Development, Implementation, and Evaluation of a Machine Learning-Based Multi-Factor Adaptive E-Learning System.

Aymane Ezzaim, Aziz Dahbi, Abdelfatteh Haidine, Abdelhak Aqqal

Abstract— **Adaptive learning aims to tailor the learning experience, including content, navigation, presentation, and strategies, based on learners' cognitive and affective factors. However, many existing adaptive learning systems often fail to meet the diverse needs and preferences of learners, typically relying on unique factors such as learning style. To address this, a robust framework is proposed, incorporating an artificial intelligence (AI) driven adaptive learning model capable of considering multiple factors, including past performance, hobbies, and learning style. The approach leverages the k-means clustering algorithm to group learners with similar leisure interests and incorporates Support Vector Regression to predict student performance, utilizing demographic data and past performance as metrics. Furthermore, the implementation of the Personalized Study Guide plugin, based on k-means clustering, enables the system to create personalized learning paths tailored to individual learning styles. By adopting this approach, the objective is to enhance learner engagement and performance through the development of a robust adaptive learning system.**

Index Terms— **Adaptive learning, Artificial intelligence, learner engagement, learner performance, Education, Machine learning**

I. Introduction

In recent years, with the development of digital technology and online learning platforms, the sector of education has seen a tremendous revolution. Adaptive learning, in particular, has experienced remarkable progress. These developments have their earliest historical roots in the 1950s, marking the advent of teaching machines, which set the stage for the idea of adaptive learning [1]. The first uses of the term "adaptive" to describe the adjusting of difficulty to student performance was in the 1950s with a teaching device called SAKI [2]. The second phase was the emergence of computer-aided instruction systems based on programmed instruction in the 1960's [3], [4]. In the 1980s, with the increase of computer capacities and the development of sophisticated software, a new trend of adaptive systems emerged. This period saw the introduction of "Intelligent Tutoring Systems (ITS)," which enable automatic adaptation to learners' needs and performance [5]. After that, specifically in the 1990s with the advent of the internet, another set of adaptive learning systems was deployed, namely "Adaptive Hypermedia Systems (AHS)" which are a more developed version of Hypertext [6]. Then, in conjunction with technological developments, the emergence of web technologies, artificial intelligence (AI) and machine learning (ML) techniques, as well as the shift from constructivism to behaviorism, a new term, adaptive learning systems, has developed. This is seen as a further phase in the evolution of computer-based instruction [7].

Learners are not uniform in nature; instead, they manifest as unique individuals characterized by diverse origins, learning backgrounds, preferences, cognitive styles, and affective characteristics [8], [9]. The navigation of these heterogeneous characteristics poses a formidable challenge for educators. In essence, without appropriate guidance and support, educators may encounter difficulties in modifying their instructional strategies to accommodate the intricate mosaic of individual traits [10]. Conversely, even within the realm of available e-learning platforms, students may grapple with the task of selecting pertinent material owing the vast amount of instructional resources [11]. For this reason, it is essential to provide an adaptive learning system with sophisticated algorithms capable of providing relevant learning material to each student. Additionally, it is critical to point out that the current adaptive learning systems tend to narrowly focus on a single factor, frequently the learner's preferred learning style, while ignoring the multitude of other factors that have a significant impact on a learner's motivation and performance. This absence leaves a significant gap in fully addressing the complex dynamics required to produce really successful tailored learning experiences. This offers a chance for the creation of complete solutions that take into account a variety of factors in order to better equip teachers and students in the quest of successful, adaptive learning.

When delineating learner profiles, antecedent academic performance, leisure interests, and learning style assume crucial functions. An understanding of the abilities and

Manuscript received October 12, 2023; revised July 23, 2024.

Aymane EZZAIM is a PhD candidate in artificial intelligence at Laboratory of Information Technologies, National School of Applied Sciences, Chouaib Doukkali University, El Jadida 24002, Morocco (Corresponding author to provide e-mail: ezzaim.a@ucd.ac.ma).

Aziz Dahbi is a professor of Engineering at Laboratory of Information Technologies, National School of Applied Sciences, Chouaib Doukkali University, El Jadida 24002, Morocco (e-mail: dahbi.a@ucd.ac.ma).

Abdelfatteh Haidine is a professor of Engineering at Laboratory of Information Technologies, National School of Applied Sciences, Chouaib Doukkali University, El Jadida 24002, Morocco (e-mail: haidine.a@ucd.ac.ma).

Abdelhak Aqqal is a professor of Engineering at Laboratory of Information Technologies, National School of Applied Sciences, Chouaib Doukkali University, El Jadida 24002, Morocco (e-mail: aqqal.a@ucd.ac.ma).

challenges of a student is derived from an examination of prior performance and knowledge, affording invaluable perspectives. This comprehension facilitates the precise customization of support interventions to address specific needs [12], [13], [14]. On the other hand, Leisure interests serve as a medium through which formal education and personal excitement might be connected. This intermediary role includes fostering passion, granting decision autonomy, encouraging active participation in the learning process, and, all at the same time, offering a more accurate and nuanced picture of the student's profile [15], [16]. The predominant focus of contemporary research endeavors, namely learning style, elucidates the optimal cognitive processes through which an individual assimilates and retains knowledge [17], [18]. Through the acquisition of knowledge and adept adjustment of these factors, the dissemination of instructional materials is aligned with the discerned needs and preferences of the students.

Data collection methods, like surveys, may be time-consuming and limited, susceptible to bias, and inflexible for dynamic learner needs [19]. To surmount these constraints, integrating machine learning techniques is crucial. Automation using artificial intelligence enables rapid and effective processing of extensive datasets, minimizing biases and expanding the scope of insights [20], [21]. Continuous refinement ensures machine learning integration enhances precision in personalized education, maintaining alignment with evolving learner needs [19], [22], [23].

This paper aims to answer important research questions by pursuing improvements in the AI-based adaptive e-learning field and addressing the diverse requirements of students with sophisticated solutions. Its specific goal is to clarify the efficient planning and execution of a multi-factor AI-based adaptive learning system that is driven by machine learning, with an emphasis on maximizing student engagement and educational outcomes. The study also seeks to determine how such a system affects students' performance. The development of a creative solution intended to improve the educational process is guided by these questions taken together. The suggested approach entails tailoring content delivery to specific students by utilizing data on their interests, performance indicators, and automatically generated learning style predictions.

Section 5 further explains the strategy, which employs various machine-learning methods to enhance the E-learning environment. The process initiates by clustering students who share common leisure interests, employing K-means clustering—a robust unsupervised learning technique. Subsequently, demographics, past performance, and pre-test scores are utilized to harness the predictive power of a gradient boosting regressor, a supervised learning method, for creating a comprehensive performance measure. For predicting the unique learning style of every learner, artificial neural networks are proposed, representing another supervised learning approach. The integration of the decision tree algorithm into the methodology enables the careful adaptation of educational information based on the learning preferences of each individual. Our approach is intended to mark the beginning of a new phase in AI-based adaptive learning, emphasizing the importance of personalization and engagement by incorporating a range of ML algorithms.

The remainder of this article is divided into the following sections: Section 2 defines important terms related to artificial intelligence, adaptive learning, and learning style, while Section 3 provides a detailed examination of the Felder-Silverman Learning Style Model (FSLSM), along with an explanation of the rationale for selecting this model. Moving forward, Section 4 offers a thorough review of the related literature. Additionally, Section 5 outlines the techniques employed in the strategy.

II. Background

A. Artificial Intelligence

Artificial Intelligence (AI) refers to the capacity of computers to replicate human behavior and perform tasks that typically require human intelligence [24]. The overarching objective of this interdisciplinary field is the automation of processes currently reliant on human intelligence [25]. AI involves the utilization of machines for tasks encompassing information perception, synthesis, and inference [24], [26]. Such applications extend to domains like computer vision, speech recognition, and language translation [26]. As per the Oxford English Dictionary, artificial intelligence denotes the intelligence manifested by machines, distinct from the intelligence exhibited by humans and non-human animals. In essence, AI encapsulates the ability of machines to execute operations such as information perception, synthesis, and inference that traditionally demand human intelligence.

Artificial Intelligence (AI) also presents itself as a flexible set of tools with a wide range of educational applications. These encompass the development of interactive learning assistants (chatbots) for personalized interactions, adaptive tutoring systems that respond to individual learning needs, and curriculum design and teaching methods influenced by data-driven algorithms. This educational paradigm highlights the significance of AI in improving learning outcomes, transforming teaching methods, and leveraging analytics to tailor instruction to each student's unique needs [27], [28].

B. Adaptive Learning

As mentioned in the introduction the adaptation mechanism was static, based on the characteristics of the learner determined at the time of the first access to the system [29]. On the contrary, today with the emergence of AI techniques, E-learning, real-time data mining and analysis algorithms, this mechanism has become dynamic, realized during the learning process, based not only on dialogues, questionnaires or parameters but also on the learner-system interaction, in order to deduce two major aspects: cognitive status and affective status [30], [31]. Adaptive learning can be interpreted in various ways, as detailed in the following table (See Table I).

TABLE I
ADAPTIVE LEARNING DEFINITIONS

Perspective	Ref.	Definition
Research topic	[32]	Adaptive learning is a research topic dedicated to providing individualized learning experiences tailored to cater to the distinct needs of each learner.
Approach	[19], [33]	Adaptive learning is an approach that prioritizes individual student abilities and needs, integrating information and pedagogical technologies to facilitate interactive and productive learning activities through new technologies.
Educational technology	[32]	Researchers concur that adaptive learning, an educational technology, holds promise for enhancing learner experiences, improving access, and elevating the quality of higher education. It emphasizes delivering personalized learning experiences tailored to meet each learner's unique needs.
Developed system	[34], [35], [36]	Rather than being a technology or method, adaptive learning is a developed system that seeks to determine the most adaptive learning experience by adjusting for a range of individual factors, including gender, learning motivation, cognitive type, and learning style.

Furthermore, it should be noted that, as noted in [7], various categories of adaptation have been delineated by researchers like Paramythis and Loidl Reisinger [37], Brusilovsky [38], and Stoyanov & Kirschner [39], including:

TABLE II
ADAPTATION CATEGORIES

Adaptation categories	Ref.	Definition
Adaptive interaction	[37]	Aim to improve the user experience by facilitating his interactions with the system.
Content discovery and assembly	[37]	This form is concerned with how adaptive techniques could be used to synthesize content from various sources.
Adaptive collaboration support	[37]	Focuses on integrating the social dimension in an adaptive way into learning processes.
Adaptive assessment	[40]	Adaptive assessment means delivering questions or problems that are tailored to the learner's current knowledge.
Adaptive problem-solving support	[40]	The purpose of this adaptation is to help the learner with immediate advice based on a knowledge base.
Adaptive course delivery	[37]	Refers to adapting courses to the individual characteristics of the learner.

C. Learner Performance

According to [41], "Learner performance" pertains to the augmentation of a learner's knowledge and abilities resulting from their engagement in educational activities. In essence, learner performance can be seen as an indicator of the outcome, either successful or unsuccessful, achieved during the learning process [42]. In the context of education, it is crucial to comprehend the intricate relationship between prior performance and future performance. As highlighted in [43], prior performance often serves as a valuable resource for supervisors, guiding their expectations when assessing current performance. Furthermore, an extensive body of research in school districts consistently underscores the significance of past performance as the most reliable predictor of future performance [44]. For instance, in the study discussed [45], the authors observed a notable correlation between performance on previous standardized tests and both performance expectations and current performance levels. The authors of [46] continue by stating that the knowledge tracing methodologies essentially presuppose that the learner's past performance can aid in anticipating their future performance. In this context, past performance serves as a crucial yardstick for assessing the learner's prior successes and potential for development. In [47], a prior performance based strategy was put out for customizing multimedia environments to learners by providing an adaptive guiding mechanism and customized suggestion. In [48], the authors extracted the learner's competence from their past performance and then provided customized feedback. In the paper [49], an algorithm was employed to utilize a learner's previous performance data for the purpose of determining the appropriate difficulty level for forthcoming texts. The results of this study [50] underscore that prior knowledge/performance stand out as the most influential indicators of success in MOOCs. It is evident that through the assessment and utilization of historical data, adaptive learning systems can tailor their strategies to address knowledge deficiencies, fortify existing competencies, and ultimately guide learners towards improved future performance. How can machine-learning techniques be effectively utilized to predict learner performance? Moreover, what kind of data should be employed for this purpose? In [51], the performance of learners was predicted using their log data and a Deep Neural Network (DNN). The model's main goal was to improve learners' knowledge by delivering personalized online tests. In [12], student academic performance was predicted using supervised learning techniques, considering student grades, demographic, social, and school-related features. Three specific supervised learning algorithms, namely J48, NNge, and MLP, were applied. The outcomes revealed that J48 outperformed the others, attaining the highest accuracy of 95.78% [52]. Using students' online behavior [53], this study successfully employed a multiple regression model to predict their academic performance. In [54], social status's impact on learners' training was used to predict performance. Four classifiers (oneR, MLP, J48, and IB1) were applied to the data, with IB1 achieving the highest accuracy at 82%. In [55], a small student academic dataset was analyzed with three decision tree methods (Reptree, J48, M5P), with Reptree achieving over 90% accuracy. In [18], authors examined at socio-demographic (education, employment, gender, status, handicap, etc.) and course attributes (course program, course block, etc.) data to investigate early student success prediction using machine learning. This study [56] used a variety of classifiers (Model Tree, NN, Linear Regression, Locally Weighted Linear Regression, and Support Vector Machine) to predict student performance based on student demographic information, e-learning system logs, academic records, and admission information. The low mean absolute error (MAE) of the model tree predictor was particularly noteworthy. Naive Bayes (NB), Decision Tree (DT), and Multilayer Perceptron (MLP) prove to be proficient algorithms in forecasting student performance as well [57]. Ahmed et al.'s study [58] employed demographic data from 399 students and three classifiers (Decision Tree, Rule-based, and Naive Bayes) to predict student performance. The findings highlight the rule-based classifier as the top performer, achieving an accuracy of 71.3%. For the purpose of identifying at-risk student, a dataset comprising 32,593 student records with demographic and system interaction data was used in [58]. According to the author in [59], academic success is highly influenced by demographic data in addition to academic considerations. For more precise estimates of student success, they advise combining non-academic factors with academic ones. This study [60] intends to improve the analysis of academic performance by merging prior outcomes with student characteristics including age, demographics, review attitude, and family history. For this reason, a variety of machine learning algorithms were used to the advantage of academic instructors looking for performance enhancement techniques. The authors in [61] used a feature set that included demographic, pre-college admission, and transcript data for dropout detection based on performance prediction. For categorization, they used the Logistic Regression (LG), RF, and KNN algorithms, with LG attaining the highest accuracy.

In summary, these studies highlight how crucial prior performance and past data in predicting future learner performance. They underscore that past academic achievements, demographic information, and historical behavioral data serve as vital indicators for assessing and forecasting student success. Machine learning techniques, including decision trees, regression models, and neural networks, have proven effective in this regard. These approaches enable adaptive learning systems to better understand students' potential and personalize learning experiences, driving learners toward improved performance. The choice of data, which includes demographic, academic, and behavioral information, plays a critical role in the accuracy of these predictions, underscoring the value of a holistic approach to learner assessment and support.

D. Learner engagement

Learner engagement, a multifaceted concept pivotal to effective education, holds a central position in academia and has garnered growing attention and scrutiny [62]. Drawing from numerous studies, learner engagement is characterized by active participation across behavioral, emotional, and cognitive dimensions of learning, resulting in heightened achievement and satisfaction [63], [64]. In the context of learning, distinguishing between engagement and motivation is crucial. While motivation propels the desire to participate in learning activities, engagement encompasses active involvement in tasks and interaction with the learning environment [65], [66], [67].

The construct of learner engagement is a multidimensional concept, often delineated into several key dimensions. Among these, behavioral engagement is readily observable through students' active participation in classroom activities and their enthusiastic involvement in learning tasks. Affective engagement encompasses a spectrum of emotions experienced by students during the learning process, ranging from happiness and interest to boredom and anxiety. Additionally, cognitive engagement reflects the mental effort exerted by students as they critically reflect on their learning strategies and engage in deep processing of course material. Moreover, social engagement has emerged as a crucial dimension, emphasizing the significance of interpersonal interactions and collaborative learning experiences within the academic community. Together, these dimensions contribute to a comprehensive understanding of learner engagement and its impact on academic success [62], [68], [69].

E. Learning Style

Learning style can be defined as the manner in which a learner perceives, engages with, and responds to their learning environment [70], encompassing their preferred approach to absorbing, processing, and retaining knowledge, and involving the strategies they employ to meet the demands of their learning context [13], [71]. Learning style also represents a facet of an individual's personality that influences how they acquire knowledge and their preferences for various learning approaches [72], [73], [74], [75]. It encompasses a unique learning preference in each person, characterized as a combination of cognitive, emotional, and psychological factors, according to Keefe's definition, which is widely accepted by major theorists [70], [74], [75].

Each learner has distinctive psychological characteristics, thus, it is critical to employ learning style models (LSMs) as markers to determine their preferred learning strategies and resources. There are several LSMs available, including, Kolb [76], Honey and Mumford [77], Felder and Silverman [78], VARK [79], Dunn [80], Pask [81], Gregorc [82] etc. In the study, the Felder and Silverman's model (FSLSM) was selected based on its widespread adoption in education and popularity in adaptive learning systems, owing to its straightforward implementation [10]. Unlike models assuming fixed learning styles, FSLSM acknowledges that learners' preferences and behaviors can change, which suits the dynamics of online learning environments [83], [84]. FSLSM utilizes the Index of Learning Styles (ILS), an online questionnaire, to categorize learning styles into four dimensions: Active/Reflective, Visual/Verbal, Sequential/Global, and Sensing/Intuitive. Active learners prefer hands-on group work, while reflective learners choose solitary or familiar partner work. Visual learners favor visual aids, while verbal learners prefer written and spoken explanations. Sequential learners thrive on step-by-step learning, while global learners prefer holistic thinking. Sensing learners focus on concrete thinking, while intuitive learners lean toward conceptual and innovative thinking [78].

Following the examination of well-known learning style models, let us turn the focus to the detection technique, a crucial component in creating learning style-based adaptive learning systems. Two methods for identifying learning styles exist: traditional static and automated. Traditional methods rely on explicit questionnaires (e.g., ILS, LSQ, K-LSI), assuming fixed learning styles, making them less effective due to subjectivity and inattentiveness [83]. According to the comparison made by [19], traditional approaches for evaluating learning styles may be prone to subjectivity, response biases, and memory limits, which may result in mistakes. Additionally, they could find it difficult to completely understand each learner's preferences and complexity [85]. Furthermore, when used with large student populations, these techniques can be time- and resource-consuming. In contrast, automated methods overcome these limitations using technologies like data mining, AI, and sensors [86]. They analyze log files, use clustering (e.g., fuzzy c-means), and learning objects to choose an appropriate learning style [83]. AI techniques, including rule-based and data-driven models, predict learning styles effectively. In addition, they enhance accuracy through real-time data collection and analysis. They provide precision, adaptability, and scalability while continually monitoring a large number of learners [19]. Eye-tracking measures eye movements in real-time to determine preferences, enhancing attentiveness during learning [86].

Several studies have employed an AI-based automated method to determine learning styles. For instance, in this work, learning styles were identified using a variety of AI classification algorithms, including Naive Bayes, logistic regression, conjunctive rule, and the J48 decision tree. With a success rate of 87.42%, the J48 decision tree had the best overall accuracy [87]. In a separate experiment, the authors used gradient-enhanced decision trees for automatic learning style detection, yielding an accuracy of 84.95% [88]. For In this study [84], learner session sequences were classified into eight FSLSM classes using the Gravity Search based Back Propagation Neural Network (GSBPNN) algorithm. The results indicate that GSBPNN achieved 95.93% accuracy with 200 iterations, with increasing iterations improving accuracy but increasing execution time. To offer personalized content in a smart learning environment, an ANN-based learning agent was created. It classifies learning styles based on metacognitive skills and FSLSM. This approach fills a gap left by decision tree algorithms, which struggle with dynamic style detection using real-time data [89]. By integrating the Naive Bayesian approach for learning style recognition with a modified K-Means algorithm to create cluster labels from each test data set, this research [90] established an autonomous learning style detection model. This study [91] employed various AI algorithms, including Random Forest, Naïve Bayes, Logistic Regression, K-nearest neighbor, and Linear discriminant analysis, for automated learning style detection. In [92], 30 fuzzy rules classified learning styles based on the Active/Reflective dimension of the FSLSM using data from both offline (age, education, area of interest, and hobby) and online (mouse movement, time spent, scroll distance, and number of visits). In [93], machine learning and web usage mining were combined to automatically identify a learner's preferred learning style from their online learning platform log file behavior.

Overall, incorporating learning styles as a factor in adaptive learning systems offers a personalized and effective approach to education. Understanding how each learner perceives, processes, and retains knowledge allows for tailored learning experiences. Leveraging AI-driven methods for learning style detection enhances precision and adaptability, ensuring that educational content aligns with individual preferences. By accommodating these preferences, adaptive systems can optimize engagement and learning outcomes, making learning more efficient and enjoyable for students. This highlights the compelling reasons to integrate this factor into the next system.

F. Leisure Interests

As previously stated in the introduction, adaptive learning systems have made notable advancements in tailoring education to suit the specific requirements of individual students. Although these systems often concentrate on learning styles, academic performance, and knowledge levels, it is also necessary to take into account students' leisure interests as a crucial component in fostering engagement, motivation, and successful learning outcomes [15], [16].

The term interest can be defined as a predisposition or habitual tendency of an individual to attend to and engage with a specific category of objects, persons, or events [94]. Interest is a motivating factor associated with a particular piece of material that includes both value-related and intrinsic factors. Numerous studies stress the importance of interest in text comprehension depth, the use of learning strategies, and the emotional impact of the learning process [95].

Learner leisure interests refer to the hobbies, activities, and areas of personal enjoyment and recreation (e.g. Sports, Computer games, Computer science, Music etc.) that individuals engage in when they are not working [96], [97].

Incorporating leisure interests into education offers numerous benefits. Aligning educational content with students' hobbies and interests boosts motivation, resulting in sustained engagement [98], [99]. This prolonged engagement is particularly valuable, as students who derive enjoyment from learning are inclined to remain active on educational platforms [100].

In summary, while adaptive learning systems have greatly improved personalized education, it is vital to also consider students' leisure interests alongside factors like learning styles and academic performance. Learner leisure interests encompass personal hobbies and activities individuals engage in outside formal learning. Integrating these interests into education provides substantial benefits, enhancing motivation and ensuring continued engagement.

G. AI-Enabled Adaptive Learning Systems (AI-Enabled ALS)

Kabudi claims that various data analysis and AI techniques have been applied to create systems that adapt to student preferences and learning styles [48]. This interventions, often referred to as AI-enabled ALS, tries to offer answers to the problems that students encounter, including the usage of antiquated adaptive technologies, learner disengagement, poor motivation, and others [101]. X. Wan claims that AI-enabled adaptive systems begin by analyzing mega data that represents the learner's cognitive and affective status and use this information to train models based on artificial intelligence algorithms to predict/recommend personalized learning content, different learning paths, and successful learning strategies [102]. AI-enabled ALS is not always a standalone system; it is often integrated into a Learning Management System (LMS) to enhance content navigation and sequencing. These modules also offer answer correction with explanations, access to online knowledge resources, and multilingual learning services [103], [104].

The utilization of adaptive learning systems, as highlighted in numerous studies, offers several benefits. Foremost among these is the provision of tailored learning experiences, matching individual preferences and learning styles regarding material, complexity, and user interface. They bring advantages like faster learning, improved outcomes, and addressing cognitive overload and navigation challenges [105]. Adaptive learning systems, as discussed in [106], efficiently manage display levels of different educational pages according to unique learner characteristics. They also group learners with comparable traits to facilitate collaborative learning, as highlighted in [107]. These systems also offer valuable benefits to teachers, enabling diverse teaching methods, easy identification of learning styles, and efficient content analysis to address student difficulties [7].

However, despite the extensive discussion of AI-based adaptive learning systems in the literature, their real-world implementation has been limited, with few practical applications identified [108]. This challenge arises from the complexity of implementing such systems [109], [110]. While various techniques and technologies, including AI, have been employed to facilitate the adaptation of learning systems to learners' strategies and personal traits, there has been limited effort to tailor these systems to learners' skills and abilities [109], [111], [112]. Designing these systems is critical, as improper identification of background, prior knowledge, and learning style can lead to challenging issues. Designers must particularly pay attention to courses necessitating practical or technical expertise as prerequisites [111]. Key questions to consider in this phase include: What information is required to establish an effective user model and how should it be gathered? Is allowing learners to choose their preferred learning method effective? Should adaptation be confined to presentation mode or extend to the system's appearance? [7]. The literature also highlights the necessity of a comprehensive system accommodating all possible adjustments for individual learner unique needs and requirements [113], [114].

To tackle the challenges outlined above, it becomes evident that a well-structured and comprehensive system architecture is imperative. This architecture must account for diverse learner needs, including learning styles, prior knowledge/performance, and content complexity. It must adapt the presentation modes and appearance of the system, according to the interests of the learners. Incorporating AI and machine learning is essential to capture learners' evolving skills. A robust architecture is the foundation for adaptive learning systems, enhancing individualized education outcomes.

In the subsequent section, studies employing AI-driven adaptive learning systems will be explored, with an examination of their limitations.

III. Related work

The design and implementation of AI-based adaptive learning system architectures have been the subject of several case studies. This section will highlight the relevant work that addressed this topic in terms of technologies and factors taken into consideration.

This study suggests an adaptive learning system design that is tailored to the learner's learning style and is meant to support students as they advance in their online education. This architecture attempts to deliver educational content that is customized to learners' learning preferences using a learning path analysis algorithm based on time-series learning history data. As can be deducted, this architecture adopts a unique statically identified factor [115].

With the help of Intelligent Blackboard Agents and Object Petri Nets, this study [116] presents an adaptive multi-agent E-learning system architecture that aims to give learners the flexibility to adjust to their preferences in the online learning environment. This system contain the crucial agents that give the Learner and the creator of educational content the key functionalities, and they provide the services that the Human Agent needs in order to interact with the system, govern communication, and mediate it. In other words, the adaptation process in this solution incorporates intelligent agents that gather and analyze evaluation results and information about the learning process to make decisions about adaptation and sequencing of the content. A limitation of using Intelligent Blackboard Agents and Object Petri Nets in adaptive e-learning systems is the potential complexity and resource-intensiveness of these technologies, which can make implementation and maintenance challenging for educational institutions with limited resources.

Another study conducted in 2020 proposed a system architectural design of an adaptive virtual learning environment. This system uses the J48 decision tree algorithm to identify students' learning styles and then tailor course content and user interfaces to them based on data mining findings of learner behavioral attributes [117].

This study also makes use of one factor, learning style, to give the most appropriate learning materials in an online course made with the Moodle Learning Management System. Using decision trees, one of the most effective and extensively used classifier algorithms, learning styles were identified. The system architecture that was suggested in this research was divided into four phases: WebLog (behavior) detection, data processing, decision tree classification based on Felder Silverman Learning Style Model (FSLSM), and learning style acquisition [118].

The authors of this study [119] propose a system architecture that adopts a hybrid dynamic user model. The term "hybrid" refers to the static and dynamic modeling modules that aim to detect learner behaviors and knowledge. This system considers three variables. Prior knowledge and objective statement are recognized using the static modeling module, and the knowledge progression calculation is identified through the dynamic modeling module. The learning style is first detected statically and then dynamically. The authors recommend using the J48 decision to identify learning styles based on FSLSM.

In [120], researchers developed a web-based adaptive learning system based on students' cognitive styles. They used a neural network to identify cognitive styles through online browsing behavior and adapted learning content accordingly. Testing the system with computer science students, it accurately identified cognitive styles and improved learning engagement. However, the study had two limitations: the need to compare different methods for determining learning styles and the exclusive focus on engagement, neglecting other metrics like performance.

The author discusses creating an adaptive e-learning model implemented in Moodle LMS, adapting content, format, and pedagogy based on a micro-adaptive approach considering prior knowledge and learning styles. It combines static (questionnaire) and dynamic (real-time monitoring) personalization techniques. Three core elements include the adaptation module (choosing personalized courses based on learner style), student model (tailoring interactions to student characteristics), and expert system (making recommendations and decisions using data analysis) [121].

This adaptive learning system assesses learners' skills through a test, offering personalized content based on their performance. It employs algorithms like Personalized Page Ranking to optimize page importance and Navies Bayes classification to categorize learners into high, medium, and low skill levels. While it improves learner classification and material adaptation, it lacks an automated AI-based expert system for questionnaire selection and performance prediction, presenting limitations [122].

This study [31] introduces an adaptive learning system that considers both cognitive and affective states of learners. Using an expert system with fuzzy inference, it selects appropriate learning materials for each student based on factors like material version, learning level (cognitive performance), and emotional readiness (affective performance).

In [22], a hybrid item response theory and regression tree approach addresses the cold start problem in adaptive learning. It uses existing learner data and responses, alongside background variables, to estimate abilities and missing data. The trained model predicts the abilities of new learners based on their background information. However, practical applicability is limited, and dataset sizes are small.

In [123], the Learning Intelligent System (LIS) predicts failure risk using a model trained with four machine-learning algorithms (Naive Bayes, Decision Tree, K-Nearest Neighbors, and Support Vector Machine). When at-risk learners are identified, it provides data to teachers through a dashboard and offers personalized feedback with recommendations. Future goals involve refining the system for skill-based recommendations, faster feedback, and dropout prediction to improve engagement and course completion.

This study [124] uses the "SPOnto" ontology in the "Class Quiz" adaptive learning system to model learner profiles effectively. They employ machine-learning algorithms, such as Logistic Regression, Support Vector, Multinomial Naive Bayes, XGBoost, and CNN-LSTMa, to classify learners based on various datasets representing intelligence type, player type, and learning disabilities. Future work aims to enhance performance with larger datasets and expand ontology relationships.

In [125], the authors compared three classes of Deep Auto Encoders (CDAE, DAE-CF, and DAE-CI) with a popularity model to enhance learner preference prediction in an Adaptive E-Learning System (AES). They utilized a dataset from a MOOC with 3757 students, focusing on student interactions with learning objects. Results showed that the Popularity model offered global recommendations but not specific adaptability for individual students, making it useful for addressing the cold start problem.

Overall, this section delves into diverse AI-based adaptive learning systems, striving to personalize student experiences through various factors. Despite promising results in enhancing learning and engagement, these approaches encounter challenges like practicality, limited datasets, and the need for refinement. To achieve genuinely effective and engaging educational experiences in the future, it is vital to blend various AI techniques and introduce additional individual factors alongside the commonly employed ones with significant impact. The table 3 displays a research compilation detailing the input variables used in the implemented adaptive learning systems.

TABLE III
INPUT FACTORS IN THE IMPLEMENTED ADAPTIVE LEARNING SYSTEMS

Ref.	Input Factors	Ref.	Input Factors
[126]	Learning style	[31]	Cognitive performance Affective performance
[127]	Learning style	[121]	Prior knowledge Learning styles
[128]	Learning style	[120]	Cognitive styles
[129]	Learning style	[107]	Prior knowledge Objective statement Knowledge evolution
[93]	Learning style	[118]	Learning style
[125]	Learning style	[117]	Learning style
[124]	Intelligence type Player type Learning disabilities	[116]	Learner preferences
[22]	Background variables	[105]	Learning style
[122]	Learner performance	[130]	Knowledge level Learning styles
[115]	Learning style	[131]	Knowledge level
[132]	Learning style	[133]	Knowledge level

Based on the findings from the table 3, it can be inferred that a majority of the examined adaptive learning systems, specifically 77% (n=17), primarily rely on a single factor during the adaptation process. In contrast, a smaller proportion, 14% (n=3), incorporate two factors, while 9% incorporate three factors into their adaptation mechanisms. Among the factors employed, learning style emerges as the most prevalent, accounting for 41% of the cases. Following this, knowledge level is the next most frequently used factor, contributing to 21% (n=6). Learner performance and learner preferences each constitute 7% of the used factors, while the remaining individually contribute 3% to the overall distribution.

The prevailing trend in prior research within this domain predominantly revolves around adaptation models that predominantly factor in a single aspect, typically focusing on learning styles as per the FSLSM. Considering this, an innovative multi-factor design is proposed, emphasizing the need for a comprehensive approach. In pursuit of a more personalized and effective adaptive learning paradigm, the recommended architecture integrates not only learning styles but also other pivotal elements. The architecture aspires to elevate the adaptability of the learning process beyond traditional single-factor approaches by encompassing a broader spectrum of influential factors.

IV. Methodology

This research systematically developed an adaptive learning solution using the ADDIE (Analysis, Design, Development, Implementation, and Evaluation) instructional design framework [134]. The ADDIE model guided the approach, ensuring a methodical and comprehensive development process of the adaptive learning system.

A. Analysis and Design

During the analysis and design phase, an extensive review of the literature was employed, extracting insights from academic works to inform the development of the adaptive learning solution [27], [28], [135], [136]. The approach during this phase was meticulously designed to create a robust and effective adaptive learning system, focusing particularly on addressing learner needs and optimizing educational outcomes. The strategy implemented crucial processes to ensure the reliability and performance of the proposed solution.

The primary objective in this phase is to seamlessly integrate learners' learning styles, performance metrics, and leisure interests, aiming to enhance engagement and personalize the educational experience. The review of literature covered multiple scientific databases, and the stringent selection process focused on articles directly related to AI and Adaptive Learning Integration.

During this process, relevant details were meticulously extracted, with a specific focus on the construction and execution of adaptive learning systems. An in-depth analysis was conducted to uncover recurring themes, emerging trends, and areas needing further investigation. Leveraging these insights, an innovative architecture is proposed for the adaptive learning system, intended to improve this approach by integrating various components.

B. Development

In the development phase, the focus shifted towards the creation of the adaptive learning solution. This phase commenced with the preparation of a performance prediction machine learning model, laying the foundation for accurate anticipations of learners' academic achievements. Subsequently, the creation of a leisure clustering model was undertaken, aimed at discerning and accommodating students' individual leisure preferences within the learning environment. These predictive and clustering models were seamlessly integrated into the Moodle Learning Management System (LMS) as plugin. Moreover, the implementation strategy took into account the utilization of improved version of the Personalized Study Guide plugin, a crucial component facilitating the generation of personalized learning paths tailored to students' distinct learning styles [137]. To address this limitation, the plugin was enhanced by incorporating a mechanism to extract the extension of resource file types (e.g., .pdf, .pptx, .mp3, .mp4) and assign weights based on the Felder-Silverman Learning Style Model (FSLSM) (See Table 4). The weights were extracted from a Systematic Literature Review investigating the Relationship Between Learning Styles and Learning Objects, thereby ensuring a more comprehensive and effective adaptation process [138]. This comprehensive approach during the development phase ensures a technologically sophisticated and learner-centric adaptive learning system within the Moodle LMS framework.

TABLE IV
Weighted Distribution of FSLSM Dimensions Across File Types

FSLSM Dimensions	Images	Videos	Audio	Presentation	Document
Active	0.05	0.11	0.0	0.05	0.02
Reflective	0.05	0.11	0.0	0.22	0.33
Sensing	0.18	0.14	0.2	0.2	0.11
Intuitive	0.13	0.09	0.0	0.1	0.12
Visual	0.44	0.34	0.0	0.15	0.02
Verbal	0.05	0.09	0.8	0.07	0.3
Sequential	0.03	0.06	0.0	0.15	0.09
Global	0.08	0.06	0.0	0.07	0.02
Active	0.05	0.11	0.0	0.05	0.02
Reflective	0.05	0.11	0.0	0.22	0.33
Sensing	0.18	0.14	0.2	0.2	0.11

The developmental phase of the study entailed harnessing the collected data to construct a performance prediction model. Notably, prior investigations had yielded a predictive model, cultivated on a dataset comprising 100 records, which relied on gradient boosting regressor and underwent practical application [139], [140], [141]. In this current study, the dataset was augmented to encompass 500 student records, thereby amplifying the robustness and comprehensiveness of the analysis. Moreover, enhancements to this new model iteration included the substitution of age with failing years and the inclusion of diploma field as a feature. This adjustment allowed for a more nuanced understanding of student performance predictors. Initial data collection included demographic, previous learning metrics, self-esteem (SE), and emotional intelligence (EQ) information. Subsequently, an array of machine learning algorithms was applied to identify the optimal predictive model, enhancing the accuracy and efficacy of the approach.

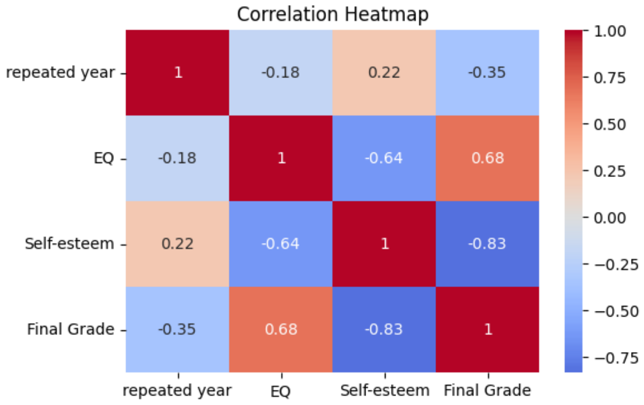

Fig. 1. Correlation Heat map

Data processing encompassed systematic coding, essential for machine learning algorithms, and a correlation matrix heat map aided in pattern identification. The results in Figure 1 demonstrated significant correlations between student attributes and final grades, with higher self-esteem (-0.83) and emotional intelligence (EQ) (0.68) demonstrating strong associations with improved academic performance. Additionally, the correlation coefficient (-0.35) between students who have never repeated a grade and academic performance further reinforces the importance of academic continuity in enhancing student outcomes. These results suggest that high levels of self-esteem and EQ could serve as positive predictors of final grades, highlighting their potential importance in academic success.

During the data processing phase, a classification scheme was devised whereby final grades were categorized into distinct performance levels. Specifically, grades below 10 were classified as "low" performance, while grades ranging from 10 to less than 15 were categorized as "medium" performance. Grades equal to or exceeding 15 were designated as "good" performance. This systematic classification framework was implemented to streamline the analysis process and facilitate the extraction of relationships between various features and academic performance.

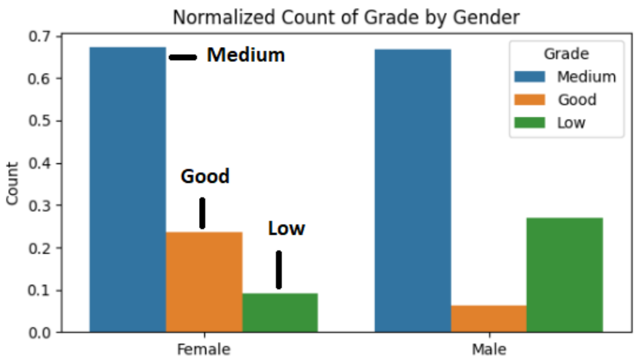

Fig. 1. Gender-Based Distribution of Students across Academic Grades

Figure 2 presents the gender-based distribution of students according to grade classification (good, medium, low). Analysis reveals a noteworthy difference in academic achievement between male and female students, particularly in obtaining good grades. Specifically, approximately 24% of female students achieve good grades, contrasting with approximately 7% among males. This observation suggests a disparity in academic performance, indicating a higher propensity for females to excel academically and attain good grades compared to males in Morocco.

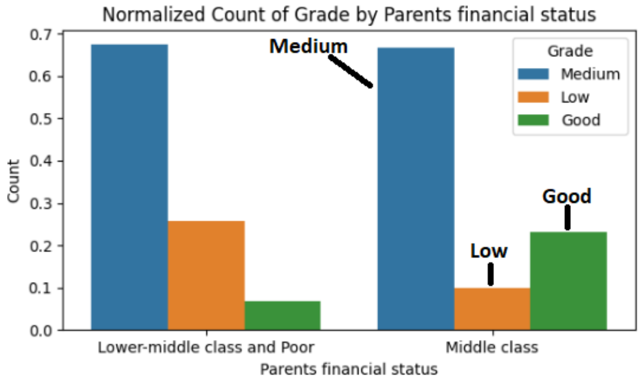

Fig. 3. Student Distribution by Parental Financial Background and Academic Performance

The observed pattern in Figure 3 indicates that students from lower-middle class and poor families demonstrate a propensity for achieving medium grades, with a higher proportion inclined towards low grades rather than good grades. This trend contrasts with students from middle-class families, where the distribution tends to be more balanced, and encompassing good and low grades alongside medium grades.

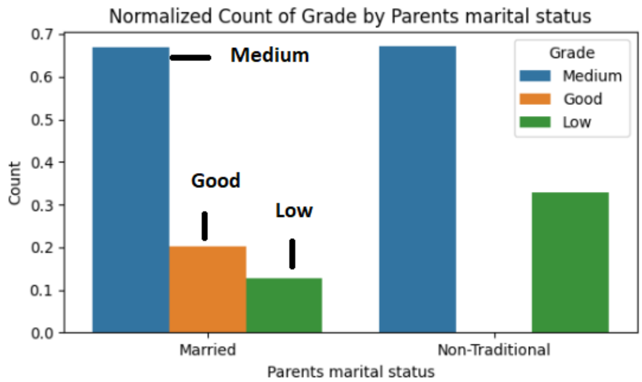

Fig. 4. Academic Performance Based on Parents' Marital Status

The figure 4 depicts the distribution of students based on their parents' marital status. Students from married families show a distribution where the majority fall into the medium grade category (68%), followed by 20% achieving good grades and 12% with low grades. In contrast, students from non-traditional families exhibit a different distribution. None of the graduates from non-traditional families achieved good grades, with 68% falling into the medium grade category and 32% into the low grade category. It's important to note that the term "non-traditional families" encompasses those with divorced, widowed, or adopted parents, and this categorization is made due to their relatively low representation in the dataset. This results indicates a potential influence of family structure on academic performance, with students from non-traditional families facing additional challenges that may impact their educational outcomes.

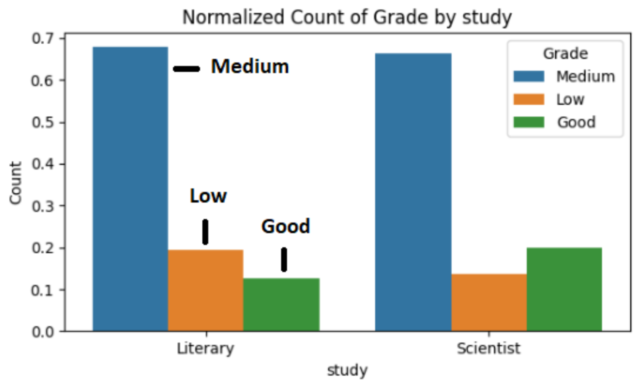

Fig. 5. Grade Distribution by Diploma Field

The figure 5 illustrates the normalized count of student grades categorized by their diploma field. Among students from scientific fields, approximately 21% achieved good grades, while 67% obtained medium grades and 12% received low grades. In contrast, students from literary fields had 11% achieving good grades, 69% obtaining medium grades, and 20% receiving low grades. Overall, students from scientific fields tend to achieve better academic performance, with a higher proportion obtaining good grades compared to their counterparts from literary fields.

TABLE V
STATISTICAL SIGNIFICANCE OF FACTORS INFLUENCING STUDENT PERFORMANCE

Factors	Statistical Significance (p_values)
Study	3.835825e-02
Repeated Years	6.754928e-11
Gender	1.590963e-10
EQ	7.279355e-24
Self-esteem	8.627776e-81
Parents Financial Status	9.415623e-09
Parents Marital Status	3.673004e-08
Boarders	7.950530e-01

The table 5 presents the p-values various factors in relation to student performance. Factors such as repeated years, gender, EQ, self-esteem, parents' financial status and parents' marital status all have statistically significant p-values less than 0.05, indicating a strong association with student performance. Conversely, the factor boarders has a p-value of 0.795, indicating a lack of significant association with student performance. However, retaining boarder status in the analysis allows for a more nuanced exploration of the educational landscape. While not directly correlated with academic outcomes in this dataset, delving into boarder status can unravel a captivating tapestry of insights, transcending mere academic metrics. This approach ensures a comprehensive understanding of student performance, where socio-emotional well-being and environmental influences intertwine with academic success, creating an intricate mosaic of factors to consider. Overall, these results suggest that factors such as repeated years, EQ, self-esteem, and parental background serve as robust predictors in the analysis.

The predictive model was constructed leveraging a variety of machine learning algorithms, including Random Forest Regressor (RFR), Linear Regression (LR), Gradient Boosting Regressor (GBR), Support Vector Regression (SVR), and Multi-Layer Perceptron Regressor (MLPR) (See Table 6). It is pertinent to acknowledge that the initial model was trained on a dataset comprising 100 students, where the Gradient Boosting Regressor (GBR) demonstrated superior predictive accuracy, yielding an R-squared score of 0.9 [139]. Following this, the model underwent augmentation with an additional 400 records, leading to the selection of the Support Vector Regression (SVR) as the optimal performer, attaining an R-squared score of 0.88. It is noteworthy that the expansion of the dataset from 100 to 500 records introduced complexities impacting model generalization, resulting in a marginal 2% reduction in predictive accuracy. However, it is imperative to underscore that this reduction is not inherently deleterious, particularly considering the advantages conferred by enhancing the dataset records. Enlarging the dataset ensures a more comprehensive representation, capturing a wider spectrum of student profiles and scenarios. This not only enhances the model's generalization capabilities but also augments its robustness and reliability in real-world applications. Furthermore, the increased dataset size facilitates more extensive feature analysis and model training, potentially unveiling deeper insights into the determinants of student performance. Consequently, while the slight decline in predictive accuracy may appear unfavorable initially, it is offset by the substantial benefits derived from augmenting the dataset records.

TABLE VI
COMPARISON OF MACHINE LEARNING REGRESSION MODELS FOR STUDENT PERFORMANCE PREDICTION

	RFR	LR	GBR	SVR	MLPR
Mean Squared Error	1.15	0.94	1.11	0.90	0.94
Root Mean Squared Error	1.07	0.97	1.05	0.95	0.97
R-squared Score	0.85	0.88	0.86	0.88	0.88

Based on the metrics presented above, both the Support Vector Regression (SVR) and Multi-Layer Perceptron Regressor (MLPR) showcase notable performance, boasting the lowest Mean Squared Error and Root Mean Squared Error values. These lower errors signify superior predictive accuracy. Additionally, both models achieve high R-squared scores, indicating strong correlations between predicted and actual student performance. Therefore, considering these metrics, either the SVR or MLPR would be suitable choices for predicting student performance. However, SVR was selected over MLPR due to its slightly lower Mean Squared Error and Root Mean Squared Error, indicating slightly superior predictive accuracy. In addition, given its kernel trick approach, Support Vector Regression (SVR) is generally regarded as more suitable for smaller to medium-sized datasets, where it can efficiently handle high-dimensional data and complex relationships [142]. This makes SVR particularly adept at capturing intricate patterns and nuances within the data, resulting in robust predictive performance [143]. Therefore, in addition to its superior performance metrics in this context, the SVR's compatibility with smaller datasets further justifies its selection as the preferred model for predicting student performance.

The developed performance prediction model underwent successful deployment and implementation as a Flask API. This deployment allowed seamless integration into various applications and systems, providing real-time predictions. The Flask API, renowned for its flexibility and simplicity, facilitated the model's accessibility and usability [144], [145]. Furthermore, the model was efficiently hosted on the PythonAnywhere solution, ensuring reliable and scalable performance [146]. This deployment strategy ensures the adaptability and widespread applicability of the predictive model, contributing to its effective utilization in diverse educational settings.

The development of a clustering model for students based on their chosen leisure interests commenced with the meticulous collection and analysis of data from 400 students. Each student provided information on three personal leisure activities. The gathered leisure data was methodically prepared, transforming it into a structured format where each row represented a student. Columns denoted various leisure categories, with binary values indicating whether the student expressed interest in a particular category. This well-organized dataset was then subjected to the K-means clustering algorithm [147]. This straightforward and computationally efficient algorithm was applied to categorize students according to their binary engagement across various leisure activities. These categories include music and dance, movies and series, social media, science and technology, active sports, video games, and pets. Each student was systematically assigned to a cluster, revealing distinctive patterns in their leisure preferences.

Following the clustering phase, the predictive capabilities of the Gradient Boosting Regressor (GBR) were leveraged. GBR is recognized for its effectiveness in capturing complex relationships in data [148]. The GBR model was trained on the clustered dataset to construct a predictive framework. It exhibits notable performance, yielding a Mean Squared Error of 0.003 and an impressive R-squared Score of 0.994. These results underscore its efficacy in accurately predicting student performance based on the clustered dataset.

For new students entering the system, the approach involves assigning them to the cluster that aligns with their binary leisure preferences using the pre-trained prediction model. This assigned cluster serves as a valuable prediction, providing insights into the likely leisure interests of the new students.

After evaluating the model performance, it was deployed and seamlessly integrated into a Flask script as a web service, effectively serving as an API. This deployment allowed the Moodle plugin to make predictions by sending requests to the API. Leveraging the GBR, students were accurately categorized into three distinctive clusters, highlighting similarities in their leisure preferences. Subsequently, each student's choices were labeled within their respective clusters, contributing to the model's heightened predictive accuracy. This strategic approach not only unveils inherent patterns in students' leisure preferences but also facilitates accurate predictions for new students and significantly enriches the overall personalization of the adaptive learning system, enhancing its ability to tailor educational experiences based on individual leisure preferences.

In the pursuit of personalized education that incorporates learning style factors, the integration of the enhanced version of the "Personalized Study Guide (PSG)" Moodle plug-in has emerged as pivotal. This plug-in, designed to craft personalized learning paths based on individual learning styles, serves as a pivotal component in the approach. The primary goal is to identify and accommodate students' distinct learning preferences through the PSG, fostering engagement and motivation. Utilizing two distinctive methods for learning style identification – the Inventory of Learning Styles (ILS) questionnaire by Felder and Silverman and an analysis of prior Moodle activity patterns – the PSG adeptly assesses students' preferences. By assigning learning-style weightings to each resource and activity, the PSG tailors its suggestions, creating a unique and captivating learning journey for each student. To enhance predictive capabilities, the PSG collaborates with the Behavior Analytics plug-in (BA), employing clustering analysis to identify centroids and subsequently applying the k-means algorithm for effective student grouping. This synergistic approach ensures the PSG generates personalized learning paths that align seamlessly with students' preferences and behaviors, contributing to a more individualized and impactful educational experience [137], [149], [150], [151], [152].

The development phase yielded a sophisticated adaptive learning solution within Moodle. It integrated predictive models for academic performance and leisure clustering, seamlessly deployed as plugin. The models, including SVR and GBR, demonstrated robustness and adaptability. Additionally, the incorporation of the "Personalized Study Guide" plugin ensured tailored learning paths aligned with individual preferences and behaviors, enhancing the overall personalization of the adaptive learning experience.

C. Implementation

In the implementation phase, the learner profile was enhanced with custom fields. Students provided personal details during the enrollment phase, such as gender, repeated years, parents' financial and marital status, residency status, and leisure interests. The plugin automatically filled in additional information like the performance index and leisure cluster. Subsequently, the Bar-On EQ test, Rosenberg SE test, and diagnostic assessment were prepared using the Moodle quiz activity. Subsequently, the "Profile Field-based Cohort Membership" plugin was implemented to categorize students into cohorts based on their performance grade, and to enroll them into appropriate courses accordingly. Additionally, restriction mechanisms based on profile fields were employed to selectively display sections relevant to users' leisure interests while concealing irrelevant content. Next, three courses were created in Moodle catering to low, middle, and high-performance students. Each course featured learning materials adapted to one performance level and diverse learning styles, organized by the "Personalized Study Guide" plugin. Each course had three sections, corresponding to cohorts representing leisure preferences. For instance, a student with a low performance cohort membership, a sport leisure cluster, and a verbal learning style would be enrolled in the low-performance student course, accessing the section with sports-themed resources (e.g. Excel Skills for Sports Analytics) in PDFs, videos, emails, and announcements (See table 12). To facilitate the creation of course materials, custom assets generated by AI tools like OpenAI's DALL-E 2 for images, ChatGPT-4 for text, and other AI tools for transcription and video creation were utilized. This approach ensures a rich database of educational materials tailored to students' interests and academic levels.

D. Evaluation

In the evaluation phase, the effect of the adaptive learning solution on student performance and engagement within the accredited computer science program in Moroccan high schools was rigorously assessed. Employing a quantitative research methodology facilitated comprehensive data collection and analysis through statistical, relationship, and descriptive analyses. The experiment involved two distinct groups, G1 and G2, within the Moulay Alhassan High School's common core level, connected to the prefecture of Aïn Chock Province, Casablanca, Morocco. In this study, 73 participants from the scientific fields, comprising 52% men and 48% women, underwent a random selection process for allocation into the experimental (G1) and control groups (G2). G1, consisting of 38 students, received the AI-based adaptive learning solution with a flipped classroom strategy, serving as the focal point for assessing the solution's effects on their learning experiences [153]. Simultaneously, the control group (G2), comprising 35 students, underwent traditional teaching methods, providing a vital baseline for comparison. This comparative approach allowed us to evaluate and contrast the efficacy of the adaptive learning system against traditional instruction, offering crucial perspectives on the possible benefits of adopting adaptive learning systems within high school computer science education in Morocco.

Two assessment tools were employed for the study:

Engagement Questionnaire: A five-point Likert scale questionnaire, derived from the research of Hiver et al. and Wang et al., was employed to assess student engagement across multiple dimensions [154], [155]. The questionnaire underwent translation from English to French and Arabic to accommodate diverse linguistic backgrounds. Comprising 32 items, it encompasses four distinct dimensions: behavioral (8 items), emotional (11 items), cognitive (8 items) and social engagement (5 items). In accordance with the methodology proposed by Zhiyong Li and Jiaying Li, questionnaires were administered to both control and experimental groups before and after the intervention [62]. Upon data collection from the pre-questionnaire and post-questionnaire phases, the mean scores across the four engagement scales were computed and subjected to analysis. Independent sample t-tests were employed to compare the control and experimental groups both pre- and post-intervention. Additionally, paired sample t-tests were utilized to compare the pre- and post-intervention results within the experimental group, as well as within the control group before and after traditional teaching sessions. Participants were instructed to assess their sentiments regarding the course by indicating their agreement with statements using a Likert scale ranging from "never true of me" (1) to "always true of me" (5), with the exception of questions 3, 4, 5, 6, 9, 12, 13, 15, 20, and 22, which were reversed. Following the questionnaire administration, Cronbach's alpha coefficients were computed for each engagement sub-scale: behavioral engagement (8 items, $\alpha = 0.98$), emotional engagement (11 items, $\alpha = 0.97$), cognitive engagement (8 items, $\alpha = 0.99$), and social engagement (5 items, $\alpha = 0.97$). These high Cronbach's alpha values indicate strong internal consistency reliability of the sub-scales, suggesting that the items within each sub-scale consistently measure the same underlying construct.

Performance Assessment: To measure learner performance, an extensive summative evaluation was performed at the end of the course, using various techniques like short answers, multiple-choice questions, and practical exercises. Both sets of participants completed the same evaluation in the same conditions, ensuring a fair comparison. The evaluation aimed to analyze the AI-based adaptive learning's effectiveness compared to traditional methods in terms of student performance. The diverse evaluation strategy assessed understanding, problem-solving, critical thinking, and overall curriculum mastery. This approach allowed a comprehensive comparison between the AI-based adaptive learning and traditional teaching methods concerning performance and engagement.

V. System Architecture

This work incorporates the material described in the previous part and expands upon the previous works in adaptive learning and artificial intelligence [27], [28], [135], [139], [140], [141], [152], [156]. Additionally, an architecture for the adaptive system was designed to consider several factors, with a particular emphasis on accommodating individual learning styles [157].

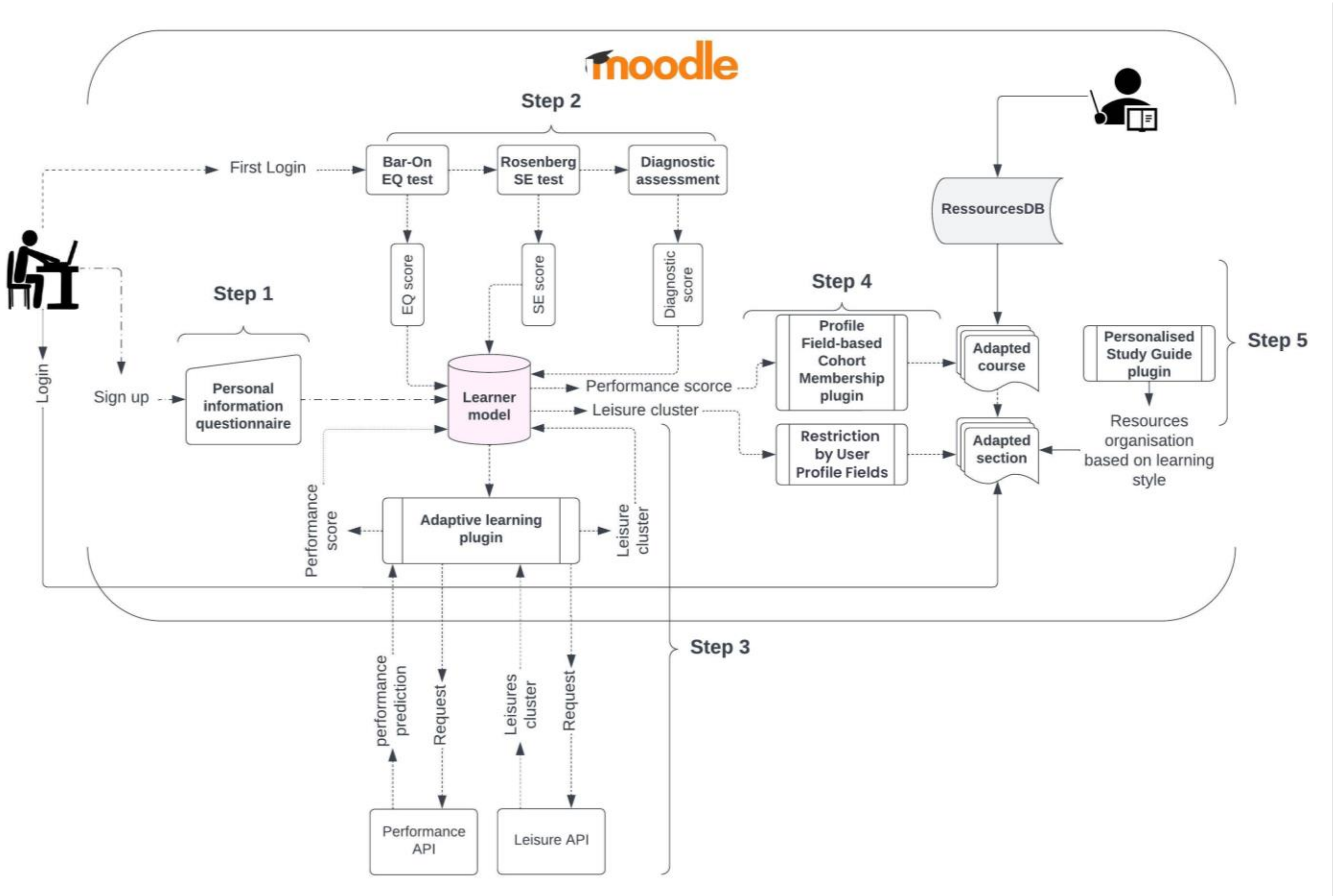

Fig. 6. System Architecture

As shown in figure 6, the suggested framework considers three key aspect throughout the adaptation phase: learning style, leisure interests, and performance level. Following this paradigm, the prescribed procedure for providing tailored educational materials to each learner is outlined as follows.

The integration of the adaptive learning system into the Moodle Learning Management System (LMS) marks the foundational step towards its seamless incorporation into the educational environment. This integration streamlines retrieval of student information, instructional materials, and other essential system features, ensuring a holistic learning experience. Moreover, the plugin will collaborate with complementary plugins such as Profile field-based cohort membership, and the Personalized Study Guide, enhancing the system's capabilities and providing learners with comprehensive support tailored to their individual needs.

Data collection constitutes a crucial phase in the adaptive learning framework, encompassing two key components: gathering information on students' leisure interests and collecting data related to their psychological, learning and demographic characteristics. During enrollment, students are prompted to provide details about their leisure preferences, including favorite activities and sports, laying the groundwork for subsequent clustering based on leisure interests. Simultaneously, the system collects demographic data such as gender, parental economic and marital situation, and location of residence, alongside learning metrics like repeated years and diploma field, emotional intelligence and self-esteem metrics. These data points are selected for their proven impact on student achievement, acknowledging the multifaceted nature of factors influencing academic success [59], [139], [140], [141], [158].

Clustering students according to their leisure interests forms the basis for personalizing the learning experience. Employing the K-Means clustering algorithm, students are categorized into distinct clusters based on their leisure choices, enabling the identification of common interests within each group. Descriptive labels are assigned to these clusters, reflecting the shared preferences and interests of the students therein, thereby facilitating targeted content delivery and engagement strategies.

The supervised machine learning algorithm GBR, trained with student selections as input and labeled clusters as target labels, is the key to predicting the interest profiles of new students. By leveraging this predictive model, the system can forecast the cluster label for incoming students, thereby guaranteeing access to course material aligned with their interests.

Classification of students according to their performance involves deriving performance metrics from collected data. Utilizing the SVR model, learning metrics, demographic information, emotional intelligence and self-esteem scores are analyzed to forecast average grades, culminating in the Predicted Performance indicator. Additionally, course-specific placement test scores contribute to the overall performance metric, computed using assigned weights to yield a Final Performance score. Based on this classification, learners are enrolled in courses tailored to their performance level, enabling targeted educational interventions and support.

Final Performance = (0.2 * PreTestScore) + (0.8 *

PredictedPerformance).

Content adaptation represents the culmination of the adaptive learning process, guided by predictions derived from students' interest profiles and performance metrics. For example, students with moderate academic performance and a keen interest in video games and sports are guided to courses customized to their skill level (Level I), which corresponds to an intermediate level. These courses are enriched with resources focusing on gaming and sports themes, such as videos featuring renowned athletes like Cristiano Ronaldo explaining computer structures. Utilizing the Personalized Study Guide plugin, the content delivery undergoes dynamic adjustments to match the students' preferred learning styles, thus enhancing engagement and comprehension, particularly catering to verbal learners in this scenario.

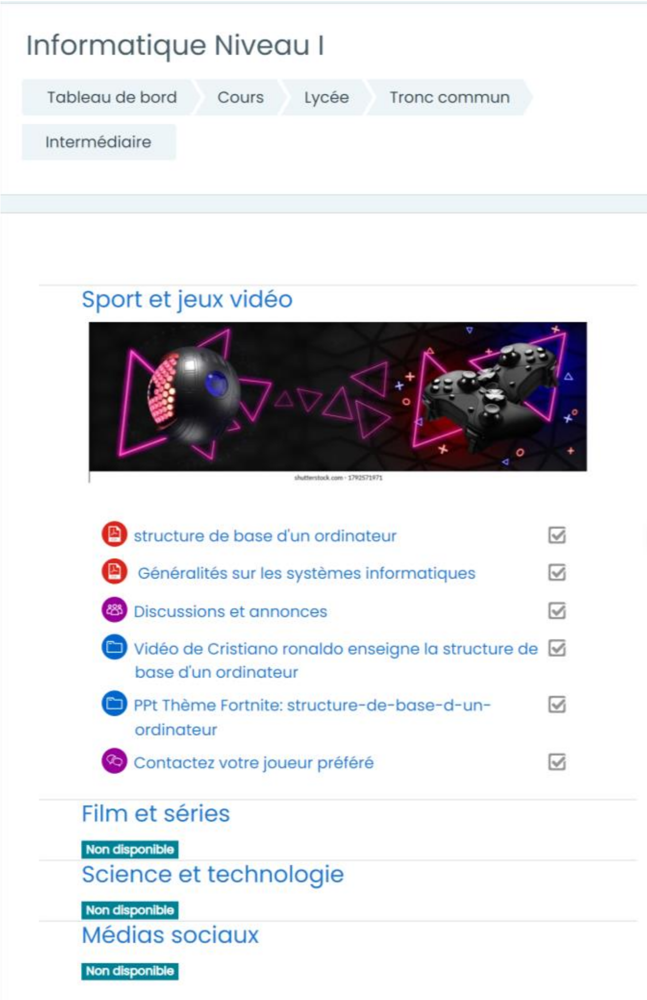

Fig. 7. Course Demo.

VI. RESULT

The following section presents the outcomes of implementing the adaptive learning system within the Moodle LMS framework. The impact on student performance and engagement in Moroccan high schools' computer science program was assessed. Quantitative methods were employed to conduct comprehensive data analysis, comparing two groups: one receiving the adaptive learning solution and the other receiving traditional teaching methods. The evaluation, employing an engagement questionnaire and Performance Assessment, aimed to gauge learner engagement and performance effectively.

TABLE VII
PERFORMANCE DISTRIBUTION - EXPERIMENTAL GROUP

Performance grades	Predicted values	Pre-test scores	Final Performances
Low performance	11 (29%)	13 (34%)	11 (29%)
Medium performance	20 (53%)	22 (58%)	22 (58%)
High performance	7 (18%)	3 (8%)	5 (13%)

Table 7 illustrates the distribution of students based on various metrics, including predicted values, pre-test scores, and final performance values derived from the provided formula. A comparison between pre-test scores and predicted values reveals that initially, four students did not align with their predicted values. However, upon calculating final performance using the proposed formula, this discrepancy decreased to only two students. This suggests that the adjustments made in "Final Performance" effectively mitigate the differences observed between "Predicted values" and "Pre-test," resulting in a reduced gap in the distribution of students across categories.

Table 7 also delineates the distribution of students within the experimental group (G1) across various pre-test score ranges. A noteworthy proportion of students had lower beginning performance levels, as seen by the 34% of students who scored below 10 on the pre-test. About 22% of students had scores between 10 and 15, indicating that this subset performed at a moderate level. 3% of students, on the other hand, received scores of 15 or higher, indicating a minority with greater starting proficiency levels. Before students were exposed to the adaptive learning system, they came from a variety of backgrounds, and this distribution provides important light on their starting places and performance levels.

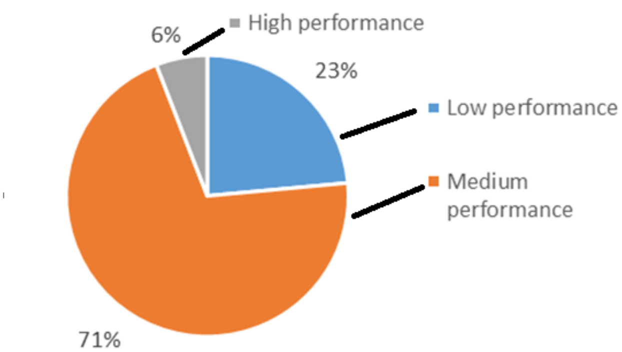

Fig. 8. Pre-Test Score Distribution among Control Group Students.

The Figure 8 illustrates the pre-test score distribution among the control group students, revealing that 23% scored below 10, 71% scored between 10 and 15, and merely 6% attained a score of 15 or higher.

Interesting insights are highlighted by the distribution of students according to different performance levels, as shown in Table 7, which is based on the predictions of the model and the subsequent calculation of the final performance. The approach was validated by the projected values, which show only slight deviations from the pre-test scores.

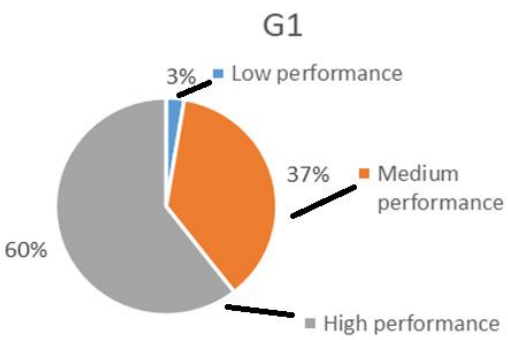

Fig. 9. Post-Test Score Distribution among Experimental Group Students

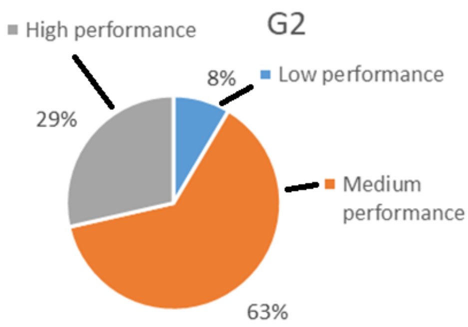

Fig. 10. Post-Test Score Distribution among Control Group Students

The pre-test score distributions depicted in Table 7 and Figure 8 provide a baseline assessment of student performance prior to any intervention.

Comparing these pre-test distributions with the post-test score distributions in Figures 9 and 10 reveals the progress made after the intervention. In the experimental group (Figure 9), only 3% of students achieved low post-test scores, 37% attained middle scores, and 60% reached high scores. Meanwhile, in the control group (Figure 10), 8% scored low, 63% achieved middle scores, and 29% attained high scores.

Based on the comparison, it appears that both groups benefited from the intervention, as gains in post-test scores were noted high performance levels. It is also interesting that the experimental group's high-level performance post-test scores are higher than those of the control group, indicating a greater enhancement in learner performance after the intervention. This trend reinforces the efficacy of the adaptive learning solution in guiding students to suitable courses based on their predicted performance.

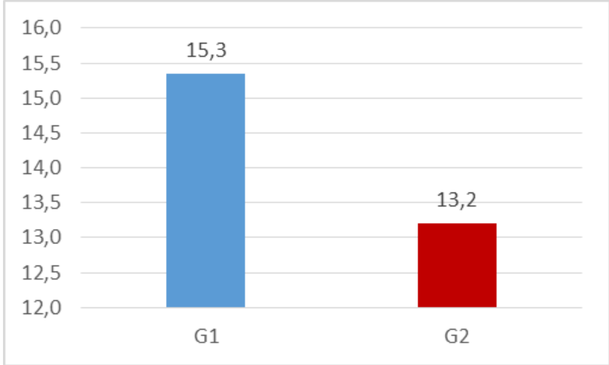

Fig. 11. Comparing the Overall Average between the Two Groups G1 and G2.

The overall average score for Experimental Group (G1) is 15.3, while for Control Group (G2) it is 13.2. This indicates that, on average, students in Group 1 performed better compared to those in Group 2. The higher average score in G1 suggests that the adaptive learning system implemented in this group might have contributed to improved performance outcomes compared to traditional teaching methods employed in G2.

In addition to performance analysis, this study used a questionnaire to examine the impact of adaptive learning on learners' behavioral, emotional, cognitive, and social engagement throughout the experience.

Prior to commencing the experiment, it was imperative to verify the absence of statistically significant differences in engagement dimensions between the experimental and control groups. To ascertain this, the initial engagement questionnaire was administered before the experiment's commencement. Subsequently, independent sample t-tests were conducted using Python to analyze the mean scores of each engagement scale (See Table 8).

TABLE VIII
COMPARISON OF THE CONTROL AND EXPERIMENT PRE-TEST RESULTS

Engagement	Group	Mean	SD	t	p
Behavioral engagement	G1	3.42	1.16	-0.825	0.41
	G2	3.50	1.26		
Emotional engagement	G1	3.86	1.13	-0.451	0.65
	G2	3.89	1.2		
Cognitive engagement	G1	3.24	1.27	-1.75	0.08
	G2	3.42	1.28		
Social engagement	G1	3.48	1.25	-1.95	0.05
	G2	3.73	1.27		

$p > 0.05$.

The analysis indicated that the variation in behavioral, emotional, cognitive, and social engagement between G1 and G2 was 0.41, 0.65, 0.08, and 0.05, respectively ($p > 0.05$), signifying no statistically significant distinction between the two groups. These outcomes were anticipated given that participants were randomly allocated to the groups and all classified as pre-intermediate by the school administration.

TABLE IX
COMPARISON OF EXPERIMENT PRE-TEST AND POST-TEST RESULTS

Engagement	Group	Mean	SD	t	p
Behavioral engagement	Pre-test	3.42	1.16	-4.51	0.00*
	Post-test	3.84	1.12		
Emotional engagement	Pre-test	3.86	1.13	-4.68	0.00*
	Post-test	4.17	0.79		
Cognitive engagement	Pre-test	3.24	1.27	-9.74	0.00*
	Post-test	4.09	0.82		
Social engagement	Pre-test	3.48	1.25	-5.31	0.00*
	Post-test	5.31	0.92		

*p < 0.05.

TABLE X
COMPARISON OF THE CONTROL AND EXPERIMENT POST-TEST RESULTS

Engagement	Group	Mean	SD	t	p
Behavioral engagement	G1	3.84	1.12	3.06	0.002*
	G2	3.55	1.18		
Emotional engagement	G1	4.17	0.79	2.6	0.01*
	G2	3.99	1.13		
Cognitive engagement	G1	4.09	0.82	6.64	0.00*
	G2	3.51	1.25		
Social engagement	G1	5.31	0.92	0.98	0.32
	G2	3.97	1.17		

*p < 0.05.

TABLE XI
COMPARISON OF CONTROL PRE-TEST AND POST-TEST RESULTS

Engagement	Group	Mean	SD	t	p
Behavioral engagement	Pre-test	3.50	1.26	-0.41	0.68
	Post-test	3.55	1.18		
Emotional engagement	Pre-test	3.89	1.2	-1.21	0.23
	Post-test	3.99	1.13		
Cognitive engagement	Pre-test	3.42	1.28	-0.77	0.44
	Post-test	3.51	1.25		
Social engagement	Pre-test	3.73	1.27	-1.79	0.07
	Post-test	3.97	1.17		

p > 0.05.

Comparing pre-test and post-test scores in the experimental group G1 (see Table 9) revealed significant improvements across all four engagement dimensions ($p < 0.05$). Specifically, the mean score of Social engagement in the post-test (M = 5.31) surpassed that in the pre-test (M = 3.48). Similarly, the mean scores of Cognitive engagement (M = 4.09), Emotional engagement (M = 4.17), and Behavioral engagement (M = 3.84) were also higher than those in the pre-test (M = 3.24, 3.86, 3.42, respectively) ($p < 0.05$), indicating statistically significant differences.

Analysis of the post-test questionnaires of the experimental group G1 and the control group G2 (see Table 10) revealed significant differences. In the experimental group G1, the mean score of post-test questionnaires for Behavioral engagement (M = 3.84) was significantly higher than that in the control group G2 (M = 3.55) ($p < 0.05$). Correspondingly, in Cognitive engagement and Emotional engagement, the mean scores of the post-test in the G1 (M = 4.09, 4.17) were notably higher than those in the control group G2 (M = 3.51, 3.99) ($p < 0.05$). Nevertheless, it is noteworthy that in group G1, despite the mean post-test score for social engagement (M = 5.31) being higher than that of group G2 (M = 3.97), this difference did not achieve statistical significance.

Additionally, the mean scores of pre-tests and post-tests in the control group were examined (see Table 11). The analysis indicated that the mean scores of behavioral, emotional, cognitive, and social engagement in the post-tests were higher than those in the pre-tests. Nevertheless, the difference did not reach statistical significance ($p > 0.05$).

VII. DISCUSSION

In this study, an adaptive learning solution was meticulously developed guided by the ADDIE instructional design framework, ensuring a systematic and comprehensive approach throughout the process. The analysis and design phase focused on integrating insights from literature to create a robust adaptive learning system, emphasizing learner needs and educational optimization. This phase laid the groundwork for seamlessly integrating learning styles, performance metrics, and leisure interests, aimed at enhancing engagement and personalization. The development phase involved creating predictive and clustering models seamlessly integrated into the Moodle LMS framework, ensuring a technologically sophisticated and learner-centric system. Using machine learning algorithms, a performance prediction model and a clustering model based on students' leisure interests were developed. These models, along with the Personalized Study Guide plugin, facilitated the generation of personalized learning paths tailored to individual needs, enriching the learning experience.

In the implementation phase, the adaptive learning system was integrated into the Moodle LMS, allowing access to learner data and course materials. Custom fields enhanced the learner profile, capturing personal details and performance metrics. Students were enrolled in courses and assigned to cohorts based on performance and leisure preferences, ensuring targeted content delivery. Course materials were tailored to individual preferences and learning styles, leveraging AI-generated assets for rich educational resources. Finally, in the evaluation phase, the influence of the adaptive learning solution on student performance and engagement was rigorously assessed. Using quantitative methods, a comparison was conducted between two groups: one receiving the adaptive learning solution and the other traditional teaching. Evaluation instruments, encompassing engagement and performance assessments, provided valuable insights into learner involvement and academic achievement.

The results indicate a positive impact of the adaptive learning system on student performance and engagement. Comparing pre-test and post-test score distributions revealed significant progress in both groups, with the experimental group showing higher improvements, particularly in high-level performance scores. The overall average score was higher in the experimental group, suggesting improved performance outcomes compared to traditional teaching methods. Moreover, the experimental group demonstrated significantly higher levels of engagement compared to the control group, indicating the efficacy of adaptive learning interventions in enhancing student participation and motivation. The integration of predictive modeling techniques further facilitated the early identification of at-risk students, allowing for timely interventions and targeted support to address their unique needs. This not only promotes academic success but also fosters a supportive and nurturing learning environment conducive to student growth and development. However, it is imperative to acknowledge that external elements like socio-economic status and individual learning inclinations could impact student engagement and academic performance, necessitating deeper exploration. Subsequent research initiatives should delve into these aspects extensively and evaluate the enduring impacts of adaptive learning interventions on academic achievements and student accomplishments.

TABLE XII
FSLSM-BASED LEARNING OBJECT FORMATS [84]

FSLSM Dimensions		Learning objects formats
Processing	Active	Videos, PPTs, Demo, Exercise, Assignments
	Reflective	PDFs, PPTs, Videos, Announcements, References
Perception	Sensing	Examples, PDFs, Videos, Practical Material
	Intuitive	PDFs, PPTs, Videos, Forum, Topic, List, References
Input	Visual	Images, Charts, Videos, References
	Verbal	PDFs, Videos, Email, Announcements
Understanding	Sequential	Exercise, References, Assignments, Sequential
	Global	Topic Lists, References, Exercise, Assignment

Moving forward, the overarching objective is to construct a more refined predictive model aimed at directly forecasting student grades, thereby enhancing accuracy and efficacy in educational outcomes. Simultaneously, a recommendation system is planned for development, leveraging cosine similarity to suggest learning materials tailored to individual learning styles. This initiative seeks to foster a personalized learning experience conducive to improved engagement and comprehension. Additionally, exploration of alternative formulas is planned to strike a balance between predicted values and diagnostic assessment scores, aiming to further refine the predictive process. Furthermore, efforts will be directed towards crafting a more intuitive and advanced plugin designed to minimize the need for high technical expertise during pre-configuration. Additionally, additional features such as absenteeism rates are intended to be incorporated into the predictive model to capture a more comprehensive understanding of student performance determinants. This upgraded plugin will automate the setup of all essential components, including questionnaires, profile custom fields, and additional plugins, thereby simplifying the implementation process and encouraging widespread utilization. By streamlining the setup procedures, the aim is to broaden the accessibility and usability of the adaptive learning system, thereby enhancing its efficacy and suitability across diverse academic settings. Through these concerted efforts, the aim is to advance the field of adaptive learning and contribute to fostering academic success and student well-being.

VIII. CONCLUSION

Among the different adaptation approaches, the machine learning approach stands as one of the pillars of AI-enabled Adaptive Learning Systems (ALS), offering a range of algorithms that enable:

- Suggest appropriate learning materials based on the learner's most influential factors, especially using reinforcement learning [159].
- Quickly identify similar users based on the extracted data using k-means algorithm as machine learning clustering methods, resulting in the recommendation of appropriate items for the new user [160].
- Successfully personalizing learning units and evaluating their acceptance and use through learning analytics and decision-making [161].

In conclusion, it should be mentioned that this field of study, which has roots in the 1950s, was and continues to be a rich one that tracks technical advancement and pedagogical innovations, which support the ongoing development of the educational sector. In light of this, the study attempted to introduce an adaptable learning system architecture based on AI that surpasses traditional one-size-fits-all approaches. This advanced system takes into account a number of factors and uses a multi-phase strategy to ensure the delivery of appropriate learning content that is in line with each learner's preferences, performance level, and learning style. The architecture strives to provide a thorough personalization process by embracing both affective and cognitive dimension. It leverages data-driven approaches, sophisticated AI technologies, and meticulous content adaptation, including algorithms such as k-means clustering, Support Vector Regressor and Gradient Boosting Regressor to enhance the precision of the system.

There are many benefits to the creation of this adaptive learning system. First, by concentrating on each learner's unique requirements and interests, the system has the ability to speed up knowledge acquisition by removing extraneous content. Furthermore, the adjustment to the preferences of the learner, will conduct to the increase their level of engagement.

The research represents a significant step forward in the development and implementation of an adaptive learning solution within the Moodle Learning Management System framework. The implementation of the system in Moroccan high schools yielded promising results, as evidenced by improvements in student performance and engagement. Looking ahead, future research endeavors will focus on expanding the participant pool, refining the adaptive learning system, and enhancing its accessibility and usability.

REFERENCES

[1] “The Decline and Fall of the Laws of Learning, - W. J. McKEACHIE, 1974.” Accessed: Dec. 18, 2021. [Online]. Available: https://journals.sagepub.com/doi/abs/10.3102/0013189X003003007?journalCode=edra
[2] G. Pask, “SAKI: Twenty-five years of adaptive training into the microprocessor era,” International Journal of Man-Machine Studies,

vol. 17, no. 1, pp. 69–74, Jul. 1982, doi: 10.1016/S0020-7373(82)80009-6.

[3] G. K. Randhawa and M. Jackson, "The role of artificial intelligence in learning and professional development for healthcare professionals," Healthc Manage Forum, vol. 33, no. 1, pp. 19–24, Jan. 2020, doi: 10.1177/0840470419869032.

[4] M. P. Driscoll, Psychology of learning for instruction, 3. ed., Internat. ed. Boston: Pearson A and B, 2005.

[5] J. Psotka, L. D. Massey, and S. A. Mutter, Intelligent tutoring systems: Lessons learned. Psychology Press, 1988.

[6] C. Wilson and B. Scott, "Adaptive systems in education: a review and conceptual unification," The International Journal of Information and Learning Technology, vol. 34, no. 1, pp. 2–19, Jan. 2017, doi: 10.1108/IJILT-09-2016-0040.

[7] N. Kara and N. Sevim, "Adaptive Learning Systems: Beyond Teaching Machines," Contemporary Educational Technology, vol. 4, no. 2, pp. 108–120, 2013.

[8] A. Çebi, R. D. Araújo, and P. Brusilovsky, "Do individual characteristics affect online learning behaviors? An analysis of learners sequential patterns," Journal of Research on Technology in Education, vol. 55, no. 4, pp. 663–683, Jul. 2023, doi: 10.1080/15391523.2022.2027301.

[9] K. Mangaroska, K. Sharma, D. Gašević, and M. Giannakos, "Exploring students' cognitive and affective states during problem solving through multimodal data: Lessons learned from a programming activity," Journal of Computer Assisted Learning, vol. 38, no. 1, pp. 40–59, 2022, doi: 10.1111/jcal.12590.

[10] W. Kaiss, K. Mansouri, and F. Poirier, "Effectiveness of an Adaptive Learning Chatbot on Students' Learning Outcomes Based on Learning Styles," International Journal of Emerging Technologies in Learning (iJET), vol. 18, no. 13, Art. no. 13, Jul. 2023, doi: 10.3991/ijet.v18i13.39329.

[11] P. K. Udupi, P. Malali, and H. Noronha, "Big data integration for transition from e-learning to smart learning framework," in 2016 3rd MEC International Conference on Big Data and Smart City (ICBDSC), Mar. 2016, pp. 1–4. doi: 10.1109/ICBDSC.2016.7460379.

[12] T. Hailikari, A. Nevgi, and E. Komulainen, "Academic self-beliefs and prior knowledge as predictors of student achievement in Mathematics: A structural model," Educational psychology, vol. 28, no. 1, pp. 59–71, 2008.

[13] M. D. Ariastuti and A. Y. Wahyudin, "EXPLORING ACADEMIC PERFORMANCE AND LEARNING STYLE OF UNDERGRADUATE STUDENTS IN ENGLISH EDUCATION PROGRAM," Journal of English Language Teaching and Learning, vol. 3, no. 1, Art. no. 1, Jul. 2022, doi: 10.33365/jeltl.v3i1.1817.

[14] E. S. Twilhaar, J. F. de Kieviet, C. S. Aarnoudse-Moens, R. M. van Elburg, and J. Oosterlaan, "Academic performance of children born preterm: a meta-analysis and meta-regression," Archives of Disease in Childhood-Fetal and Neonatal Edition, vol. 103, no. 4, pp. F322–F330, 2018.

[15] P. D. Randolph, "Construction and psychometric evaluation of the revised leisure preference inventory: toward an understanding of leisure versus vocationally derived interests," PhD Thesis, Texas Tech University, 1992.

[16] D. D. Hendel and R. Harrold, "Changes in Clark-Trow Subcultures from 1976 to 2006: Implications for Addressing Undergraduates' Leisure Interests.," College Student Affairs Journal, vol. 27, no. 1, pp. 8–23, 2007.

[17] M. S. Hasibuan and L. Nugroho, "Detecting learning style using hybrid model," in 2016 IEEE Conference on e-Learning, e-Management and e-Services (IC3e), Oct. 2016, pp. 107–111. doi: 10.1109/IC3e.2016.8009049.

[18] R. Dunn, "Learning style: State of the science," Theory Into Practice, vol. 23, no. 1, pp. 10–19, Jan. 1984, doi: 10.1080/00405848409543084.

[19] C. Waladi, M. Khaldi, and M. L. Sefian, "Machine Learning Approach for an Adaptive E-Learning System Based on Kolb Learning Styles," International Journal of Emerging Technologies in Learning (iJET), vol. 18, no. 12, Art. no. 12, Jun. 2023, doi: 10.3991/ijet.v18i12.39327.

[20] Y. Roh, G. Heo, and S. E. Whang, "A survey on data collection for machine learning: a big data-ai integration perspective," IEEE Transactions on Knowledge and Data Engineering, vol. 33, no. 4, pp. 1328–1347, 2019.

[21] C. Bolton, V. Machová, M. Kovacova, and K. Valaskova, "The power of human–machine collaboration: Artificial intelligence, business automation, and the smart economy," Economics, Management, and Financial Markets, vol. 13, no. 4, pp. 51–56, 2018.

[22] K. Pliakos, S.-H. Joo, J. Y. Park, F. Cornillie, C. Vens, and W. Van den Noortgate, "Integrating machine learning into item response theory for addressing the cold start problem in adaptive learning systems," Computers & Education, vol. 137, pp. 91–103, Aug. 2019, doi: 10.1016/j.compedu.2019.04.009.

[23] J. Isabona, A. L. Imoize, and Y. Kim, "Machine learning-based boosted regression ensemble combined with hyperparameter tuning for optimal adaptive learning," Sensors, vol. 22, no. 10, p. 3776, 2022.

[24] D. Noble and R. Noble, Eds., "Artificial Intelligence," in Understanding Living Systems, in Understanding Life. , Cambridge: Cambridge University Press, 2023, pp. 99–112. doi: 10.1017/9781009277396.009.

[25] Y. S. Pongtambing et al., "Peluang dan Tantangan Kecerdasan Buatan Bagi Generasi Muda," Bakti Sekawan : Jurnal Pengabdian Masyarakat, vol. 3, no. 1, Art. no. 1, Jun. 2023, doi: 10.35746/bakwan.v3i1.362.

[26] A. F. Ola, "Artificial intelligence (AI) is intelligence—perceiving, synthesizing, and inferring information—," OSF Preprints, Art. no. 37m9k, Jan. 2023, Accessed: Feb. 03, 2024. [Online]. Available: https://ideas.repec.org//p/osf/osfxxx/37m9k.html

[27] A. Ezzaim, F. Kharroubi, A. Dahbi, A. Aqqal, and A. Haidine, "Artificial intelligence in education - State of the art," International Journal of Computer Engineering and Data Science (IJCEDS), vol. 2, no. 2, Art. no. 2, Jun. 2022, Accessed: Oct. 27, 2022. [Online]. Available: http://www.ijceds.com/ijceds/article/view/37

[28] A. Ezzaim, A. Dahbi, N. Assad, and A. Haidine, "AI-Based Adaptive Learning - State of the Art," in International Conference on Advanced Intelligent Systems for Sustainable Development, J. Kacprzyk, M. Ezziyyani, and V. E. Balas, Eds., in Lecture Notes in Networks and Systems. Cham: Springer Nature Switzerland, 2023, pp. 155–167. doi: 10.1007/978-3-031-26384-2_14.

[29] M. Vandewaetere, P. Desmet, and G. Clarebout, "The contribution of learner characteristics in the development of computer-based adaptive learning environments," Computers in Human Behavior, vol. 27, no. 1, pp. 118–130, Jan. 2011, doi: 10.1016/j.chb.2010.07.038.

[30] S. Ennouamani and Z. Mahani, "An overview of adaptive e-learning systems," in 2017 Eighth International Conference on Intelligent Computing and Information Systems (ICICIS), Dec. 2017, pp. 342–347. doi: 10.1109/INTELCIS.2017.8260060.

[31] G.-J. Hwang, H.-Y. Sung, S.-C. Chang, and X.-C. Huang, "A fuzzy expert system-based adaptive learning approach to improving students' learning performances by considering affective and cognitive factors," Computers and Education: Artificial Intelligence, vol. 1, p. 100003, Jan. 2020, doi: 10.1016/j.caeai.2020.100003.

[32] J. Vassoyan, J.-J. Vie, and P. Lemberger, "Towards Scalable Adaptive Learning with Graph Neural Networks and Reinforcement Learning." arXiv, May 10, 2023. Accessed: Jan. 08, 2024. [Online]. Available: http://arxiv.org/abs/2305.06398

[33] T. T. Tursynova, K. M. Saginov, and S. M. Bakhisheva, "Application of adaptive learning technology in the educational process," jour, no. 2, pp. 98–112, Jun. 2023, doi: 10.52512/2306-5079-2023-94-2-98-112.

[34] C. Lu, M. Chang, Kinshuk, E. Huang, and C.-W. Chen, "Context-Aware Mobile Role Playing Game for Learning," in The New Development of Technology Enhanced Learning: Concept, Research and Best Practices, R. Huang, Kinshuk, and N.-S. Chen, Eds., in Lecture Notes in Educational Technology. , Berlin, Heidelberg: Springer, 2014, pp. 131–146. doi: 10.1007/978-3-642-38291-8_8.

[35] Y. Wang and H.-C. Liao, "Adaptive learning for ESL based on computation," British Journal of Educational Technology, vol. 42, no. 1, pp. 66–87, 2011, doi: 10.1111/j.1467-8535.2009.00981.x.

[36] K. Scheiter et al., "Adaptive multimedia: Using gaze-contingent instructional guidance to provide personalized processing support," Computers & Education, vol. 139, pp. 31–47, Oct. 2019, doi: 10.1016/j.compedu.2019.05.005.

[37] A. Paramythis and S. Loidl-Reisinger, "Adaptive learning environments and e-learning standards," in Second european conference on e-learning, 2003, pp. 369–379.

[38] P. Brusilovsky, "Adaptive and Intelligent Technologies for Web-based Eduction.," KI, vol. 13, pp. 19–25, Jan. 1999.

[39] S. Stoyanov and P. Kirchner, "Expert concept mapping method for defining the characteristics of adaptive E-learning: ALFANET project case," ETR&D, vol. 52, no. 2, pp. 41–54, Jun. 2004, doi: 10.1007/BF02504838.

[40] C. Vu Minh, "Constructivist learning : an operational approach for designing adaptive learning environments supporting cognitive flexibility/," UCL - Université Catholique de Louvain, 2005. Accessed: Dec. 28, 2021. [Online]. Available: https://dial.uclouvain.be/pr/boreal/object/boreal:5145

[41] M. M. Ariffin, A. Oxley, and S. Sulaiman, "Evaluating game-based learning effectiveness in higher education," Procedia-Social and Behavioral Sciences, vol. 123, pp. 20–27, 2014.

[42] M. A. Maisela, "Exploring the impact of ICT integration on learner performance in Grade 10 Physical Sciences," Oct. 2021, Accessed: Aug. 31, 2023. [Online]. Available: https://uir.unisa.ac.za/handle/10500/29901

[43] A. Woods, "Subjective adjustments to objective performance measures: The influence of prior performance," Accounting, Organizations and Society, vol. 37, no. 6, pp. 403–425, 2012.

[44] M. F. Hamidullah, V. M. Wilkins, and K. J. Meier, "Looking for their Dick Vermeil: How prior performance influences the selection decision," Public Organization Review, vol. 9, pp. 1–14, 2009.

[45] K. E. Howard and K. A. Anderson, "STEREOTYPE THREAT IN MIDDLE SCHOOL The Effects of Prior Performance on Expectancy and Test Performance.," Middle Grades Research Journal, vol. 5, no. 3, 2010.

[46] B. L. Schroeder, W. L. Van Buskirk^1, M. Aros, J. E. Hochreiter^1, and N. W. Fraulini, "Check for updates Which is Better Individualized Training for a Novel, Complex Task? Learner Control vs.," in Adaptive Instructional Systems: 5th International Conference, AIS 2023, Held as Part of the 25th HCI International Conference, HCII 2023, Copenhagen, Denmark, July 23–28, 2023, Proceedings, Springer Nature, 2023, p. 236.

[47] S. Kalyuga, "Tailoring Multimedia Environments to Learner Cognitive Characteristics," in Managing Cognitive Load in Adaptive Multimedia Learning, IGI Global, 2009, pp. 221–245. doi: 10.4018/978-1-60566-048-6.ch010.

[48] M. E. Perreault and K. E. French, "External-focus feedback benefits free-throw learning in children," Research quarterly for exercise and sport, vol. 86, no. 4, pp. 422–427, 2015.

[49] R. Rod, A. Laura, and B. Renu, "Literacy: From the perspective of text and discourse theory," Journal of Language and Education, vol. 5, no. 3 (19), pp. 56–69, 2019.

[50] G. Kennedy, C. Coffrin, P. de Barba, and L. Corrin, "Predicting success: how learners' prior knowledge, skills and activities predict MOOC performance," in Proceedings of the Fifth International Conference on Learning Analytics And Knowledge, in LAK '15. New York, NY, USA: Association for Computing Machinery, Mar. 2015, pp. 136–140. doi: 10.1145/2723576.2723593.

[51] Priyanka Shirsat, "Developing Deep Neural Network for Learner Performance Prediction in EKhool Online Learning Platform," MR, vol. 3, no. 4, pp. 24–31, Oct. 2020, doi: 10.46253/j.mr.v3i4.a3.

[52] M. Imran, S. Latif, D. Mehmood, and M. S. Shah, "Student Academic Performance Prediction using Supervised Learning Techniques," International Journal of Emerging Technologies in Learning (iJET), vol. 14, no. 14, Art. no. 14, Jul. 2019, doi: 10.3991/ijet.v14i14.10310.

[53] Z. Xu, H. Yuan, and Q. Liu, "Student Performance Prediction Based on Blended Learning," IEEE Transactions on Education, vol. 64, no. 1, pp. 66–73, Feb. 2021, doi: 10.1109/TE.2020.3008751.

[54] A. K. Pal and S. Pal, "Data mining techniques in EDM for predicting the performance of students," International Journal of Computer and Information Technology, vol. 2, no. 06, pp. 2279–0764, 2013.

[55] S. Natek and M. Zwilling, "Student data mining solution–knowledge management system related to higher education institutions," Expert Systems with Applications, vol. 41, no. 14, pp. 6400–6407, Oct. 2014, doi: 10.1016/j.eswa.2014.04.024.

[56] S. B. Kotsiantis, "Use of machine learning techniques for educational proposes: a decision support system for forecasting students' grades," Artif Intell Rev, vol. 37, no. 4, pp. 331–344, Apr. 2012, doi: 10.1007/s10462-011-9234-x.

[57] E. Osmanbegovic and M. Suljic, "Data Mining Approach for Predicting Student Performance," Economic Review: Journal of Economics and Business, vol. 10, no. 1, pp. 3–12, 2012.

[58] A. Ahmed and I. S. Elaraby, "Data mining: A prediction for student's performance using classification method," World Journal of Computer Application and Technology, vol. 2, no. 2, pp. 43–47, 2014.

[59] D. Aggarwal, S. Mittal, and V. Bali, "Significance of Non-Academic Parameters for Predicting Student Performance Using Ensemble Learning Techniques," IJSDA, vol. 10, no. 3, pp. 38–49, Jul. 2021, doi: 10.4018/IJSDA.2021070103.

[60] A. O. Oyedeji, A. M. Salami, O. Folorunsho, and O. R. Abolade, "Analysis and Prediction of Student Academic Performance Using Machine Learning," JITCE (Journal of Information Technology and Computer Engineering), vol. 4, no. 01, Art. no. 01, Mar. 2020, doi: 10.25077/jitce.4.01.10-15.2020.

[61] C. Márquez-Vera, A. Cano, C. Romero, A. Y. M. Noaman, H. Mousa Fardoun, and S. Ventura, "Early dropout prediction using data mining: a case study with high school students," Expert Systems, vol. 33, no. 1, pp. 107–124, 2016, doi: 10.1111/exsy.12135.

[62] Z. Li and J. Li, "Using the Flipped Classroom to Promote Learner Engagement for the Sustainable Development of Language Skills: A Mixed-Methods Study," Sustainability, vol. 14, no. 10, Art. no. 10, Jan. 2022, doi: 10.3390/su14105983.

[63] H. Çiğdem and S. Öncü, "Learner Engagement in the Metaverse: A Community of Inquiry for Self-Regulated Learners," in Shaping the Future of Online Learning: Education in the Metaverse, IGI Global, 2023, pp. 17–36. doi: 10.4018/978-1-6684-6513-4.ch002.

[64] K. Kipp and K. L. Rice, "Building Engagement in K-12 Online Learning," in Handbook of Research on Emerging Practices and Methods for K-12 Online and Blended Learning, IGI Global, 2019, pp. 171–192. doi: 10.4018/978-1-5225-8009-6.ch008.

[65] S. Mercer and Z. Dörnyei, Engaging Language Learners in Contemporary Classrooms. Cambridge University Press, 2020.

[66] G. P. Poudel, "Students' Motivation of, and Engagement in Reading with Stories," Shiksha Shastra Saurabh, pp. 30–43, Dec. 2022, doi: 10.3126/sss.v23i1.51931.

[67] E. I. Alzaanin, "Using the Motivation and Engagement Wheel to Examine the Interplay Between Learner Engagement, Motivation, Year Level, and Academic Achievement in an EFL Tertiary Context," Journal of Language Teaching and Research, vol. 14, no. 3, Art. no. 3, May 2023, doi: 10.17507/jltr.1403.25.

[68] J. A. Fredricks, P. C. Blumenfeld, and A. H. Paris, "School Engagement: Potential of the Concept, State of the Evidence," Review of Educational Research, vol. 74, no. 1, pp. 59–109, Mar. 2004, doi: 10.3102/00346543074001059.

[69] E. R. Kahu, "Framing student engagement in higher education," Studies in Higher Education, Jun. 2013, Accessed: May 09, 2024. [Online]. Available: https://www.tandfonline.com/doi/abs/10.1080/03075079.2011.598505

[70] J. Feldman, A. Monteserin, and A. Amandi, "Automatic detection of learning styles: state of the art," Artif Intell Rev, vol. 44, no. 2, pp. 157–186, Aug. 2015, doi: 10.1007/s10462-014-9422-6.

[71] C. Refugio and L. Guzman, "STUDENTS' LEARNING STYLE INVENTORY," 2018. doi: 10.13140/RG.2.2.30531.25124.

[72] A. Furnham, "Personality and learning style: A study of three instruments," Personality and Individual Differences, vol. 13, no. 4, pp. 429–438, Apr. 1992, doi: 10.1016/0191-8869(92)90071-V.

[73] W. Xu, "Learning Styles and Their Implications in Learning and Teaching," TPLS, vol. 1, no. 4, pp. 413–416, Apr. 2011, doi: 10.4304/tpls.1.4.413-416.

[74] E. Sadler-Smith, "'Learning Styles' and Instructional Design," Innovations in Education and Training International, vol. 33, no. 4, pp. 185–193, Nov. 1996, doi: 10.1080/1355800960330405.

[75] K. Hyland, "Culture and Learning: A Study of the learning style preferences of Japanese Students," RELC Journal, vol. 24, no. 2, pp. 69–87, Dec. 1993, doi: 10.1177/003368829302400204.

[76] C. Manolis, D. J. Burns, R. Assudani, and R. Chinta, "Assessing experiential learning styles: A methodological reconstruction and validation of the Kolb Learning Style Inventory," Learning and Individual Differences, vol. 23, pp. 44–52, Feb. 2013, doi: 10.1016/j.lindif.2012.10.009.

[77] P. Honey and A. Mumford, Using your learning styles. Chartered Institute of Personnel and Development, 1986.

[78] R. M. Felder and L. K. Silverman, "Learning and teaching styles in engineering education," Engineering education, vol. 78, no. 7, pp. 674–681, 1988.

[79] L. Alkooheji and A. Al-Hattami, "Learning Style Preferences among College Students," International Education Studies, vol. 11, no. 10, pp. 50–63, 2018.

[80] R. Dunn, "Understanding the Dunn and Dunn Learning Styles Model and the Need for Individual Diagnosis and Prescription," Journal of Reading, Writing, and Learning Disabilities International, vol. 6, no. 3, pp. 223–247, Jan. 1990, doi: 10.1080/0748763900060303.

[81] G. Pask, "Styles and Strategies of Learning," British Journal of Educational Psychology, vol. 46, no. 2, pp. 128–148, 1976, doi: 10.1111/j.2044-8279.1976.tb02305.x.

[82] A. F. Gregorc, Gregorc style delineator: development, technical, and administration manual. Maynard, MA: Gabriel Systems, Inc., 1982.

[83] O. El Aissaoui, Y. El Alami El Madani, L. Oughdir, and Y. El Allioui, “A fuzzy classification approach for learning style prediction based on web mining technique in e-learning environments,” Educ Inf Technol, no. 3, pp. 1943–1959, May 2019, doi: 10.1007/s10639-018-9820-5.

[84] S. V. Kolekar, R. M. Pai, and M. P. M. M, “Prediction of Learner’s Profile based on Learning Styles in Adaptive E-learning System,” International Journal of Emerging Technologies in Learning (iJET), vol. 12, no. 06, Art. no. 06, Jun. 2017, doi: 10.3991/ijet.v12i06.6579.

[85] C. Romero and S. Ventura, “Educational data mining: A survey from 1995 to 2005,” Expert Systems with Applications, vol. 33, no. 1, pp. 135–146, Jul. 2007, doi: 10.1016/j.eswa.2006.04.005.

[86] S. Wibirama, A. P. Sidhawara, G. Lukhayu Pritalia, and T. B. Adji, “A Survey of Learning Style Detection Method using Eye-Tracking and Machine Learning in Multimedia Learning,” in 2020 International Symposium on Community-centric Systems (CcS), Sep. 2020, pp. 1–6. doi: 10.1109/CcS49175.2020.9231447.

[87] R. R. I. Maaliw and M. A. Ballera, “Classification of Learning Styles in Virtual Learning Environment Using J48 Decision Tree,” International Association for the Development of the Information Society, Oct. 2017. Accessed: Dec. 21, 2022. [Online]. Available: https://eric.ed.gov/?id=ED579490

[88] Y. Ikawati, M. U. H. Al Rasyid, and I. Winarno, “Student Behavior Analysis to Detect Learning Styles in Moodle Learning Management System,” in 2020 International Electronics Symposium (IES), Sep. 2020, pp. 501–506. doi: 10.1109/IES50839.2020.9231567.

[89] Y. Gambo and M. Shakir, “An Artificial Neural Network (ANN)-Based Learning Agent for Classifying Learning Styles in Self-Regulated Smart Learning Environment,” International Journal of Emerging Technologies in Learning (iJET), vol. 16, no. 18, pp. 185–199, Sep. 2021.

[90] N. Hidayat, R. Wardoyo, S. N. Azhari, and H. D. Surjono, “Enhanced performance of the automatic learning style detection model using a combination of modified k-means algorithm and naive bayesian,” International Journal of Advanced Computer Science and Applications, vol. 11, no. 3, pp. 638–648, 2020.

[91] F. Rasheed and A. Wahid, “Learning style detection in E-learning systems using machine learning techniques,” Expert Systems with Applications, vol. 174, p. 114774, Jul. 2021, doi: 10.1016/j.eswa.2021.114774.

[92] L. J. DEBORAH, R. SATHIYASEELAN, S. AUDITHAN, and P. VIJAYAKUMAR, “Fuzzy-logic based learning style prediction in e-learning using web interface information,” Sadhana, vol. 40, no. 2, pp. 379–394, Apr. 2015, doi: 10.1007/s12046-015-0334-1.

[93] O. E. Aissaoui, Y. E. A. El madani, L. Oughdir, and Y. E. Allioui, “Combining supervised and unsupervised machine learning algorithms to predict the learners’ learning styles,” Procedia Computer Science, vol. 148, pp. 87–96, Jan. 2019, doi: 10.1016/j.procs.2019.01.012.

[94] L. Hoffmann, J. Baumert, A. Krapp, and K. Renninger, “Interest and learning: Proceedings of the Seeon Conference on Interest and Gender,” 1998.

[95] U. Schiefele, “Interest, Learning, and Motivation,” Educational Psychologist, vol. 26, no. 3–4, pp. 299–323, Jun. 1991, doi: 10.1080/00461520.1991.9653136.

[96] L. I. A. R. Dewi, “A cultural portrait of ‘little c’ themes in an English textbook used by Indonesian junior high school students: A content analysis,” Aksara, vol. 20, no. 2, p. 360838, 2019.

[97] J. L. Korell, “A Corpus-based Study of Gender Representation in ELE Textbooks — Language, Illustrations and Topic Areas,” Journal of Language Teaching and Research, vol. 12, no. 2, Art. no. 2, Mar. 2021, doi: 10.17507/jltr.1202.01.

[98] K. A. Renninger, J. E. Bachrach, and S. K. Posey, “Learner interest and achievement motivation,” Social psychological perspectives, vol. 15, pp. 461–491, 2008.

[99] E. R. Lai, “Motivation: A literature review,” Person Research’s Report, vol. 6, pp. 40–41, 2011.

[100] H. Herpratiwi and T. Ahmad, “Learning interest and discipline on learning motivation,” 2021.

[101] T. Kabudi, I. Pappas, and D. Olsen, Systematic Literature Mapping on AI-enabled Contemporary Learning Systems. 2020.

[102] X. Wan, “A study on the current development of Artificial Intelligence in education industry in China,” in 2021 7th International Conference on Education and Training Technologies, in ICETT 2021. New York, NY, USA: Association for Computing Machinery, Jul. 2021, pp. 28–35. doi: 10.1145/3463531.3463536.

[103] S. Adamu and J. Awwalu, “The role of artificial intelligence (AI) in adaptive elearning system (AES) content FORMATION: risks and opportunities involved,” arXiv preprint arXiv:1903.00934, 2019.

[104] B. C. Surve and B. R. Londhe, “Artificial Intelligence based assessment and development of student’s Non-cognitive skills in Professional Education through an online Learning Management System,” in 2020 Fourth International Conference on Inventive Systems and Control (ICISC), IEEE, 2020, pp. 329–336.

[105] H. A. El-Sabagh, “Adaptive e-learning environment based on learning styles and its impact on development students’ engagement,” International Journal of Educational Technology in Higher Education, vol. 18, no. 1, p. 53, Oct. 2021, doi: 10.1186/s41239-021-00289-4.

[106] N. A. Anindyaputri, R. A. Yuana, and P. Hatta, “Enhancing Students’ Ability in Learning Process of Programming Language using Adaptive Learning Systems: A Literature Review,” Open Engineering, vol. 10, no. 1, pp. 820–829, Jan. 2020, doi: 10.1515/eng-2020-0092.

[107] K. Agustini, “The Adaptive Elearning System Design : Student Learning Style Trend Analysis,” presented at the 2nd International Conference on Innovative Research Across Disciplines (ICIRAD 2017), Atlantis Press, Aug. 2017, pp. 50–54. doi: 10.2991/icirad-17.2017.10.

[108] C. Imhof, P. Bergamin, and S. McGarrity, “Implementation of Adaptive Learning Systems: Current State and Potential,” in Online Teaching and Learning in Higher Education, P. Isaias, D. G. Sampson, and D. Ifenthaler, Eds., in Cognition and Exploratory Learning in the Digital Age. , Cham: Springer International Publishing, 2020, pp. 93–115. doi: 10.1007/978-3-030-48190-2_6.

[109] T. Kabudi, Identifying Design Principles for an AI-enabled Adaptive Learning Systems. 2021.

[110] N. Morze, L. Varchenko-Trotsenko, T. Terletska, and E. Smyrnova-Trybulska, “Implementation of adaptive learning at higher education institutions by means of Moodle LMS,” J. Phys.: Conf. Ser., vol. 1840, no. 1, p. 012062, Mar. 2021, doi: 10.1088/1742-6596/1840/1/012062.

[111] J. J. Ramirez-Echeverry, F. Restrepo-Calle, and F. González, UNCODE: INTERACTIVE SYSTEM FOR LEARNING AND AUTOMATIC EVALUATION OF COMPUTER PROGRAMMING SKILLS. 2018. doi: 10.21125/edulearn.2018.1632.

[112] V. C. Vijay, “A Knowledge Based Educational (KBEd) framework for enhancing practical skills in engineering distance learners through an augmented reality environment,” doctoral, Birmingham City University, 2017. Accessed: Jan. 12, 2022. [Online]. Available: http://www.open-access.bcu.ac.uk/7223/

[113] A. Klašnja-Milićević, M. Ivanović, B. Vesin, and Z. Budimac, “Enhancing e-learning systems with personalized recommendation based on collaborative tagging techniques,” Appl Intell, vol. 48, no. 6, pp. 1519–1535, Jun. 2018, doi: 10.1007/s10489-017-1051-8.

[114] Y. Hernández, L. E. Sucar, and G. Arroyo-Figueroa, “Evaluating an Affective Student Model for Intelligent Learning Environments,” in Advances in Artificial Intelligence – IBERAMIA 2010, A. Kuri-Morales and G. R. Simari, Eds., in Lecture Notes in Computer Science. Berlin, Heidelberg: Springer, 2010, pp. 473–482. doi: 10.1007/978-3-642-16952-6_48.

[115] C.-C. Chen, P.-S. Chiu, and Y.-M. Huang, “The learning style-based adaptive learning system architecture,” International Journal of Online Pedagogy and Course Design (IJOPCD), vol. 5, no. 2, pp. 1–10, 2015.

[116] S. Hammami and H. Mathkour, “Adaptive e-learning system based on agents and object petri nets (AELS-A/OPN),” Computer Applications in Engineering Education, vol. 23, no. 2, pp. 170–190, 2015, doi: 10.1002/cae.21587.

[117] R. R. Maaliw, “Adaptive Virtual Learning Environment Based on Learning Styles for Personalizing E-Learning System: Design and Implementation,” Mar. 2020. Accessed: Dec. 21, 2022. [Online]. Available: https://eric.ed.gov/?id=ED610591

[118] T. Sheeba and R. Krishnan, “Automatic detection of students learning style in learning management system,” in Smart technologies and innovation for a sustainable future, Springer, 2019, pp. 45–53.

[119] I. Karagiannis and M. Satratzemi, “Implementation of an Adaptive Mechanism in Moodle Based on a Hybrid Dynamic User Model,” in The Challenges of the Digital Transformation in Education, M. E. Auer and T. Tsiatsos, Eds., in Advances in Intelligent Systems and

Computing. Cham: Springer International Publishing, 2020, pp. 377–388. doi: 10.1007/978-3-030-11932-4_36.
[120] J.-J. Lo, Y.-C. Chan, and S.-W. Yeh, "Designing an adaptive web-based learning system based on students' cognitive styles identified online," Computers & Education, vol. 58, no. 1, pp. 209–222, Jan. 2012, doi: 10.1016/j.compedu.2011.08.018.
[121] B. Arsovic and N. Stefanovic, "E-learning based on the adaptive learning model: case study in Serbia," Sādhanā, vol. 45, no. 1, p. 266, 2020.
[122] S. Jagadeesan and J. Subbiah, "RETRACTED ARTICLE: Real-time personalization and recommendation in Adaptive Learning Management System," Journal of ambient intelligence and humanized computing, vol. 11, no. 11, pp. 4731–4741, 2020.
[123] A.-E. Guerrero-Roldán, M. E. Rodríguez-González, D. Bañeres, A. Elasri-Ejjaberi, and P. Cortadas, "Experiences in the use of an adaptive intelligent system to enhance online learners' performance: a case study in Economics and Business courses," International Journal of Educational Technology in Higher Education, vol. 18, pp. 1–27, 2021.
[124] S. Missaoui and A. Maalel, "Student's profile modeling in an adaptive gamified learning environment," Education and Information Technologies, vol. 26, no. 5, pp. 6367–6381, 2021.
[125] E. Gomede, R. M. de Barros, and L. de S. Mendes, "Deep auto encoders to adaptive E-learning recommender system," Computers and Education: Artificial Intelligence, vol. 2, p. 100009, Jan. 2021, doi: 10.1016/j.caeai.2021.100009.
[126] I. Karagiannis and M. Satratzemi, "An adaptive mechanism for Moodle based on automatic detection of learning styles," Educ Inf Technol, vol. 23, no. 3, pp. 1331–1357, May 2018, doi: 10.1007/s10639-017-9663-5.
[127] E. Gomede, R. Miranda de Barros, and L. de Souza Mendes, "Use of Deep Multi-Target Prediction to Identify Learning Styles," Applied Sciences, vol. 10, no. 5, p. 1756, Jan. 2020, doi: 10.3390/app10051756.
[128] L. X. Li and S. S. Abdul Rahman, "Students' learning style detection using tree augmented naive Bayes," Royal Society Open Science, vol. 5, no. 7, p. 172108, doi: 10.1098/rsos.172108.
[129] N. Ugarte, M. Larrañaga, and A. Arruarte, "The Use of Recommender Systems in Formal Learning. A Systematic Literature Mapping," JUCS - Journal of Universal Computer Science, vol. 28, no. 4, pp. 414–442, Apr. 2022, doi: 10.3897/jucs.69711.
[130] A. Aziz, R. El-Khoribi, and S. Taie, "ADAPTIVE E-LEARNING RECOMMENDATION MODEL BASED ON THE KNOWLEDGE LEVEL AND LEARNING STYLE," Journal of Theoretical and Applied Information Technology, vol. 99, p. 22, Nov. 2021.
[131] S. Sfenrianto, Y. B. Hartarto, H. Akbar, M. Mukhtar, E. Efriadi, and M. Wahyudi, "An adaptive learning system based on knowledge level for English learning," International Journal of Emerging Technologies in Learning (Online), vol. 13, no. 12, p. 191, 2018.
[132] M. Siadaty and F. Taghiyareh, "PALS2: Pedagogically adaptive learning system based on learning styles," in Seventh IEEE International Conference on Advanced Learning Technologies (ICALT 2007), IEEE, 2007, pp. 616–618.
[133] H. K. M. Al-Chalabi, A. M. A. Hussein, and U. C. Apoki, "An Adaptive Learning System Based on Learner's Knowledge Level," in 2021 13th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), IEEE, 2021, pp. 1–4.
[134] Y. Sun, "Exploring the Construction of Curriculum System of Theater and Film Studies Based on ADDIE Model," Applied Mathematics and Nonlinear Sciences, vol. 9, no. 1, Jan. 2024, Accessed: Feb. 03, 2024. [Online]. Available: https://sciendo.com/article/10.2478/amns.2023.1.00208
[135] A. Ezzaim, A. Dahbi, A. Aqqal, and A. Haidine, "The Future of Education-A Survey of Current Scientific Research Trends," in Proceedings of the 8th International Conference on Advanced Intelligent Systems and Informatics 2022, A. E. Hassanien, V. Snášel, M. Tang, T.-W. Sung, and K.-C. Chang, Eds., in Lecture Notes on Data Engineering and Communications Technologies. Cham: Springer International Publishing, 2023, pp. 422–436. doi: 10.1007/978-3-031-20601-6_37.
[136] A. Ezzaim, A. Dahbi, A. Haidine, and A. Aqqal, "AI-Based Adaptive Learning: A Systematic Mapping of the Literature," JUCS - Journal of Universal Computer Science, vol. 29, no. 10, Art. no. 10, Oct. 2023, doi: 10.3897/jucs.90528.
[137] T. Krahn, R. Kuo, and M. Chang, "Personalized Study Guide: A Moodle Plug-in Generating Personal Learning Path for Students," in Augmented Intelligence and Intelligent Tutoring Systems, C. Frasson, P. Mylonas, and C. Troussas, Eds., in Lecture Notes in Computer Science. Cham: Springer Nature Switzerland, 2023, pp. 333–341. doi: 10.1007/978-3-031-32883-1_30.
[138] L. Assis, A. C. Rodrigues, A. Vivas, C. G. Pitangui, C. M. Silva, and F. A. Dorça, "Relationship Between Learning Styles and Learning Objects: A Systematic Literature Review," IJDET, vol. 20, no. 1, pp. 1–18, Jan. 2022, doi: 10.4018/IJDET.296698.
[139] A. Ezzaim, A. Dahbi, A. Aqqal, and A. Haidin, "Prediction of Learner Performance Based on Self-esteem Using Machine Learning Techniques: Comparative Analysis," in Artificial Intelligence, Data Science and Applications, Y. Farhaoui, A. Hussain, T. Saba, H. Taherdoost, and A. Verma, Eds., in Lecture Notes in Networks and Systems. Cham: Springer Nature Switzerland, 2024, pp. 248–253. doi: 10.1007/978-3-031-48573-2_36.
[140] A. Ezzaim, A. Dahbi, A. Aqqal, and A. Haidin, "Novel Machine Learning Approach for an Adaptive Learning System Based on Learner Performance," in Artificial Intelligence, Data Science and Applications, Y. Farhaoui, A. Hussain, T. Saba, H. Taherdoost, and A. Verma, Eds., in Lecture Notes in Networks and Systems. Cham: Springer Nature Switzerland, 2024, pp. 267–272. doi: 10.1007/978-3-031-48573-2_39.
[141] A. Ezzaim, A. Dahbi, A. Haidine, and A. Aqqal, "Enhancing Academic Outcomes through an Adaptive Learning Framework Utilizing a Novel Machine Learning-Based Performance Prediction Method," Data and Metadata, vol. 2, pp. 164–164, Dec. 2023, doi: 10.56294/dm2023164.
[142] M. Salem and M. G. Khalil, "The Support Vector Regression Model: A new Improvement for some Data Reduction Methods with Application," Pak.j.stat.oper.res., vol. 18, no. 2, pp. 427–435, Jun. 2022, doi: 10.18187/pjsor.v18i2.4049.
[143] M. Sabzekar and S. M. H. Hasheminejad, "Robust regression using support vector regressions," Chaos, Solitons & Fractals, vol. 144, p. 110738, Mar. 2021, doi: 10.1016/j.chaos.2021.110738.
[144] R. Y. Azhari, "WEB SERVICE FRAMEWORK : FLASK DAN FASTAPI," Technology and Informatics Insight Journal, vol. 1, no. 1, Art. no. 1, Feb. 2022, doi: 10.32639/tiij.v1i1.54.
[145] S. Narayanan, N. M. Balamurugan, M. K, and P. B. Palas, "Leveraging Machine Learning Methods for Multiple Disease Prediction using Python ML Libraries and Flask API," in 2022 International Conference on Applied Artificial Intelligence and Computing (ICAAIC), May 2022, pp. 694–701. doi: 10.1109/ICAAIC53929.2022.9792807.
[146] N. Negrey, "A Live Programming Environment for Python," Master's Theses, Jun. 2017, doi: 10.15368/theses.2017.56.
[147] A. M. Ikotun, A. E. Ezugwu, L. Abualigah, B. Abuhaija, and J. Heming, "K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data," Information Sciences, vol. 622, pp. 178–210, Apr. 2023, doi: 10.1016/j.ins.2022.11.139.
[148] R. Nasiboglu and E. Nasibov, "FyzzyGBR—A gradient boosting regression software with fuzzy target values," Software Impacts, vol. 14, p. 100430, Dec. 2022, doi: 10.1016/j.simpa.2022.100430.
[149] R. Kuo, T. Krahn, and M. Chang, "Behaviour Analytics-A Moodle Plug-in to Visualize Students' Learning Patterns," in International Conference on Intelligent Tutoring Systems, Springer, 2021, pp. 232–238.
[150] "Moodle plugins directory: Behaviour Analytics." Accessed: Aug. 05, 2023. [Online]. Available: https://moodle.org/plugins/block_behaviour
[151] "Moodle plugins directory: Personalised Study Guide format." Accessed: Aug. 05, 2023. [Online]. Available: https://moodle.org/plugins/format_psg
[152] A. Ezzaim, A. Dahbi, A. Haidine, and A. Aqqal, "The Impact of Implementing a Moodle Plug-in as an AI-based Adaptive Learning Solution on Learning Effectiveness: Case of Morocco," International Journal of Interactive Mobile Technologies (iJIM), vol. 18, no. 01, Art. no. 01, Jan. 2024, doi: 10.3991/ijim.v18i01.46309.
[153] W. E. B. Anacona, D. V. L. Aguilar, D. I. G. Peñaherrera, and C. L. P. Jiménes, "Flipped classroom as a learning strategy in reading comprehension: a case study of higher education," in 2023 IEEE Global Engineering Education Conference (EDUCON), May 2023, pp. 1–5. doi: 10.1109/EDUCON54358.2023.10125149.
[154] P. Hiver, S. (Ashlee) Zhou, S. Tahmouresi, Y. Sang, and M. Papi, "Why stories matter: Exploring learner engagement and metacognition through narratives of the L2 learning experience," System, vol. 91, p. 102260, Jul. 2020, doi: 10.1016/j.system.2020.102260.
[155] M.-T. Wang, J. Fredricks, F. Ye, T. Hofkens, and J. S. Linn, "Conceptualization and Assessment of Adolescents' Engagement

and Disengagement in School," European Journal of Psychological Assessment, vol. 35, no. 4, pp. 592–606, Jul. 2019, doi: 10.1027/1015-5759/a000431.

[156] A. Ezzaim, A. Dahbi, A. Haidine, and A. Aqqal, "AI-Based Adaptive Learning: A Systematic Mapping of the Literature," JOURNAL OF UNIVERSAL COMPUTER SCIENCE, vol. 29, pp. 1161–1197, Oct. 2023, doi: 10.3897/jucs.90528.

[157] G.-J. Hwang, H.-Y. Sung, C.-M. Hung, and I. Huang, "A learning style perspective to investigate the necessity of developing adaptive learning systems," Journal of Educational Technology & Society, vol. 16, no. 2, pp. 188–197, 2013.

[158] B. Albreiki, N. Zaki, and H. Alashwal, "A Systematic Literature Review of Student' Performance Prediction Using Machine Learning Techniques," Education Sciences, vol. 11, no. 9, Art. no. 9, Sep. 2021, doi: 10.3390/educsci11090552.

[159] D. Shawky and A. Badawi, "A Reinforcement Learning-Based Adaptive Learning System," in The International Conference on Advanced Machine Learning Technologies and Applications (AMLTA2018), A. E. Hassanien, M. F. Tolba, M. Elhoseny, and M. Mostafa, Eds., in Advances in Intelligent Systems and Computing. Cham: Springer International Publishing, 2018, pp. 221–231. doi: 10.1007/978-3-319-74690-6_22.

[160] Z. Xuekong, C. Lei, L. Shirong, and W. Pin, "Study on and Realization of Hybrid Recommendation-Based Adaptive Learning System," Journal of Software Engineering, vol. 9, pp. 886–894, 2015, doi: 10.3923/jse.2015.886.894.

[161] E. Kurilovas, "Advanced machine learning approaches to personalise learning: learning analytics and decision making," Behaviour & Information Technology, vol. 38, no. 4, pp. 410–421, 2019.