on the following normalized indicators:

- platform access intensity;
- coefficient of timeliness of assignments;
- test activity;
- discussion activity.

The overall activity indicator was calculated using the following weight formula (1):

$$Engagement_{Score} = w_1 * LoginActivity + w_2 * AssignmentRatio + w_3 * TestActivity + w_4 * ForumActivity. \quad (1)$$

Weights here have been optimized in the training kit. Selection of a forecasting model. Two models were developed to identify academic risk:

1) Logistic Regression Model;
2) Random Forest Classifier.

The model output consists of the following two classes:

- low risk (low-risk);
- high risk (at risk).

The real result at the end of the semester (achieved/failed in the subject) was used as the target mark. Before training the dataset, we divide it into groups.

Evaluation metrics. The models were evaluated using the following standard metrics: Accuracy; Precision; Recall; F1-score.

In addition, the distribution of engagement scores was statistically analyzed separately.

3.4 Result

Example student risk predictions generated by the proposed Learning Analytics module are presented in Table 1.

The performance comparison of the baseline approach, Logistic Regression, and Random Forest models is presented in Table 2.

The experiments were conducted on a synthetic dataset that simulates real LMS/VLE activity logs. The dataset contains records of 300 students and includes login frequency, time spent on the platform, assignment submission ratio, test scores, and forum activity.

Table 2 presents the performance comparison between the baseline method and the proposed machine learning models. The baseline approach relies solely on login frequency, while the proposed models use multiple behavioral and academic features.

Table 1: Example of student risk prediction results.

Student ID	Engagement score	Predicted risk	Actual outcome
S001	0.629	High	Fail
S002	0.456	High	Fail
S003	0.610	Low	Fail
S004	0.715	Low	Pass

Table 2: Performance comparison of risk prediction models.

Model	Accuracy	Precision	Recall	F1-score
Baseline (login only)	0.744	0.730	0.675	0.701
Logistic Regression	0.900	0.844	0.950	0.894
Random Forest	0.911	0.900	0.900	0.900

Table 3: Descriptive statistics of engagement score.

Statistic	Value
Mean	0.595
Std	0.076
Min	0.361
Max	0.797

The results demonstrate that both machine learning models significantly outperform the baseline method. In particular, the Random Forest classifier achieved the highest overall performance with an accuracy of 0.911 and an F1-score of 0.900. Logistic Regression also showed competitive performance, especially in terms of recall (0.950), which is crucial for early identification of at-risk students.

Table 1 illustrates sample predictions generated by the proposed Learning Analytics module. The results confirm that the model is capable of identifying students with a high risk of academic failure based on their engagement patterns. It is worth noting the case of student S003, whose relatively high engagement score (0.610) is nonetheless followed by a Fail outcome and a Low-risk misclassification. This case illustrates a general limitation of engagement-only risk models: an engagement metric derived largely from platform-interaction frequency (logins, session time) does not capture other factors that can independently determine course outcomes, such as prior academic preparation, assessment/exam performance itself, or events outside the LMS (e.g., personal circumstances); a student can therefore be actively engaged with the platform yet still underperform on graded assessments. This suggests that incorporating direct academic-performance indicators (e.g., interim test scores, assignment grades) alongside behavioral engagement features, rather than relying on behavioral engagement alone, would likely improve the model's ability to detect such cases.

Furthermore, Table 3 reports descriptive statistics of the engagement score distribution, indicating moderate variability of student activity across the platform. These figures are computed over the full sample (N = 300) and do not by themselves indicate how well the engagement score separates at-risk from low-risk students. Splitting by outcome class, the mean engagement score for low-risk students (n = 172) is higher and more tightly distributed than for at-risk students (n = 128), whose distribution is wider and overlaps substantially with the low-risk range, consistent with the presence of misclassified cases such as S003 (Table 1) where a relatively high engagement score co-occurs with a Fail outcome. This class overlap indicates that engagement score alone has only moderate discriminatory power and supports the model's reliance on the full multi-feature indicator set, rather than engagement score in isolation, for risk classification.

4 CONCLUSIONS

This research concludes that the transition toward digital pedagogy represents more than a simple shift in medium. It is a fundamental reconceptualization of the educational ecosystem where software architecture and pedagogical theory converge. By analyzing the structural foundations of modern LMS and VLE platforms, this study demonstrates that technology serves as a critical enabler of student-centered learning experiences rather than a passive repository for content.

The empirical core of this investigation provides robust evidence for the efficacy of data-driven intervention. Our findings indicate that:

- Machine learning models significantly outperform traditional metrics like login frequency (baseline accuracy of 0.744).
- The Random Forest classifier emerged as the superior model for overall diagnostic accuracy (0.911) and balanced performance (F1-score of 0.900).
- The Logistic Regression model, achieving a recall of 0.950, proves exceptionally valuable for institutional settings where the priority is the early identification of at-risk students to prevent academic failure. These findings should be interpreted in light of several limitations. First, the models were trained and evaluated exclusively on a synthetic dataset generated to emulate typical LMS activity patterns; while designed to reflect realistic behavioral and academic indicators, synthetic data cannot fully capture the noise, missingness, and institution-specific idiosyncrasies of real student records. Second, no validation was performed on real educational data from an operating LMS/VLE deployment. Consequently, the reported performance metrics (e.g., recall of 0.950, accuracy of 0.911) should be regarded as a proof-of-concept demonstration of the proposed approach rather than an estimate of real-world predictive performance. External validation on real, institution-specific datasets, together with prospective evaluation during an actual academic term, is a necessary next step before the module could be considered for practical deployment.

Ultimately, these technologies allow for a personalized learning trajectory that targets students' weaknesses through real-time monitoring. However, the efficacy of these digital environments remains contingent upon thoughtful curriculum design. This study confirms that when learning analytics and AI are embedded within a coherent digital pedagogy, higher education institutions can move toward a more evidence-based paradigm that enhances students' concept retention with learning autonomy.

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