# **DEVELOPMENT OF AN AI-BASED ADAPTIVE LEARNING MANAGEMENT SYSTEM SUPPORTING STUDENTS' UNIQUE LEARNING STYLES**

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# **Chapter 1**

# **INTRODUCTION**

# **Background of the Study**

To meet the demands of a fast-changing, information-driven society, educational systems must integrate technological tools that support flexible, individualized, and accessible learning (Atmaca-Aksoy, 2024). An LMS platform cultivates an environment for engagement and learner achievement, allowing learners to register for classes, track their grades, and check updates and course announcements. Fundamentally, an LMS behaves as a platform to distribute and oversee educational material (Bradley, 2020). Phan et al. (2022) state that systems like the LMS turn learning into a more active and interactive process, requiring more effort from students and increasing the retention of knowledge and the acquisition of new skills. Technology doesn’t simply provide convenience but a more efficient learning environment; this provides an opportunity for innovations like the integration of artificial intelligence.

Chen et al. (2020) defines artificial intelligence as the culmination of computers, computer-related technologies, machines, and information communication technology innovations and developments to give computers the ability to perform near-human or human-like functions. In line with the use of new technology, artificial intelligence has also been extensively utilized in the education sector. Artificial intelligence has a wide range of applications, including adaptive learning. Daugherty et al. (2022) state that adaptive learning provides students with the means to acquire information according to their individual needs and cognitive differences, thus facilitating the learning process of each individual. Despite its potential, adaptive learning has not been widely implemented in current LMS platforms.

Current learning management systems provide the same services to all users regardless of their needs. Students learn according to their preferred methods and a key move in making education flexible is to evaluate these preferences (Aldahwan & Alsaeed, 2020). Traditional one-size-fits-all educational approaches struggle to cater adequately to this individual variability, leading to suboptimal learning experiences and potentially hindering learners' overall performance (Das et al., 2023). The incorporation of AI into LMS has become a prominent area of research in the field of education, coinciding with the advent of AI. This signifies a considerable advancement towards personalized learning methodologies, which are regarded as the most groundbreaking innovation brought about by AI in the realm of learning. The application of these technologies enables the provision of personalized learning experiences based on comprehensive student data (Kaleci, 2025).

Every learner possesses a unique set of strengths, weaknesses, and interests, which can significantly impact their academic performance and engagement in the learning process. It is of particular importance for example, in Massive Open Online Courses (MOOC), where the same course is followed by thousands of learners, all with different background, knowledge and culture, making it impossible, to provide efficient one-size fits-all learning environments (Paquette et al., 2021).

Educational experts often formulate policies that address a single or relatively small set of problems and then implement them, believing the solution they advocate will be efficient, complete, widely scalable, comprehensive, and easily implemented. Unfortunately, linear approaches are rarely sufficient to address complex issues as they are essentially incapable of generating viable solutions for a broader audience. In contrast, complex systems are characterized by “highly connected networks of semi-independent agents from which system-wide patterns emerge that can learn and adapt over time” (Gunawardena et al., 2023).

The researchers' proposed solution is to develop a learning management system that utilizes artificial intelligence to adapt to learners' specific styles or preferences in studying to give them a more personalized learning experience. In the researchers’ study, the Felder-Silverman Learning Style Model (FSLSM) was applied to categorize students’ learning styles. This model defines each learner based on their distinct preferences across its dimensions. The system will be able to identify these learning styles using machine learning, specifically through the Random Forest algorithm.

# **Objectives of the Study**

**General Objective**

This project aims to develop a learning management system designed to adapt to the students’ specific preferences when it comes to studying.

**Specific Objectives**

This project aims to develop a learning management system that utilizes artificial intelligence to adapt to each learner’s unique study preferences, providing a more personalized learning experience. The goal is to make learning more personalized by allowing students to facilitate their learning using their preferred methods. The system will use the Felder-Silverman Learning Style Model (FSLSM) and apply the Random Forest algorithm to classify students’ learning styles.

1. To design an AI-Assisted learning management system that adapts course materials to students' interests in order to boost performance and engagement
2. To develop a web-based assistive learning platform using the following tools:

* **Next.js:** Next.js enables you to create full-stack web applications by extending the latest React features and integrating powerful Rust-based JavaScript tooling for the fastest builds.
* **MongoDB:** Simplifies data management with its intuitive document model, mapping unique objects to distinct documents.
* **Firebase:** It provides a suite of tools and services to help developers build and run mobile and web applications, offering solutions for authentication, database management, hosting, storage, analytics, and more.
* **Tailwind:** A utility-first CSS framework that allows for rapid UI development by providing pre-designed, customizable classes.
* **Jupyter Notebook:** Provides the necessary visualization for graphics like charts and graphs.
* **Render.com:** A cloud platform for deploying and hosting web applications, static sites, APIs, and databases, offering features like automatic deployments, managed databases, and scalability.
* **Gemini AI:** An artificial intelligence model used for providing intelligent features and personalized feedback within the learning platform.
* **Git:** Used for version control and collaborative development throughout the project lifecycle, ensuring efficient code management and tracking of changes.
* **XGBoost:** The main component that will be used to determine the learning style of each student.

1. To evaluate the functionality of digital learning features through the use of test cases.
2. To evaluate the system by using Functionality, Usability, Reliability, Performance, and Supportability (FURPS).

# **Scope and Limitations of the Study**

**Scope of the System**

1. **Functionalities:** Core LMS functionalities like course management, learning content management, and learning objects.
2. **Monitoring and Management:** The system allows facilitators to oversee and manage a student’s activities.
3. **Performance Feedback:** The system delivers feedback on the student’s performance to support their learning.
4. **Security and Data Privacy:** Implement strict data privacy and security measures to protect the students' information.
5. **Administrative Controls:** Tools for managing users, courses, system settings, and perhaps monitoring overall platform health and usage.
6. **Content Personalization:** The system can take a teacher’s lesson and automatically reformat it so it’s easier for different kinds of learners to understand.
7. **Content Generation:** From the uploaded lesson, the system can automatically create quizzes, practice questions, or activities.
8. **Multimedia Learning Materials:** A single piece of content can be turned into different formats: text, audio narration, visual diagrams, or interactive activities.
9. **Supervised Machine Learning (Classification):** The system applies supervised ML, specifically XGBoost, to classify students’ learning styles based on the Felder-Silverman Learning Style Model (FSLSM). This allows the platform to adapt course materials according to individual preferences.
10. **Rule-Based Algorithm:** To generate initial labels by mapping students’ behaviors, such as time spent on videos, replay counts, or forum participation, into preliminary categories. These labels serve only as a starting point for training the machine learning model, which then learns more accurate patterns from the data.

**Limitations of the System**

1. **Initial Adaptability Limitation:** Newly registered students initially see a default view of lectures because the system has no prior data on their learning style. AI-driven content suggestions are unavailable at this stage, so any personalization must be done manually.
2. **Assistance:** The AI-generated content does not provide direct answers to the students’ assigned activities.
3. **Cookies:** The cookies are inherently unstable as a data source since they can be deleted, blocked, or disabled by users, and they do not persist across devices or browsers. This leads to inconsistencies in engagement data, where some students may appear to have complete interaction histories while others appear fragmented or incomplete.
4. **Learning Model:** The Supervised ML (Random Forest/XGBoost) requires sufficient labeled training data; predictions may be inaccurate if the dataset is small or unbalanced.

# **Chapter 2**

**CONCEPTUAL FRAMEWORK**

# **Review of Related Literature and Studies**

**Technology in Education**

Technology has always had an impact on education. Individualized learning has been the aim of technological innovations since 1966. Computers were introduced in higher education in the seventies with the promise to customize education according to the individual. Computers were a decentralized technology operating at the faculty or university level to enrich classroom learning (Photopoulos et al., 2022). The integration of technology in education brings various benefits that empower both educators and learners in their education, creating a more dynamic, inclusive, and effective learning environment. It provides access and connectivity and overall convenience for the learning process (Kalyani, 2024).

Digital technology devices are prevalent in the culture of today’s students and the general education classroom. With this increased use and availability of technology in the general education classroom, teachers are expected to make learning successful and engaging for all students (Viner et al., 2021). Students use more technological resources, leading them to use the available devices and become more independent learners, deciding on the time, space, direction, and pace of their learning, involving them with greater presence in learning and the acquisition of their own knowledge (Torres-Martín et al., 2022). Engaging with new material becomes less two-dimensional by allowing students to customize their experiences by way of new technology (Burbules et al., 2020).

**Online Learning Environments**

Methods like face-to-face education have been the standard form of education. However, with the advancement of technology, online learning is becoming more popular. Although considered traditional, face-to-face and newer methods of learning like online learning mechanisms are indeed the learning methodologies that we can depend on in the 21st century. Many of our academic institutions rely on the effective way of teaching our learners and how we can develop a transformative learning innovation for their learning pleasures. Teachers must continually develop instructional strategies using innovative technology tools to ensure optimal development of students' critical thinking skills and overall academic performance in both asynchronous and synchronous learning environments. The effectiveness of online learning compared to face-to-face learning is a subject of much debate (Lee, 2024).

There are several key differences between online and traditional education. Firstly, traditional training takes place in a specific place and at a specific time. Students are given a schedule of their weekly lessons and the teacher expects them to attend the lesson at the specified time. This time dependency complicates the traditional approach to education for some students with external commitments such as family or work. In these cases, the online education approach provides much-needed flexibility (Culduz, 2024a).

**E-learning, Online Learning and Distance Learning**

E-learning refers to all educational activities carried out synchronously or asynchronously by individuals or groups working online or offline, through networked or independent computers and other electronic devices. Online education is a form of e-learning defined as learning experiences in synchronous or asynchronous environments using different devices with internet access. to deliver educational programs, courses, and certifications. In these environments, students can be anywhere to learn and interact with instructors and other students. Distance learning, on the other hand, is a form of education whose main elements include the physical separation of teachers and students during teaching and the use of various technologies to facilitate student-teacher and student-student communication. These forms of learning have numerous benefits (Culduz, 2024b).

**Learning Management System**

|  |
| --- |
| ***Figure 1. The Structure of the Learning Management System*** |
| *Source: https://tinyurl.com/3dvbdp26* |

In Figure 1, learning management systems have beneficial effects on academic performance among students and foster a favorable perception of their usage. Features such as accessibility, flexibility, interactivity, and availability of learning materials are what make the learning management system favorable for students (Furqon et al., 2023). Adzharuddin (2013) stated that learning management systems are used worldwide to connect students and teachers outside the traditional classroom setting. It is primarily used to share materials and activities with students and also to initiate discussions. While Zahra et al. (2024) describes a learning management system as online operations to facilitate progressive learning. The system is capable of distributing and tracking learning materials, registering in courses, tracking their grades, and staying updated with their respective courses.

**Artificial Intelligence**

Among these many new technologies is artificial intelligence. AI technologies have been increasingly applied to facilitate education and training in various subjects, including language, STEM, and medicine (Perrotta & Selwyn, 2020). There are many definitions of artificial intelligence. In the Turing test, AI is defined as the ability of machines to communicate with humans (using electronic output devices) without revealing the identity that they are not humans, where the essential judgment criterion is binary. Marvin Minsky, one of the pioneers of AI, defined AI as enabling machines to do things that require human intelligence. The symbolic school believes that AI is the operation of symbols, and the most primitive symbols correspond to the physical entities. Although the descriptions of AI are various, the core of AI is widely believed to be the research theories, methods, technologies, and applications for simulating, extending, and expanding human intelligence. Nowadays, the concept of AI has an increasingly profound impact on human life. Throughout the history of scientific and technological development, the emergence of any scientific and technological revolution is not only reflected in technology, but also changes in human social structure, moral constraints, laws, and education (Y. Jiang et al., 2022).

**Artificial Intelligence in Education**

Artificial intelligence is used in education in many ways. AI is integrated into several technologies, such as chatbots and automated grading systems. Previous research suggests that AI supports collaboration, personalization of learning experiences, adaptive feedback, profiling students' backgrounds, and monitoring their progress (Celik et al., 2022).

Wang et al. (2024) identified different categories of AIED (Artificial Intelligence in Education) applications. One of these categories is adaptive learning and personalized tutoring, the most studied among all applications. This category of AIED applications aims to customize the learning process and create an adaptive learning environment for learners based on their knowledge level, learning style, emotional state, and interest preferences. These applications have evolved significantly in recent years, transitioning from rule-based expert systems to more complex AI techniques and algorithms like neural networks and decision trees. The design of these applications has become increasingly interactive and learner-centered.

**Machine Learning**

There are many examples of artificial intelligence and its many applications; machine learning is one of the most well-known uses of artificial intelligence. The core of machine learning is knowledge discovery, the process of parsing based on a sampling data set known as ‘‘training data’’ and generating meaningful patterns and structured knowledge. For instance, machine learning can help create recommendations for students as they select classes and even choose universities. It leverages achievements, data, aspirations, and preferences of students to ‘‘match-make’’ institutions where they can be best developed (Chen et al., 2020).

**Decision Tree**

A decision tree represents a procedure for computing the outcome of a function f (x). The procedure consists of repeatedly performing tests on the input x, where the outcome of each test determines the next test, until f (x) is known with certainty or a way to predict an outcome by asking a series of questions about the input. Each answer leads to the next question, until the final result is reached. If the possible inputs (x) are limited, we could list every input–output pair. But usually, the inputs come from a very large or even endless set. In that case, instead of making a tree that only works on the sample data, we try to build one that works well for the entire range of possible inputs (Blockeel et al., 2023).

**Random Forest (Random Decision Tree)**

Another algorithm commonly used in machine learning is referred to as a random forest or a random decision tree, derived from another algorithm called a decision tree Yuan et al. (2024a) state that the Random Forest method constructs numerous decision trees during training, where each tree is constructed based on a randomly sampled subset of training data, and the final prediction is made by aggregating the predictions of all the trees. This ensemble approach enhances robustness and generalization performance, reducing the risk of overfitting by using a single decision tree. The Random Forest method is deemed a popular ML method for its effectiveness in handling complex datasets and high-dimensional feature spaces.

**XGBoosting (eXtreme Gradient Boosting)**

XGBoost, or Extreme Gradient Boosting, is a highly efficient implementation of gradient boosting, which iteratively improves predictions by fitting additional trees to the residual errors of the previous trees. XGBoost has a built-in mechanism to handle missing values by learning optimal split directions for missing data during tree construction. Thus, the model may perform well even without imputation. However, imputing missing values could still enhance predictive power by reducing potential noise introduced by the missingness itself.

**Learning Style**

Mestre (2012) describes learning styles as the various ways in which individuals prefer to receive and process information, influencing the instructional methods that teachers may employ. It encompasses the notion that recognizing and adapting to different learning styles can promote self-awareness, metacognition, and improved educational outcomes. While Kaur et al. (2023) state that learning styles refer to a set of personal traits that determine the effectiveness of teaching and learning methods for different individuals. It is an important factor in educational achievement and has been found to be positively correlated with academic performance in students.

**Various Learning Style Models**

Kolb’s learning cycle has four stages: concrete experience (CE), reflective observation (RO), abstract conceptualization (AC), and active experimentation (AE). Learners ideally move through each stage—starting with direct involvement in an experience (CE), reflecting on it from different perspectives (RO), forming ideas and theories (AC), and then testing those ideas through problem solving or decision-making (AE). Kolb’s experiential learning cycle is often applied only to short-term learning events, without considering its role in long-term learning that connects past and future experiences (Egan et al., 2023).

Honey and Mumford identified four learning styles: activist, reflector, theorist, and pragmatist. Activists learn best through trial and error, hands-on activities, and brainstorming. Theorists prefer to use logical frameworks and models to analyze and organize information. Pragmatists are eager to apply theories and techniques in real situations through systematic practice. Reflectors learn by carefully observing, reflecting on experiences, and considering how they contribute to outcomes. However, even though Honey & Mumford learning styles focused on learning from experience, it did not guarantee whether the experience was effective learning and that the meaning of learning from experience by Honey & Mumford's learning styles was ambiguous (Ferdiani et al., 2021).

The VARK model is an educational framework for classifying learning preferences. Developed in 1987 by Fleming, it helps customize content to meet individual needs. It consists of four preferences: Visual (graphs, diagrams), Auditory (podcasts, conversations), Reading/Writing (reading, writing), and kinesthetic (hands-on activities). The VARK model is criticized for lacking strong validation of its four learning categories and for showing little evidence that matching teaching to student preferences improves learning outcomes (Melhem & Al-Zoubi, 2025).

**Felder & Silverman Learning Style Model**

The Felder–Silverman learning styles model (FSLSM) was developed by Richard M. Felder and Linda K. Silverman in 1988 and is commonly referred to as the Felder–Silverman model or simply the Felder–Silverman learning styles. This model suggests that individuals have different patterns of preferences and tendencies in the way they learn and process information. The FSLSM proposes four factors or dimensions, with each dimension being an opposing pair of categories that represent an individual’s preferred approach to learning. A person’s inclination toward one category over another can vary in intensity, ranging from strong to moderate to mild. The FSLSM has garnered significant support for its comprehensive approach to understanding and enhancing educational experiences. Numerous researchers contend that learning styles play a crucial role in the educational process, underscoring the potential of the FSLSM to enhance instructional design and learner engagement by acknowledging and addressing diverse learning styles (Masegosa et al., 2024).

Carver et al. (1999) state that the Felder & Silverman Learning Style Model is the most appropriate for hypermedia courseware like the learning management system. Graf et al. (2007) state that this model is used very often in research related to learning styles in advanced learning technologies and in technology-enhanced learning that is designed for traditional learning.

**The Four Dimensions of Felder & Silverman Learning Style Model**

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| --- |
| ***Figure 2. Felder–Silverman Learning Style Dimensions.*** |
| *Source: https://tinyurl.com/3snp8t9n* |

Masegosa et al. (2024) expanded on the Felder–Silverman Learning Styles Model (FSLSM) by emphasizing its four key dimensions (Figure 2):

Information processing: active or reflective learners. This dimension refers to how learners engage with new information. Active learners prefer to engage with the learning material through physical or interactive means. They learn best by doing, discussing, and actively participating in hands-on activities. They enjoy group work, experiments, and practical applications of knowledge. Active learners often thrive in collaborative environments where they can interact with their peers and instructors. Reflective learners, in contrast to active learners, prefer to process information internally. They are introspective and thoughtful, often taking their time to think through concepts before formulating their own understanding. Reflective learners benefit from quiet environments that allow for contemplation and introspection. They prefer individual study, writing, and self-reflection to solidify their understanding of new information, being fond of lectures and seminars.

Information perception: sensing or intuitive learners. This dimension relates to how learners perceive and process information. Sensing learners rely on their senses and prefer concrete, factual information. They appreciate practical examples, real-world applications, and hands-on experiences that allow them to engage with the subject matter in a tangible way. Sensing learners pay close attention to details, prefer step-by-step instructions, and may find memorization and repetition helpful in their learning process. Sensing learners tend to become distressed when faced with challenging tasks. They typically harbor concerns regarding the efficacy of academic practices and programs. Additionally, they dislike being assessed based on vague or embedded concepts and ideas. Intuitive learners are more interested in abstract and theoretical concepts. They enjoy exploring ideas, making connections between different concepts, and identifying underlying patterns and principles. Intuitive learners thrive in environments that encourage creativity, critical thinking, and conceptual understanding. They often seek out the bigger picture and are comfortable with ambiguity and uncertainty. Activities involving computation, rote learning, and conventional practices are unattractive to them.

Information input: visual or verbal learners. This dimension describes the preferred mode of input for learners. Visual learners learn best through visual aids and representations. They prefer information presented in the form of diagrams, charts, graphs, and visual illustrations. Visual learners exhibit a higher capacity for observation, so they benefit from seeing relationships, spatial arrangements, and visual patterns. They may use color coding, mind maps, or visual organizers to enhance their understanding and retention of information. Verbal learners prefer to learn through written and spoken words. They excel in activities such as reading, writing, listening to lectures, and engaging in discussions. Verbal learners are skilled at understanding and remembering information when it is presented through words, explanations, and verbal instructions. They may benefit from reading textbooks, taking notes, and discussing concepts with others.

Information understanding: sequential or global learners. This dimension reflects the learners’ approach to organizing and processing information. Sequential learners prefer learning in a linear and step-by-step manner. They thrive when presented with a logical progression of information and appreciate clear and structured instructions. Sequential learners prefer to understand each concept thoroughly before moving on tothe next. They often excel in subjects that involve logical reasoning, problem-solving, and following well-defined processes. Global learners have a holistic approach to learning and prefer to see the big picture. They can quickly grasp overarching concepts and connections without necessarily needing detailed step-by-step instructions. Global learners enjoy synthesizing information, making associations, and understanding the broader context. They may struggle with tasks that require a linear approach or intricate, sequential details.

**Machine Learning Algorithm Performance**

Accuracy represents the proportion of correctly classified instances within the dataset and is particularly suitable for balanced data. Precision, in contrast, evaluates the proportion of predicted positive instances that are truly positive, reflecting the reliability of positive classifications, while recall measures the proportion of actual positive instances correctly identified by the model, emphasizing its capacity to capture all relevant cases. The F1 Score, defined as the harmonic mean of precision and recall, provides a balanced assessment in situations where trade-offs exist between these two measures. Model performance can also be examined through the Receiver Operating Characteristic (ROC) curve, which plots the true positive rate against the false positive rate across varying thresholds, offering a comprehensive view of classification behavior. The Area Under the Curve (AUC) further condenses this information into a single scalar value that quantifies the overall discriminative ability of the model, with higher values indicating superior performance; an AUC of 1.0 denotes perfect discrimination, whereas a value of 0.5 indicates no discriminative power, equivalent to random guessing (Schlosser et al., 2024).

Yuan et al. (2024) divided students into two clusters according to their learning behavior. Cluster 1 (91,811 students; >99% of total) showed minimal engagement, with fewer than 50% accessing courseware and only 1.68% earning a certificate. In contrast, Cluster 2 (911 students) exhibited high engagement—over 90% accessed at least half the chapters—and 53.24% achieved certification. Compared to Cluster 1, Cluster 2 students averaged substantially more active days, interactions, videos watched, chapters studied, and forum posts. For clarity, these groups are referred to as “low autonomy” and “motivated,” respectively. They also delved deeper to identify the learning pattern for which the integration framework exhibits greater improvement.

The integration framework proposed by Yuan et al. (2024) comprises two main stages: the first stage utilizes clustering analysis for online learning behaviors to explore learning categories or patterns, while the second stage employs various ML algorithms to predict students’ performance within each identified category.

|  |
| --- |
| ***Figure 3. Important Features For Students*** |
| *Source: https://tinyurl.com/ywvxhcp7* |

In Figure 3, The results suggest that interaction frequency, video consumption, and chapter completion may significantly influence the learning success for either group of students, while engagement in forum discussions, exploration of the chapters, and courseware may not. For low autonomy students, nchapters, nevents, and ndays\_act have much higher importance scores than nplay\_video, while for motivated students, nevents, nplay\_video, and ndays\_act have much higher importance scores than nchapters. Therefore, chapter completion seems to be a more important feature for successful online learning for low-autonomy students, while video consumption appears to be more important for motivated students.

Table 2:

*Separated performance for different learning patterns for machine learning algorithms based on the results of the direct approach without behavior analysis*

| Pattern | Method | Accuracy (%) | Precision (%) | Recall (%) | F1 Score (%) | AUC |
| --- | --- | --- | --- | --- | --- | --- |
| Low Autonomy | logistic regression | 96.13 | 98.67 | 96.13 | 97.09 | 0.9866 |
| decision tree | 95.38 | 98.57 | 95.38 | 96.62 | 0.9264 |
| random forest | 93.30 | 98.44 | 93.30 | 95.38 | 0.9140 |
| K-nearest neighbor | 97.67 | 98.95 | 97.67 | 98.91 | 0.9844 |
| Multilayer perceptron | 96.62 | 98.78 | 96.62 | 97.42 | 0.9903 |
| support vector classifier | 96.35 | 98.80 | 96.35 | 97.25 | 0.9869 |
| Extreme gradient boosting | 98.30 | 98.97 | 98.30 | 98.54 | 0.9936 |
| Motivated | logistic regression | 55.76 | 72.39 | 55.76 | 42.73 | 0.7600 |
| decision tree | 60.48 | 77.32 | 60.48 | 51.37 | 0.5775 |
| random forest | 53.46 | 75.17 | 53.46 | 37.48 | 0.5023 |
| K-nearest neighbor | 69.59 | 77.85 | 69.59 | 66.26 | 0.9014 |
| Multilayer perceptron | 59.93 | 75.07 | 59.93 | 50.76 | 0.7105 |
| support vector classifier | 62.79 | 76.63 | 62.79 | 55.61 | 0.7361 |
| Extreme gradient boosting | 71.90 | 76.11 | 71.90 | 70.10 | 0.7869 |
| *Source: Yuan et al., (2024)* | | | | | | |

In Table 2, the predictions for the low autonomy students by the ML methods are nearly perfect, and those for the motivated students are satisfactory. A closer inspection of the table indicates that the XGBoost method outperforms the other six ML algorithms. Specifically, for low autonomy students, the XGBoost method yields accuracy, recall, F1 score, and AUC score as high as 98.68%, 99.10%, 99.33%, and 0.9929, respectively. For motivated students, XGBoost still maintains a higher level of performance than other methods, ranking the highest for accuracy (73.72%) and AUC score (0.7960), while being the second highest for precision (73.33%) and F1 score (70.97%).

Table 4:

*Machine learning performances for learning patterns under the integration framework*

| Pattern | Method | Accuracy (%) | Precision (%) | Recall (%) | F1 Score (%) | AUC |
| --- | --- | --- | --- | --- | --- | --- |
| Low Autonomy | logistic regression | 95.53 | 99.76 | 95.66 | 97.67 | 0.9816 |
| decision tree | 93.32 | 99.90 | 93.25 | 96.47 | 0.9633 |
| random forest | 90.20 | 99.75 | 90.21 | 94.74 | 0.9651 |
| K-nearest neighbor | 97.89 | 99.90 | 97.94 | 98.91 | 0.9865 |
| Multilayer perceptron | 95.94 | 99.81 | 96.04 | 97.88 | 0.9853 |
| support vector classifier | 96.53 | 99.85 | 96.59 | 98.19 | 0.9842 |
| Extreme gradient boosting | 99.18 | 99.77 | 96.59 | 99.58 | 0.9971 |
| Motivated | logistic regression | 95.53 | 99.76 | 95.66 | 97.67 | 0.9816 |
| decision tree | 93.32 | 99.90 | 93.25 | 96.47 | 0.9633 |
| random forest | 90.20 | 99.75 | 90.21 | 94.74 | 0.9651 |
| K-nearest neighbor | 97.89 | 99.90 | 97.94 | 98.91 | 0.9865 |
| Multilayer perceptron | 95.94 | 99.81 | 96.04 | 97.88 | 0.9853 |
| support vector classifier | 96.53 | 99.85 | 96.59 | 98.19 | 0.9842 |
| Extreme gradient boosting | 99.18 | 99.77 | 96.59 | 99.58 | 0.9971 |
| *Source: Yuan et al., (2024)* | | | | | | |

As illustrated in Table 6, the accuracy rates range from 92.78% to 97.58%, precision rates from 98.11% to 98.62%, recall rates from 92.78% to 97.58%, F1 scores from 94.85% to 97.94%, and AUC scores from 0.9246 to 0.9908. The ROC curves for the seven ML methods under this approach are provided in Figure 8, and the FPR and TPR distributions are shown in Figure 9. Again, XGBoost performs the best, while RF performs the worst among the ML methods.

Table 3.

Mapping activity types to learning style features based on FSLSM

| **Dimensions** | **FSLSM Classification** | **VLE Activity Type** |
| --- | --- | --- |
| Processing | Active/Reflective | Forumng, oucollaborate, ouwiki, glossary, htmlactivity |
| Perception | Sensitive/Intuitive | oucontent, questionnaire, quiz, externalquez |
| Input | Visual/Verbal | dataPlus, dualPane, folder, page, homepage, resource, url, ouelluminate,subpage |
| Understanding | Sequential/Global | Repeatactivity, sharedsubpage |
| *Source: Baihaqi (2024)* | | |

Similarly, in a study done by Baihaqi (2024), involves creating a comprehensive dataset of student interactions with learning modules. As shown in Table 3, this mapping aligns various activity types with specific learningstyle features based on the FSLSM framework, facilitating a deeper understanding of how different activities correspond to individual learning preferences. Finally, label encoding transforms categorical data into numerical format for machine learning algorithms, enabling analysis of learning patterns and the development of personalized learning recommendations.

Table 1.

*Algorithm Performance Without Tuning*

| **Algorithm** | **Precision** | **Recall** | **F1-Score** | **Accuracy** |
| --- | --- | --- | --- | --- |
| Logistic Regression | 94% | 79% | 85% | 79% |
| KNN | 69% | 74% | 71% | 74% |
| Random Forest | 99% | 99% | 99% | 99% |
| SVM | 94% | 97% | 96% | 91% |
| ANN | 94% | 94% | 94% | 99% |
| *Source: Baihaqi (2024)* | | | | |

As illustrated in table 3, Experiments were conducted using 80% of the data for each identifiedstudent training dataset, with the remaining 20% reserved for testing. The results of the algorithm performance when training with 80% of the data and testing with 20% without any tuning demonstrate the effectiveness of each classification method in predicting students' preferred learning methods

Table 2.

*Algorithm Performance With Tuning*

| **Algorithm** | **Precision** | **Recall** | **F1-Score** | **Accuracy** |
| --- | --- | --- | --- | --- |
| Logistic Regression | 98% | 95% | 97% | 92% |
| KNN | 92% | 91% | 92% | 91% |
| Random Forest | 95% | 91% | 92% | 97% |
| SVM | 95% | 94% | 94% | 97% |
| ANN | 95% | 97% | 98% | 95% |
| *Source: Baihaqi (2024)* | | | | |

To enhance the performance of the Logistic Regression model, we implemented data normalization and hyperparametertuning via GridSearch. This process yielded optimal hyperparameter combinations, resulting in significantimprovements in model performance: Precision increased to 98%, Recall to 97%, F1-Score to 97%, and Accuracy to 92%.

Table 3.

*Comparison Of Various Classifiers*

| **Dataset** | **Dimension** | **SVM** | **RF** | **NB** |
| --- | --- | --- | --- | --- |
| **Computer**  **skills for**  **humanities**  **(CSFH)** | **Input** | 0.84 | 0.87 | 0.82 |
| **Perception** | 0.91 | 0.89 | 0.57 |
| **Processing** | 0.95 | 0.99 | 0.93 |
| **Understanding** | 0.70 | 0.70 | 0.71 |
|  | **Median** | 0.88 | 0.88 | 0.76 |
| *Source: Ayyoub and Al-Kadi (2024)* | | | | |

An experiment was conducted by Ayyoub and Al-Kadi (2024) on two datasets involving educational data mining and semi-supervised machine learning: Computer Skills for Humanities Students and Computer Skills for Medical Students. Using the Felder-Silverman Learning Style Model (FSLSM), the researchers classified students’ learning preferences across four dimensions by applying a semi-supervised approach with both labeled and unlabeled data. They also experimented with other types of well-known classifiers and presented the results to justify the choice of the SVM classifier for data labeling, which is in Table 2.

Table 4.

*Results Of Labeling Computer Skills For Humanities*

| **Input Dimension** | |
| --- | --- |
| **Evaluation Metrics** | **Value** |
| Correctly Classified Instances (%) | 83.61% |
| Incorrectly Classified Instances (%) | 16.39% |
| Specificity | 0.8 |
| Precision | 0.84 |
| Recall | 0.84 |
| AUC - ROC | 0.69 |
| **Perception Dimension** | |
| **Evaluation Metrics** | **Value** |
| Correctly Classified Instances (%) | 88.76% |
| Incorrectly Classified Instances (%) | 11.24% |
| Specificity | 0.91 |
| Precision | 0.91 |
| Recall | 0.89 |
| AUC - ROC | 0.71 |
| **Processing Dimension** | |
| **Evaluation Metrics** | **Value** |
| Correctly Classified Instances (%) | 94.79% |
| Incorrectly Classified Instances (%) | 5.2% |
| Specificity | 0.99 |
| Precision | 0.95 |
| Recall | 0.95 |
| AUC - ROC | 0.74 |
| **Understanding Dimension** | |
| **Evaluation Metrics** | **Value** |
| Correctly Classified Instances (%) | 70.73% |
| Incorrectly Classified Instances (%) | 29.27% |
| Specificity | 0.75 |
| Precision | 0.71 |
| Recall | 0.71 |
| AUC - ROC | 0.59 |

*Source: Ayyoub and Al-Kadi (2024)*

In Table 4, in the Humanities dataset, the processing dimension achieved the highest accuracy at 94.79%, while the understanding dimension had the lowest at 70.73%.

Table 5.

*Results Of Labeling Computer Skills For Medical Students*

| **Input Dimension** | |
| --- | --- |
| **Evaluation Metrics** | **Value** |
| Correctly Classified Instances (%) | 84.41% |
| Incorrectly Classified Instances (%) | 15.59% |
| Specificity | 0.93 |
| Precision | 0.85 |
| Recall | 0.83 |
| AUC - ROC | 0.69 |
| **Perception Dimension** | |
| **Evaluation Metrics** | **Value** |
| Correctly Classified Instances (%) | 52.36% |
| Incorrectly Classified Instances (%) | 47.64% |
| Specificity | 0.52 |
| Precision | 0.52 |
| Recall | 0.52 |
| AUC - ROC | 0.51 |
| **Processing Dimension** | |
| **Evaluation Metrics** | **Value** |
| Correctly Classified Instances (%) | 48.94% |
| Incorrectly Classified Instances (%) | 51.06% |
| Specificity | 0.50 |
| Precision | 0.48 |
| Recall | 0.49 |
| AUC - ROC | 0.49 |
| **Understanding Dimension** | |
| **Evaluation Metrics** | **Value** |
| Correctly Classified Instances (%) | 47.98% |
| Incorrectly Classified Instances (%) | 52.02% |
| Specificity | 0.48 |
| Precision | 0.48 |
| Recall | 0.48 |
| AUC - ROC | 0.49 |

*Source: Ayyoub and Al-Kadi (2024)*

In contrast, in Table 5, for the medical dataset, the input dimension obtained the highest accuracy at 84.41%, and the understanding dimension again showed the weakest performance at 47.98%. These results highlight that the outcomes differ not only between the two datasets but also within the same dataset across different dimensions, suggesting that the SVM classifier’s effectiveness in labeling data varies depending on both the dataset characteristics and the type of learning style dimension being analyzed.

Wanniarachchi & Premadasa (2024) conducted a study to identify learning styles in an online learning environment that is based on the Felder-Silverman Learning Style Model (FSLSM). They used a Moodle plugin to track the time spent and access frequency on course activities. There were 150 students per module. Among all the machine learning algorithms applied, the decision tree achieved the highest performance. The decision tree model demonstrated consistency between 85% and 95% in identifying students’ learning styles, providing valuable insights for improving course design. The Decision Tree classifier achieved accuracies of 93.5% for Input, 86% for Perception, 89.5% for Processing, and 94% for Understanding dimensions.

Nazempour and Darabi (2023) conducted a study on methods that can find a student’s learning styles in an online learning environment and these learning styles can be utilized to enhance their pass rate each quarter. They found that throughout each quarter, boosting methods performed well in each quarter.

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| ***Figure 5. Average of calculated learning style features in Q2, Q3, and Q4.*** |
| *Source: https://tinyurl.com/3xpup35h* |

Figure 5 depicts the average of all calculated learning style features, including visual/verbal, active/reflective, sensitive/intuitive, and sequential/global, using the proposed modeling approach in Q2, Q3, and Q4. The bar charts represent that in Q2, the processing (active/reflective) learning style feature has the highest average percentage compared with other LSs (42%); however, in Q3 and Q4, the perception (sensitive/intuitive) learning style feature has the most significant values in terms of average percentage (48% and 70%). Moreover, from Q2 to Q4, the average percentage of visual/verbal, active/reflective, and sequential/global learning style features decreased. At the same time, it increased in terms of sensitive/intuitive learning style features. The (sensitive/intuitive) learning style feature has the most significant values in terms of average percentage (48% and 70%). Moreover, from Q2 to Q4, the average percentage of visual/verbal, active/reflective, and sequential/global learning style features decreased. At the same time, it increased in terms of sensitive/intuitive learning.

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| ***Figure 6. Comparing actual and calculated learning style features in Q2, Q3, and Q4*** |
| *Source: https://tinyurl.com/3xpup35h* |

In Figure 6, it compares the average percentage of actual and calculated learning style features using the proposed approach in Q2, Q3, and Q4. On average, the calculated visual/verbal learning style feature has always been less than the actual one. On the other hand, the calculated active/reflective leaning style feature is greater than or equal to the actual one in all three mentioned quarters. Moreover, the students did not interact with sequential/global learning resources in all quarter.

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| ***Figure 7. Comparing the percentage of S/NS transitions using personalized and the average of calculated LSs in Q2, Q3, and Q4.*** |
| *Source: https://tinyurl.com/3xpup35h* |

In Figure 7, NS-S indicates that the student received a “Not Satisfactory” grade in the assessment using the actual learning style features but would receive a “Satisfactory” grade if the calculated learning style features were used. Moreover, S-NS implies that if the calculated learning style features were used, the student would receive a “Not Satisfactory” grade rather than a “Satisfactory” grade in the assessment. Furthermore, S-S and NS-NS indicate that the student’s assessment grade class would not change.

**VS Code (Visual Studio Code)**

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| ***Figure 8. VS Code*** |
| Source: https://tinyurl.com/5yppm4c8 |

Visual Studio Code is a lightweight, powerful source code editor for Windows, macOS, and Linux. It supports JavaScript, TypeScript, and Node.js and has a rich ecosystem of extensions for other languages like C++, C#, Java, Python, PHP, and Go, and runtimes like .NET and Unity. Visual Studio Code allows you to extend your capability through extensions. Visual Studio Code extensions can add more features (Nandwana, n.d.).

**HTML (Hyper Text Markup Language)**

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| ***Figure 10. HTML*** |
| Source: https://tinyurl.com/59er2t2f |

HTML5 provides detailed processing models to promote consistent and interoperable implementations. It enhances and streamlines existing markup for documents while also introducing new markup and APIs to support sophisticated web applications. These same capabilities make HTML5 a strong option for cross-platform mobile apps, as it includes features tailored for use on low-power devices (HTML5 Differences From HTML4, n.d.).

**CSS (Cascading Style Sheets)**

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| ***Figure 11. CSS*** |
| Source: https://tinyurl.com/386xsvya |

Cascading Style Sheets (CSS) is a versatile language used to control the visual presentation of web pages. It enables developers to apply text styling, such as modifying the color, size, and formatting of headings and hyperlinks, as well as to design complex layouts including grid-based structures and multi-column arrangements. CSS also supports the creation of dynamic visual effects, such as animations, which enhance user engagement and interactivity. The language is organized into modules, each of which encompasses a related set of functionalities. For example, the Backgrounds and Borders module defines properties and features specific to those design elements. In addition, module reference pages often provide links to official specifications, which formally establish the standards and technical details governing CSS technologies (What Is CSS? - Learn Web Development | MDN, n.d.).

**JS (JavaScript)**

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| ***Figure 12. JS*** |
| Source: https://tinyurl.com/386xsvya |

JavaScript is a widely used programming language that enables the creation of interactive and dynamic web pages. It is employed in a variety of contexts, ranging from refreshing social media feeds to rendering animations and interactive maps, thereby enhancing the overall user experience. As a client-side scripting language, JavaScript is considered one of the core technologies of the World Wide Web, alongside HTML and CSS. Initially developed as a browser-based technology, it was designed to make web applications more responsive by allowing browsers to react to user interactions and modify the structure or presentation of webpage content in real time (What Is JavaScript? - JavaScript (JS) Explained - AWS, n.d.).

**Next.js**

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| ***Figure 13. Next.js*** |
| Source: https://tinyurl.com/22y2jn4d |

Next.js is a React framework for building full-stack web applications. You use React Components to build user interfaces and Next.js for additional features and optimizations. It also automatically configures lower-level tools like bundlers and compilers. You can instead focus on building your product and shipping quickly. Whether you're an individual developer or part of a larger team, Next.js can help you build interactive, dynamic, and fast React applications (Vercel, n.d.).

This framework has the ability to perform several data fetching mechanisms depending on application needs. Some of the data-fetching mechanisms in the Next.js framework are explained by Lazuardy & Anggraini (2022) as follows:

Client-Side Rendering (CSR) in React uses the useEffect hook to fetch data from the client. This means the page is rendered first, and then data is requested from the API after rendering. As a result, data fetching happens each time the client requests the page.

Server-Side Rendering (SSR) in Next.js uses a special function called getServerSideProps to fetch data from the server. This function runs only on the server and never in the browser. Unlike CSR, SSR data fetching works only at the page level and cannot be used inside other files or components.

Static Site Generation (SSG) in Next.js uses the getStaticProps function to fetch data from the server. This function runs only on the server, never in the browser. Like SSR, SSG data fetching works only at the page level and not inside other files or components.

With SSG, getStaticProps runs once at build time, meaning the page is generated ahead of time. This approach works best for content that doesn’t change often, making it highly performant and SEO-friendly, since the page is pre-rendered and served quickly.

Incremental Static Regeneration (ISR) in Next.js extends Static Site Generation (SSG) by adding a revalidate property inside getStaticProps. This allows static pages to be automatically updated at specific intervals without rebuilding the entire application.

Unlike regular SSG, which only fetches data once at build time, ISR can regenerate pages in the background when a request comes in after the revalidation period. This gives developers the benefits of static pages (speed and SEO) while still keeping data up to date.

**MongoDB**

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| ***Figure 14. MongoDB*** |
| Source: https://tinyurl.com/mv5hs8fw |

The NoSQL database MongoDB stands among the most popular solutions because it delivers excellent scalability, flexible features, flexible schema management, and fast response times. MongoDB implements a document-oriented methodology that enables developers to store data using BSON format, which resembles JSON but extends its capabilities through extra features. Through its schema-free data architecture, MongoDB delivers rapid development possibilities, making it the top selection for diverse systems that must adapt quickly, like real-time analytics projects, content systems, and IoT initiatives. MongoDB takes an eventual consistency model, wherein even the partition tolerance is preferred over the consistency (Dhanagari, 2024).

**Firebase**

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| ***Figure 15. Firebase*** |
| Source: https://tinyurl.com/mv5hs8fw |

Firebase is a Google-backed application development software that allows developers to develop iOS, Android, and web apps. Firebase provides tools for tracking analytics, reporting and fixing app crashes, and creating marketing and product experiments.

The Firebase Solutions framework provides a modular set of tools for addressing common challenges in mobile and web application development. It is structured around five domains: backend construction, web application hosting, feature testing and rollout, application monitoring, and user engagement with monetization. Core services such as Cloud Firestore, Realtime Database, Authentication, and Cloud Storage support scalable serverless backends, while Hosting and global CDNs enable secure and efficient web delivery. Tools like Test Lab, Crashlytics, and Remote Config facilitate iterative testing, staged deployment, and performance monitoring. Additionally, Google Analytics and AdMob enable data-driven personalization and monetization without requiring new releases. Overall, Firebase promotes a flexible, data-informed, and adaptive development ecosystem, aligning infrastructure with evolving user needs (Solutions for App Development Challenges | Firebase, n.d.).

**Tailwind**

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| ***Figure 16. Tailwind*** |
| Source: https://tinyurl.com/38znr4ru |

Tailwind CSS works by scanning all of your HTML files, JavaScript components, and any other templates for class names, generating the corresponding styles, and then writing them to a static CSS file (Installing With Vite - Installation, n.d.).

Tailwind is a set of low-level, reusable utility classes that can be used like building blocks to create virtually any design we can imagine. This utility-first framework covers the most important CSS properties, but it can be easily extended in a variety of ways. It can be used either for rapid prototyping or for creating full-blown designs. utility class is mostly a single CSS property or behavior that we can use freely in a predictable way. This gives us the freedom to combine, mix and match different settings depending on our requirements. We have greater control over each element’s appearance. We can change and fine-tune an element’s appearance much more effortlessly with utility classes (Gerchev, 2022).

**Jupyter Notebook**

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| ***Figure 17. Jupyter Notebook*** |
| Source: https://tinyurl.com/jd3tvktd |

JupyterLab is the latest web-based interactive development environment for notebooks, code, and data. Its flexible interface allows users to configure and arrange workflows in data science, scientific computing, computational journalism, and machine learning. A modular design invites extensions to expand and enrich functionality. A notebook is a shareable document that combines computer code, plain language descriptions, data, rich visualizations like 3D models, charts, graphs, and figures, and interactive controls. A notebook, along with an editor (like JupyterLab), provides a fast interactive environment for prototyping and explaining code, exploring and visualizing data, and sharing ideas with others. (Project Jupyter, n.d.).

**Render**

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| ***Figure 18. Render*** |
| Source: https://tinyurl.com/rumry2n8 |

Render streamlines application deployment by connecting directly to Git branches and automatically building and releasing code on each push. It supports web applications in a variety of languages and frameworks, such as Node.js with Express, Python with Django, and FastAPI. The platform manages infrastructure needs—including servers, networking, storage, security, and runtime upkeep—so developers can focus on building. It also provides easy scaling options and supports stateful apps through persistent disks and fully managed databases.

**Gemini AI**

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| ***Figure 19. Gemini AI*** |
| Source: https://tinyurl.com/mtdycaau |

Gemini is a multimodal large language model (LLM) developed by Google, capable of processing text, images, audio, and more. Gemini evolved into a versatile tool supporting diverse tasks such as writing, coding, brainstorming, and learning. It continues to expand in functionality, fostering productivity, creativity, and knowledge exploration (About Gemini, n.d.).

This versatility allows Gemini to generate more complete answers that fit the context, making it helpful for various tasks and applications. Moreover, Gemini is a potential source of educational technology advancement and practical applications beyond its theoretical framework (Imran & Almusharraf, 2024).

**Git**

| Git |
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| ***Figure 20. Gemini AI*** |
| Source: https://tinyurl.com/mtdycaau |

Git offers a range of advantages that make it a dominant version control system in modern software development. Its branching and merging capabilities enable developers to create, merge, and delete independent lines of development quickly and efficiently, thereby supporting flexible workflows. The system is also small and fast, with most operations performed locally, providing a significant speed advantage over centralized alternatives. As a distributed tool, Git gives each contributor a complete repository copy, ensuring both resilience and the ability to work offline. Furthermore, it guarantees data integrity by checksumming all content through SHA-1 hashes, making unauthorized changes easily detectable. The inclusion of a staging area allows developers to review and refine changes before committing, thereby enhancing control and precision in code management. Finally, Git is free and open source, ensuring accessibility without financial or licensing barriers, which further contributes to its widespread adoption in both academic and professional contexts (*Git*, n.d.).

# **Conceptual Model of the Study**

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| ***Figure 20. IPO Diagram*** |

# **Operational Definition of Terms**

* **Active learners:** Prefer to engage with material through physical or interactive means.
* **AI (Artificial Intelligence):** The ability of machines to do things that require human intelligence. The document also mentions other definitions, such as the ability of machines to communicate with humans without revealing their identity.
* **AIED (Artificial Intelligence in Education):** The application of AI technologies to facilitate education and training.
* **Asynchronous learning environments:** Environments where learning does not happen at the same time for all participants.
* **CMS (Course Management System):** A system that specializes in managing and creating learning content.
* **CSS (Cascading Style Sheets):** A language used to control the visual presentation of web pages.
* **Decision Tree:** A procedure for computing an outcome by repeatedly performing tests on an input.
* **Distance learning:** A form of education where teachers and students are physically separated, and various technologies are used to facilitate communication.
* **E-learning:** Refers to all educational activities carried out synchronously or asynchronously, through networked or independent computers and other electronic devices.
* **eXtreme Gradient Boosting (XGBoost):** An efficient implementation of gradient boosting that improves predictions by fitting additional trees to the residual errors of previous trees.
* **FSLSM (Felder-Silverman Learning Style Model):** A model that suggests individuals have different patterns and tendencies in how they learn and process information, with four dimensions.
* **Firebase:** A Google-backed software that allows developers to create iOS, Android, and web apps.
* **Global learners:** Have a holistic approach and prefer to see the big picture.
* **Honey and Mumford learning styles:** A model with four styles: activist, reflector, theorist, and pragmatist.
* **HTML (HyperText Markup Language):** Provides detailed processing models to create web applications and enhances existing markup.
* **JS (JavaScript):** A programming language that enables the creation of interactive and dynamic web pages.
* **Jupyter Notebook:** A shareable document that combines code, plain language, data, and visualizations.
* **Kolb's learning cycle:** A model with four stages: concrete experience (CE), reflective observation (RO), abstract conceptualization (AC), and active experimentation (AE).
* **LCMS (Learning Content Management System):** A collaborative platform used to create, manage, and deliver learning content.
* **LDS (Learning Design System):** A system that allows content producers to quickly analyze and design "instructionally sound learning programs".
* **Learning styles:** The various ways individuals prefer to receive and process information.
* **LMS (Learning Management System):** A system that provides a training platform to host e-learning classes, track course completion, and assessment scores.
* **LSS (Learning Support System):** A web-based environment for supporting teaching and learning activities.
* **Machine learning: A use of artificial intelligence.** Its core is "knowledge discovery," which is the process of generating meaningful patterns and structured knowledge from a dataset.
* **MongoDB:** A NoSQL database that is document-oriented and provides high scalability and flexible features.
* **Next.js:** A React framework for building full-stack web applications.
* **Online education:** A form of e-learning where learning experiences take place in synchronous or asynchronous environments using internet-connected devices.
* **PHP:** A general-purpose scripting language especially suited for web development.
* **Random Forest:** A machine learning algorithm that constructs "numerous decision trees during training" and aggregates their predictions to make a final prediction.
* **Reflective learners:** Prefer to process information internally.
* **Render:** A platform that streamlines application deployment by connecting to Git branches and automatically building and releasing code.
* **Sensing learners:** Rely on their senses and prefer concrete, factual information.
* **Sequential learners:** Prefer a linear, step-by-step learning approach.
* **Synchronous learning environments:** Environments where learning occurs at the same time for all participants.
* **Tailwind CSS:** A "utility-first framework" that works by scanning HTML and JavaScript files for class names to generate corresponding styles.
* **VARK model:** An educational framework with four learning preferences: Visual, Auditory, Reading/Writing, and Kinesthetic.
* **Verbal learners:** Prefer to learn through written and spoken words.
* **Visual learners:** Learn best through visual aids like diagrams and charts.
* **VS Code (Visual Studio Code):** A lightweight, powerful source code editor.

## **REFERENCES**

Atmaca-Aksoy, A. C. (2024). Using Technology in Science Education:A Bibliometric analysis. Journal of Education in Science Environment and Health, 230–244. <https://doi.org/10.55549/jeseh.730>

Bradley, V. M. (2021). Learning Management System (LMS) use with online instruction. International Journal of Technology in Education (IJTE), 4(1), 68-92.<https://doi.org/10.46328/ijte.36>

Phan, T. T., Vu, C., Doan, P. T., Luong, D., Bui, T., Le, T., & Nguyen, D. (2022). Two decades of studies on learning management systems in higher education: A bibliometric analysis with Scopus database, 2000-2020. Journal of University Teaching & Learning Practice, 19(3).

Chen, L., Chen, P., & Lin, Z. (2020). Artificial Intelligence in Education: A Review. IEEE Access, 8, 75264–75278. <https://doi.org/10.1109/access.2020.2988510>

Daugherty, K., Morse, R., Schmauder, A. R., Hoshaw, J., & Taylor, J. (2022) Adjusting the Future of Adaptive Learning Technologies via a SWOT Analysis. Intersection: A journal at the intersection of assessment and learning, 3(2).

Aldahwan, N. S., & Alsaeed, N. I. (2020). Use of artificial Intelligent in Learning Management System (LMS): A systematic literature review. International Journal of Computer Applications, 175(13), 16–26. https://doi.org/10.5120/ijca2020920611

Kaleci, D. (2025). Integration and application of artificial intelligence tools in the Moodle platform: A theoretical exploration. Journal of Educational Technology and Online Learning, 8(1), 100–111. <https://doi.org/10.31681/jetol.1595079>

Das, A., Malaviya, S., & Singh, M. (2023). The impact of AI-Driven personalization on learners performance. International Journal of Computer Sciences and Engineering, 11(8), 15–22. <https://doi.org/10.26438/ijcse/v11i8.1522>

Paquette, G., Marino, O., & Bejaoui, R. (2021). A new competency ontology for learning environments personalization. Smart Learning Environments, 8(1). <https://doi.org/10.1186/s40561-021-00160-z>

Gunawardena, M., Bishop, P., & Aviruppola, K. (2023). Personalized learning: The simple, the complicated, the complex and the chaotic. *Teaching and Teacher Education*, *139*, 104429. <https://doi.org/10.1016/j.tate.2023.104429>

Photopoulos, P., Tsonos, C., Stavrakas, I., & Triantis, D. (2022). Remote and In-Person Learning: Utility versus Social Experience. SN Computer Science, 4(2). <https://doi.org/10.1007/s42979-022-01539-6>

Kalyani, N. D. L. K. (2024). The role of Technology in Education: Enhancing learning outcomes and 21st century skills. International Journal of Scientific Research in Modern Science and Technology, 3(4), 05–10. <https://doi.org/10.59828/ijsrmst.v3i4.199>

Burbules, N. C., Fan, G., & Repp, P. (2020). Five trends of education and technology in a sustainable future. Geography and Sustainability, 1(2), 93–97. <https://doi.org/10.1016/j.geosus.2020.05.001>[2x.2020.1749239](https://doi.org/10.1080/1034912x.2020.1749239)

Viner, M., Singh, A., & Shaughnessy, M. F. (2021). Assistive technology to help students with disabilities. In IGI Global eBooks (pp. 579–600). <https://doi.org/10.4018/978-1-6684-3670-7.ch033>

Torres-Martín, C., Acal, C., El-Homrani, M., & Mingorance-Estrada, Á. C. (2022). Implementation of the flipped classroom and its longitudinal impact on improving academic performance. Educational Technology Research and Development, 70(3), 909–929. <https://doi.org/10.1007/s11423-022-10095-y>

Lee, Christopher M.. (2024). Online Learning versus Face to Face Learning toward Students: Which can be an effective way of Learning Methodology to our current Educational System?. 10.17632/m2prrm7c3g.1.

Culduz, M. (2024). Benefits and challenges of E-Learning, online education, and distance learning. In *Advances in higher education and professional development book series* (pp. 1–27). <https://doi.org/10.4018/979-8-3693-4131-5.ch001>

Ismail, J. (2001). The design of an e-learning system: Beyond the hype. The internet and higher education, 4(3-4), 329-336.

Volery, T., & Lord, D. (2000). Critical success factors in online education. International Journal of Educational Management, 14(5), 216–223. https://doi.org/10.1108/09513540010344731

Rekkedal, T., Qvist-Eriksen, S., Keegan, D., Súilleabháin, G. Ó., Coughlan, R., & Fritsch, H. (2003). Internet-based e-learning, pedagogy, and support systems. Norway: NKI Distance Education.

Saul Carliner. (2004). An overview of online learning.

Ally, M. (2004). Foundations of educational theory for online learning. Theory and practice of online learning, 2(1), 15-44.

Adzharuddin, N. (2013). Learning Management System (LMS) among University Students: Does It Work? International Journal of e-Education e-Business e-Management and e-Learning. <https://doi.org/10.7763/ijeeee.2013.v3.233>

Zahra, N. O. F., Amel, N. N., Soufiane, N. O., & Mohamed, N. K. (2024). From platforms to online communication tools. DIROSAT Journal of Education Social Sciences & Humanities, 2(3), 130–147. <https://doi.org/10.58355/dirosat.v2i3.68>

Balogh, Zoltan & Turčáni, Milan. (2011). Possibilities of modelling web-based education using IF-THEN rules and fuzzy petri nets in LMS. Communications in Computer and Information Science. 251. 93-106. 10.1007/978-3-642-25327-0\_9

Furqon, M., Sinaga, P., Liliasari, L., & Riza, L. S. (2023). The impact of Learning Management System (LMS) usage on students. TEM Journal, 1082–1089. <https://doi.org/10.18421/tem122-54>

Jiang, Y., Li, X., Luo, H., Yin, S., & Kaynak, O. (2022). Quo vadis artificial intelligence? *Discover Artificial Intelligence*, *2*(1). <https://doi.org/10.1007/s44163-022-00022-8>

Bradley, V. M. (2021). Learning Management System (LMS) use with online instruction. International Journal of Technology in Education (IJTE), 4(1), 68-92.<https://doi.org/10.46328/ijte.36>

Iqbal, S. (2011). Learning Management Systems (LMS): inside matters. Information Management and Business Review, 3(4), 206–216. <https://doi.org/10.22610/imbr.v3i4.935>

Perrotta, C., & Selwyn, N. (2020). Deep learning goes to school: Toward a relational understanding of AI in education. Learning, media and technology, 45(3), 251-269.

Wang, S., Wang, F., Zhu, Z., Wang, J., Tran, T., & Du, Z. (2024). Artificial intelligence in education: A systematic literature review. Expert Systems With Applications, 252, 124167. <https://doi.org/10.1016/j.eswa.2024.124167>

Celik, I., Dindar, M., Muukkonen, H., & Järvelä, S. (2022). The Promises and Challenges of Artificial Intelligence for Teachers: a Systematic Review of Research. TechTrends, 66(4), 616–630. <https://doi.org/10.1007/s11528-022-00715-y>

Mestre, L. S. (2012). The learning styles debate: do we need to match up learning styles with presentation styles? In Elsevier eBooks (pp. 1–18). https://doi.org/10.1016/b978-1-84334-688-3.50001-9

Kaur, P., Kumar, H., & Kaushal, S. (2023). Technology-Assisted Language Learning Adaptive Systems: A Comprehensive review. International Journal of Cognitive Computing in Engineering, 4, 301–313. <https://doi.org/10.1016/j.ijcce.2023.09.002>

Egan, J., Tolman, S., McBrayer, J. S., & Ballesteros, E. (2023). Reconceptualizing Kolb’s learning cycle as episodic and lifelong. *Experiential Learning and Teaching in Higher Education*, *6*(1), 24–33. <https://doi.org/10.46787/elthe.v6i1.3607>

Ferdiani, R. D., Manuharawati, M., & Khabibah, S. (2021). Activist learners’ creative thinking processes in posing and solving geometry problem. *European Journal of Educational Research*, *volume–11–2022*(volume–11–issue–1–january–2022), 117–126.<https://doi.org/10.12973/eu-jer.11.1.117>

Melhem, D. Z., & Al-Zoubi, A. M. (2025). The Effect of Universal Design for Learning (UDL)-Based VARK Model in Students with Learning Difficulties and Various Learning Preferences. *Educational Process International Journal*, *15*(1).<https://doi.org/10.22521/edupij.2025.15.152>

Masegosa, A. R., Cabañas, R., Maldonado, A. D., & Morales, M. (2024). Learning styles impact students’ perceptions on active learning methodologies: a case study on the use of live coding and short programming exercises. Education Sciences, 14(3), 250. <https://doi.org/10.3390/educsci14030250>

Carver, C. A., Howard, R. A., & Lane, W. D. (2002). Enhancing student learning through hypermedia courseware and incorporation of student learning styles. IEEE transactions on Education, 42(1), 33-38.

Graf, S., Viola, S. R., Leo, T., & Kinshuk, N. (2007). In-Depth analysis of the Felder-Silverman learning style dimensions. Journal of Research on Technology in Education, 40(1), 79–93. <https://doi.org/10.1080/15391523.2007.10782498>

Yuan, J., Qiu, X., Wu, J., Guo, J., Li, W., & Wang, Y. (2024). Integrating behavior analysis with machine learning to predict online learning performance: A scientometric review and empirical study. arXiv (Cornell University). <https://doi.org/10.48550/arxiv.2406.11847>

Chen, L., Chen, P., & Lin, Z. (2020). Artificial Intelligence in Education: a review. IEEE Access, 8, 75264–75278. <https://doi.org/10.1109/access.2020.2988510>

Blockeel, H., Devos, L., Frénay, B., Nanfack, G., & Nijssen, S. (2023). Decision trees: from efficient prediction to responsible AI. Frontiers in Artificial Intelligence, 6. <https://doi.org/10.3389/frai.2023.1124553>

Wanniarachchi, W., & Premadasa, H. (2024). Identifying the learning style of students using Machine Learning techniques: An approach of Felder Silverman Learning Style Model (FSLSM). Asian Journal of Research in Computer Science, 17(3), 15–37. https://doi.org/10.9734/ajrcos/2024/v17i3422

Nazempour, R., & Darabi, H. (2023). Personalized learning in virtual learning environments using students’ behavior analysis. *Education Sciences*, *13*(5), 457. <https://doi.org/10.3390/educsci13050457>

Nandwana, N., (n.d.). Use the Visual Studio Code extension. Microsoft Learn. <https://learn.microsoft.com/en-us/power-pages/configure/vs-code-extension#prerequisites>

*PHP*. (2025, August 28). <https://www.php.net/>

Sotnik, S., Manakov, V., & Lyashenko, V. (2023). Overview: PHP and MySQL features for creating modern web projects.

*HTML5 Differences from HTML4*. (n.d.). <https://www.w3.org/TR/html5-diff>

What is CSS? - Learn web development | MDN. (n.d.). <https://developer.mozilla.org/en-US/docs/Learn_web_development/Core/Styling_basics/What_is_CSS>

What is JavaScript? - JavaScript (JS) Explained - AWS. (n.d.). Amazon Web Services, Inc. <https://aws.amazon.com/what-is/javascript>

Vercel. (n.d.). Next.js docs. Next.js. <https://nextjs.org/docs>

Lazuardy, M. F. S., & Anggraini, D. (2022). Modern front end web architectures with react. js and next. js. Research Journal of Advanced Engineering and Science, 7(1), 132-141.

Dhanagari, N. M. R. (2024). MongoDB and Data Consistency: Bridging the Gap between Performance and Reliability. *Journal of Computer Science and Technology Studies*, *6*(2), 183–198. <https://doi.org/10.32996/jcsts.2024.6.2.21>

*Solutions for app development challenges | Firebase*. (n.d.). Firebase. <https://firebase.google.com/solutions>

Installing with Vite - Installation. (n.d.). Tailwind CSS. <https://tailwindcss.com/docs/installation/using-vite>

Gerchev, I. (2022). Tailwind CSS. O’Reilly Media. <https://www.worldcat.org/oclc/1314257318>

*Project Jupyter*. (n.d.). Home. <https://jupyter.org/>

About Gemini. (n.d.). *What is Gemini and how it works*. Gemini. <https://gemini.google/overview/#what-gemini-is>

Imran, M., & Almusharraf, N. (2024). Google Gemini as a next generation AI educational tool: a review of emerging educational technology. Smart Learning Environments, 11(1). <https://doi.org/10.1186/s40561-024-00310-z>

*Git*. (n.d.). <https://git-scm.com/>