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Systematic Review

Adaptive Learning Using Artificial Intelligence in e-Learning: A Literature Review

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Abstract: The rapid evolution of e-learning platforms, propelled by advancements in artificial intelligence (AI) and machine learning (ML), presents a transformative potential in education. This dynamic landscape necessitates an exploration of AI/ML integration in adaptive learning systems to enhance educational outcomes. This study aims to map the current utilization of AI/ML in e-learning for adaptive learning, elucidating the benefits and challenges of such integration and assessing its impact on student engagement, retention, and performance. A comprehensive literature review was conducted, focusing on articles published from 2010 onwards, to document the integration of AI/ML in e-learning. The review analyzed 63 articles, employing a systematic approach to evaluate the deployment of adaptive learning algorithms and their educational implications. Findings reveal that AI/ML algorithms are instrumental in personalizing learning experiences. These technologies have been shown to optimize learning paths, enhance engagement, and improve academic performance, with some studies reporting increased test scores. The integration of AI/ML in e-learning platforms significantly contributes to the personalization and effectiveness of the educational process. Despite challenges like data privacy and the complexity of AI/ML systems, the results underscore the potential of adaptive learning to revolutionize education by catering to individual learner needs.

Keywords: adaptive learning; artificial intelligence; e-learning; machine learning; student performance

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1. Introduction

Adaptive learning is an educational approach that utilizes technology to provide personalized learning experiences tailored to individual students' needs, preferences, and progress. It leverages data-driven algorithms and artificial intelligence to dynamically adjust the content, the delivery, and the pace of instruction based on learners' performance and engagement. By adapting to the specific requirements of each student, adaptive learning promotes effective and efficient learning, maximizes engagement, and enhances educational outcomes. We explore the significance of adaptive learning in e-learning, highlighting its benefits.

In the last few years, e-learning has grown to become a powerful approach to education that offers flexibility, scalability, and personalized learning experiences. Adaptive learning in the context of e-learning refers to the intelligent and dynamic customization of learning content, resources, and activities to meet the unique preferences and needs of individual learners. By analyzing and interpreting learner data, adaptive learning systems can make informed decisions to provide personalized learning experiences, optimize learning outcomes, and enhance student engagement.

Adaptive learning can be defined as a pedagogical approach that utilizes advanced technologies, particularly machine learning algorithms, to tailor educational content, instructional strategies, and assessment methods to individual learners. It aims to adapt the learning process in real time, based on each learner's performance, preferences, knowledge level, and learning style. Through continuous analysis of learner data, including assessment results, interaction patterns, and progress tracking, adaptive learning systems can provide timely and targeted interventions, ensuring that learners receive the most relevant and effective educational materials and activities. Because they can convey educational information and change to meet the requirements of certain students, adaptive learning systems are becoming more popular.

Educators and practitioners must be equipped to effectively utilize AI technologies and applications, tailoring them to enhance learning experiences within specific educational contexts. Additionally, it is imperative to explore how traditional skills such as critical thinking, collaboration, and creativity can be integrated and nurtured within AI-driven educational environments. Furthermore, there is a pressing need for researchers to engage in more rigorous and comprehensive research on the application of AI technologies in the realms of learning and teaching [1]. UNESCO emphasizes that AI in education offers a unique opportunity to transform teaching and learning methods and address major educational challenges, while underlining the need for policies that focus on inclusion and equity in the implementation of AI in education. Reflecting on UNESCO's recommendations for decision-makers in the education sector, the report highlights the need to explore the complex implications of AI in educational settings, in particular how it redefines essential skills and presents both opportunities and challenges in contemporary educational settings in the age of AI [2].

The use of modern technology to mold students' expectations and "abilities to access, acquire, manipulate, construct, create, and communicate information" in these digital contexts has resulted in students prospering [3]. Personalized learning platforms known as "adaptive learning systems" (ALSs) may be used to create lessons that are personalized to the learning styles and preferences of students as well as the order and level of task difficulty [4]. While the potential benefits of integrating AI/ML into e-learning platforms are vast, there remains a paucity of comprehensive research on its actual deployment, benefits, challenges, and overall impact. Understanding these aspects is crucial for educators, developers, and policymakers to harness the full potential of AI/ML-driven adaptive learning and to address any associated challenges. Given this backdrop, this study seeks to address the following research questions:

RQ1. How are AI/ML algorithms currently being deployed in e-learning platforms for adaptive learning?
RQ2. What are the perceived benefits of using AI/ML to power adaptive learning in e-learning systems?
RQ3. What challenges or limitations do educators and developers face when integrating AI/ML into e-learning platforms for adaptive learning?
RQ4. How does adaptive learning, driven by AI/ML, impact key metrics in education such as engagement, retention, and performance?
RQ5. What best practices can be identified for the integration and optimization of AI/ML algorithms in e-learning platforms to support adaptive learning?

1.1. Concept of Adaptive Learning in e-Learning

The concept of adaptive learning in e-learning revolves around the idea that learners have diverse backgrounds, learning preferences, and cognitive abilities. Traditional e-learning platforms often present the same content and activities to all learners, without considering their unique characteristics and needs. The same learning processes are experienced by all students in the existing conventional e-learning settings, since education has historically followed a "one style fits all" approach. The various learning preferences and styles of pupils are not taken into consideration in this sort of learning [5]. This approach may lead to suboptimal learning experiences, as some learners might find the content too challenging or too easy, resulting in disengagement or limited progress. Personalized learning, where education is tailored to a student's specific requirements and learning preferences, has been made possible and assisted by the development of adaptive e-learning systems [6].

Adaptive learning systems leverage machine learning algorithms to gather, analyze, and interpret vast amounts of learner data. This data-driven approach enables the system to dynamically adjust the learning experience, offering personalized contents, resources, and activities that match each learner's skills and goals by tailoring the learning pathway. Adaptive learning promotes self-paced learning, provides targeted support, and fosters a more effective and engaging educational environment. The integration of artificial intelligence techniques within adaptive learning systems empowers them to continuously learn and improve. These systems can detect patterns in learner data, identify areas of strengths and weaknesses, and generate personalized recommendations and interventions. Moreover, the adaptive learning approach enables the collection of valuable feedback and data on the effectiveness of instructional learning materials and strategies, enabling instructors and designers to refine and optimize the e-learning environment.

1.2. Adaptive Learning in the Context of e-Learning

In the context of e-learning, adaptive learning refers to the integration of adaptive techniques and technologies into online learning platforms and courses. These platforms use algorithms and AI to analyze learners' data, including their interactions with the platform, assessment results, and progress. Based on this analysis, the system adapts the content, the sequencing, and the presentation of learning materials to suit each learner's needs. The extent to which a student really picks up the pertinent knowledge or skill offered online may be used to measure the efficacy of e-learning. E-learning environments should be adaptable enough to enable a variety of constructive activities, as this acquisition is often seen as a constructive activity where the building can take numerous shapes [7]. E-learning platforms employ a diverse range of adaptive learning strategies, such as intelligent tutoring systems, learning analytics, and personalized learning paths. These strategies enable learners to receive tailored content, individualized feedback, and adaptive assessments, fostering a more engaging and effective learning experience. Adaptive learning in e-learning offers the potential to optimize learning outcomes, increase learner engagement, and support lifelong learning in a flexible and accessible manner. Delivering the correct material to the right person, at the right time, in the most suitable style is the aim of adaptive e-learning, which is associated with exemplary instruction [8]. To customize the learning process, adaptive learning systems employ a variety of learning techniques, including artificial intelligence, machine learning, and item response theories [9]. In order to benefit from a one-to-one teaching model at a reasonable cost and give each student access to their own virtual teacher, the Adaptive Learning System was created to enable students to create their own personalized teaching strategies if they have access to a computer [10].

All adaptive learning systems include a fundamental architecture known as a "closed loop" that collects data from the learner and utilizes them to evaluate progress, suggest learning activities, and deliver customized feedback [11]. Fast [12] claims that over the past 20 years, public perception of artificial intelligence's ability to boost education has improved.

1.3. Artificial Intelligence and Machine Learning

AI and ML have emerged as transformative technologies in various fields, including education. In the context of adaptive learning, AI and ML play a crucial role in enabling personalized and tailored learning experiences. AI refers to the development of intelligent machines that can simulate human intelligence and perform tasks that typically require human intelligence, such as perception, reasoning, and decision making [13].

The role of AI and ML in gathering and analyzing learner data is crucial for providing personalized learning experiences. Advantages of AI-enabled learning systems include a better learning environment, schedule flexibility, the ability to provide immediate feedback, flexibility in controlling students' learning experiences, and accelerated student development [14]. AI systems can process large amounts of data, learn from patterns and experiences, and make predictions or recommendations. With respect for each student's talents, capabilities, and academic obstacles, AI permits the implementation of a variety of teaching methods [15]. AI and ML algorithms can collect learner data from various sources, including learning management systems, online platforms, assessments, and digital resources. These algorithms can gather data on learner demographics, performance metrics, interaction patterns, learning preferences, and other relevant information. Data collection can occur in real time or asynchronously, allowing adaptive learning systems to continuously update and refine learner profiles. AI and ML techniques excel at analyzing large and complex datasets. Once learner data are collected, these algorithms can process the data to uncover patterns, correlations, and trends. Through data analysis, adaptive learning systems can identify individual learner characteristics, such as strengths, weaknesses, learning styles, and knowledge gaps. This analysis forms the foundation for creating personalized learning experiences. AI and ML algorithms can build learner models based on the analyzed data. Learner modeling involves creating representations of individual learners, including their cognitive abilities, knowledge levels, learning styles, and preferences. These models capture the unique characteristics of each learner and serve as a basis for personalizing the learning experience [16].

ML is a subset of AI that focuses on enabling computers to learn from data and improve their performance without explicit programming. ML algorithms analyze large datasets to identify patterns, correlations, and insights. By training models on existing data, ML algorithms can make predictions, classifications, and recommendations. In adaptive learning, ML is used to understand learner behavior, personalize content, and adapt instructional strategies [17]. AI and ML techniques enable the analysis of vast amounts of learner data, including performance, interactions, and preferences. By processing these data, adaptive learning systems can create learner profiles and identify individual needs and strengths. AI algorithms can then personalize learning content, adjust the level of difficulty, and offer targeted interventions to optimize learning outcomes. Personalization enhances engagement, motivation, and knowledge retention [18].

1.4. Research Scope and Objectives

The study scope is to explore the integration and the efficacy of artificial intelligence techniques in e-learning platforms to foster adaptive learning. This research aims to provide insights into how e-learning platforms can utilize adaptive algorithms to personalize content delivery, enhancing the learning experience and outcomes. The paper concludes with useful findings for both researchers and practitioners in the field, while also highlighting future research directions.

The objectives of the study are to:

- Understand the current landscape of AI/ML applications in e-learning platforms.
- Investigate the benefits and challenges of integrating adaptive learning algorithms into e-learning systems.
- Assess the impact of adaptive learning, driven by AI/ML, on student engagement, retention, and overall performance.
- Provide recommendations for educational technologists and stakeholders on how to optimally harness AI/ML for adaptive learning.

2. Research Methodology

This research aims to comprehensively document and chart the latest developments in the field, acknowledging the significant progress made in recent times. To achieve this objective, the investigation focused on sourcing articles published from 2010 onwards. The study was conducted between March and June 2023.

Publications were selected in the two largest bibliographic databases—Web of Science and Scopus. The selection of these databases was driven by their extensive collection of pertinent and up-to-date publications. The exploration focused on titles, abstracts, and key terms. This search approach resulted in the acquisition of 698 papers. To streamline this vast collection, the research underwent additional filtering, selecting articles based on the criteria detailed subsequently.

Each phrase was enclosed in quotation marks to look for an exact match (Box 1). The inclusion of wildcard characters (*) enables a broader scope of search results by accounting for variations in terminology, spelling, and word forms. In particular, the asterisk acts as a truncation symbol, allowing us to capture multiple word endings and derivations within the search term. For instance, the query "adaptiv*" would retrieve articles containing words like "adaptive", "adaptiveness", and "adaptivity", ensuring that the search is not confined to a single form of the term. Duplicates from the acquired documents were eliminated using Mendeley software (https://www.mendeley.com/ accessed on 16 May 2023), leaving 537 unique articles. Articles were deemed suitable for the study if they met specific criteria, focusing on the title, abstract, and keywords. Additionally, details such as the publisher and volume and issue numbers, as well as page numbers, were also gathered. The subsequent method for choosing articles for analysis is illustrated in Figure 1. The abstracts and complete texts of the articles underwent distribution among the collaborating authors of this review.

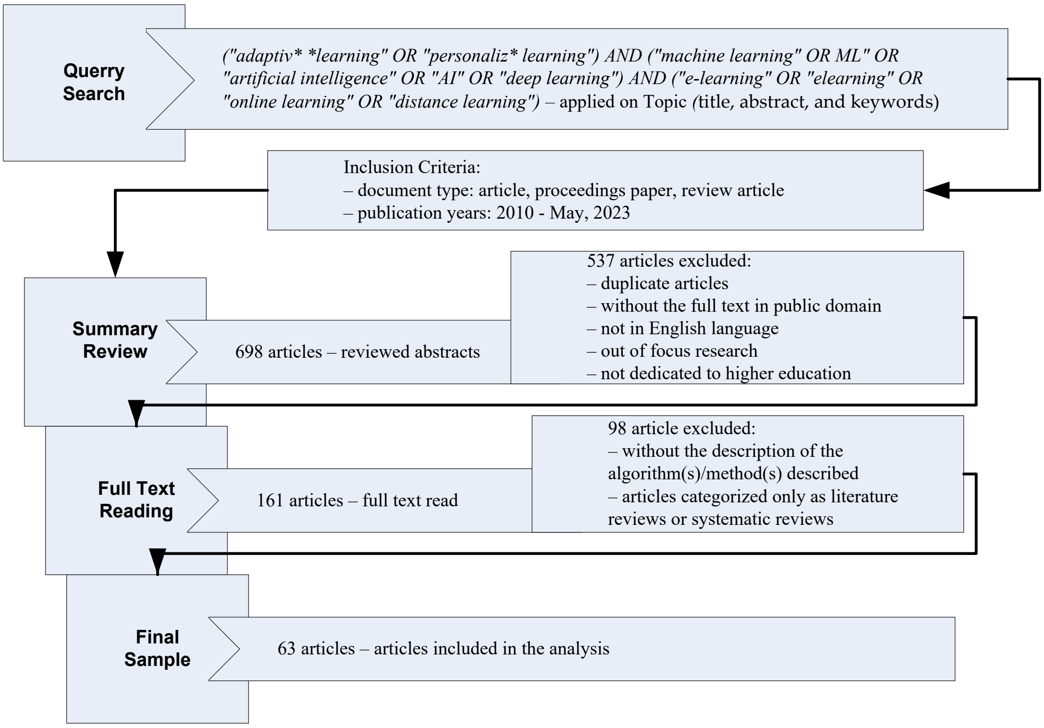

Figure 1. Literature review scheme for selecting sources.

Box 1. The search query.

("adaptiv* *learning" OR "personaliz* learning") AND ("machine learning" OR "ML" OR "artificial intelligence" OR "AI" OR "deep learning") AND ("e-learning" OR "elearning" OR "online learning" OR "distance learning")

To ensure the accuracy and integrity of our review, a rigorous process of article selection was undertaken. Subsequently, each author's judgement to include a particular article in the sample was based on extensive consultation with all the other co-authors. The method used has both the depth and rigor necessary to demonstrate an appropriate strategy for selecting articles and collecting data and evidence to meet our research objectives [19]. In the development of the literature review, the Rayyan online application was employed, enabling citation uploads, collaborative work, and project management [20]. User feedback highlights the application's effectiveness in streamlining screening processes and enhancing collaboration among researchers [21]. In its function, the tool excels by assigning a similarity score to each record during the review process, as records are categorized for inclusion, exclusion, or potential relevance [22]. Consequently, the Rayyan application was selected for its adeptness in streamlining screening and collaboration, enabling a structured approach to review article abstracts and full texts, thereby refining the final article selection for the systematic literature review. Authors, operating as reviewers under a blinded protocol, meticulously assessed articles, classifying them into three definitive categories: to be included, excluded, or tentatively considered as "maybe", ensuring an unbiased and thorough evaluation process. Disagreements among reviewers were deliberated and resolved following the removal of the blinded protocol, leading to a unanimous consensus among all authors regarding the final decision on inclusion or exclusion of articles. The final sample consisted of 63 articles.

3. Results

To directly address the research questions, we meticulously extracted and organized data from relevant articles (Table 1). Each article is identified by the citation of author under the "author ID" column. The specific algorithm or method employed to emphasize adaptive learning is cataloged under the "Algorithm/Method" column. Furthermore, to gain a deeper understanding of the application of these algorithms or methods, the "Usage/Remarks" column, where Usage details how each technique facilitates adaptability in e-learning or the platform and, in italics, Remarks describe some critical observations and insights about each article, shedding light on the nuances and particularities of the research.

Table 1. Assessment of extracted data.

Citation of Author(s)	Algorithm(s)/Method(s)	Usage/*Remarks*
[23]	Support vector machines (SVMs) k-Nearest neighbors (kNN) Naïve Bayes Random forest Logistic regression	The goal is to predict a known outcome (personality dimensions) based on input data (educational data features); this is a supervised learning task. The system focuses on developing a classifier based on supervised learning algorithms to predict the learner's personality dimensions discreetly using educational data features in an online learning system.
[24]	Density-based spatial clustering of applications with noise (DBSCAN)	DBSCAN is used to process the learners' contextual information extracted from their mobile devices. It is likely being used to group or categorize learners based on their contextual information such as background knowledge, learning time, learning location, and environmental situation. This helps in understanding how different learners interact with the material or the environment and allows the system to provide personalized, adaptive guidance. *DBSCAN is a clustering algorithm that divides a dataset into subsets based on the density of data points in the vicinity. DBSCAN is applied for clustering, which is the task of dividing the dataset into groups, based on some criteria.*

Table 1. *Cont.*

Citation of Author(s)	Algorithm(s)/Method(s)	Usage/*Remarks*
[25]	Linearization	The linearization algorithm generates a suggested learning path for students based on the Educational Concept Map (ECM). The algorithm is used to personalize the learning materials and educational resources for each student based on their self-evaluation of knowledge and learning objectives. *A linearization algorithm is a specific type of algorithmic technique used to arrange the concepts and educational relationships in the ECM in a linear order. The linearization process generates a suggested learning path for the student, indicating the sequence in which they should access the educational resources and learning materials associated with each concept.*
[26]	Neural networks Graph theory Fuzzy sets Classifications Agent systems	The paper describes the research, design, and implementation of intelligent learning environments (ILEs) that leverage a combination of expert systems, adaptive training systems, and several mathematical and computational methods to provide a personalized and efficient learning experience. The emphasis is on the integration of formal and informal learning, competency formation based on training and real-world knowledge, and the active use of simulators, virtual worlds, and augmented reality. Neural networks, graphs, fuzzy sets, classifications, and agent systems are used as methods in the creation of individual learning paths.
[27]	Ant colony optimization (ACO)	The ACO algorithm is used to optimize learning paths for different groups of students. The first stage involves grouping learners based on their knowledge patterns. The second stage then uses the ACO algorithm to determine the best learning path for each of these groups, with the end goal being a concept map tailored to the needs of each group. The use of the ACO algorithm in this context demonstrates its potential for optimizing the learning path and providing personalized learning experiences based on learners' knowledge patterns.
[28]	C4.5 decision tree	The C4.5 decision tree algorithm is used to measure and categorize a learner's knowledge level (e.g., beginner, intermediate, advanced) based on their quiz results. The results then inform the personalization of the e-learning system to cater to the individual needs of the students, which subsequently enhances their knowledge level. *The C4.5 algorithm creates a decision tree by recursively selecting the attribute that best divides the dataset into classes. It is known for handling both continuous and categorical attributes and for its ability to prune trees to avoid overfitting.*
[29]	Decision trees Neural networks Naïve Bayes	The type of ML method being employed here is predictive analytics, which focuses on making predictions about future outcomes based on historical data. The objective of using predictive analytics, as mentioned, is to gain insights into student learning behaviors, cluster student learning patterns, and explain academic performance. The intention is to further adaptive learning and improve education through insights obtained from this analysis.

Table 1. *Cont.*

Citation of Author(s)	Algorithm(s)/Method(s)	Usage/*Remarks*
[30]	Latent semantic analysis (LSA) Fuzzy C-means (FCM)	LSA is used to extract metadata from learning objects (LOs). LSA is a technique that finds patterns in relationships between terms and concepts in unstructured data, mainly used for analyzing relationships in a set of documents. Fuzzy C-means (FCM) algorithms: FCM is used to identify learning objects based on a specific form of similarity. It is a method of clustering where data points can have membership in multiple clusters, denoted by degrees of membership. *LSA falls under unsupervised learning. LSA deals with data that do not have explicit labels and is often utilized to uncover hidden structures or patterns, like topics in the data.FCM is also an unsupervised learning algorithm since clustering involves grouping data points based on their similarities without prior labels.*
[31]	Long short-term memory (LSTM) Random forest classification Convolutional neural networks (CNNs)	The machine learning algorithms used in the article are long short-term memory (LSTM), random forest classification, and convolutional neural networks (CNNs). The method employed is the creation of a comprehensive model based on deep learning to provide a highly personalized e-learning system. *The random forest classifier is used to predict the learner level, which pertains to the difficulty of the course. The random forest classifier takes in various parameters, including the assessment details of the students, to return a prediction. CNN is used in the identification of the learner style.*
[32]	Evolutionary algorithm Ant colony optimization Social network analysis (SNA)	Evolutionary algorithm used for determining relevant future educational objectives using an adequate learner e-assessment method. ACO is used for generating an adaptive learning path for each learner. SNA is used for determining the learner's motivation and social productivity to assign a specific learning rhythm to each learner. The paper seems to focus on the combination of optimization algorithms and big data technology (MapReduce) to personalize and adapt e-learning experiences. *Evolutionary algorithm inspired by the process of natural selection. It belongs to the larger class of evolutionary algorithms and is typically used to find approximate solutions to optimization and search problems.*
[33]	Genetic algorithm with forcing legality (GA) Particle swarm optimization (PSO)	Genetic algorithms and particle swarm optimization algorithms fall under the optimization and heuristic search methods. These algorithms are designed to find optimal or near-optimal solutions to problems by mimicking natural processes, such as evolution (in the case of GAs) or flocking behavior (in the case of PSO). The algorithm is utilized for creating personalized e-courses in adaptive learning systems. The goal is to efficiently select appropriate e-learning materials from a database tailored to individual learners. *GA is a type of optimization and search heuristic inspired by the process of natural selection. They are part of the evolutionary algorithms group. Particle swarm optimization is a heuristic optimization algorithm inspired by the social behavior of birds flocking or fish schooling.*

Table 1. *Cont.*

Citation of Author(s)	Algorithm(s)/Method(s)	Usage/*Remarks*
[34]	Chatbots	The application of ML algorithms is used to analyze each learner's personal requirements and generate a corresponding personalized learning path with tailored educational content. It suggests that ML algorithms are utilized to analyze learner characteristics and preferences in order to provide personalized resources and recommendations through the chatbot. *These chatbots could potentially address the issue of limited communication encountered in online learning systems. Integrating such chatbots may streamline the educational process, but their effectiveness hinges on the presence of high-quality content curated by real instructors.* *While chatbots can serve as online assistants, it is premature to conclude that they can entirely replace human instructors. Instead, chatbots are valuable tools designed to enhance instructors' capabilities and increase course accessibility.*
[35]	Support vector machines (SVMs) K-Nearest neighbors (K-NN) Naïve Bayes	The method employed is the evaluation and comparison of these algorithms in order to identify the most suitable one for implementing adaptive pedagogy in intelligent tutoring systems. The aim is to determine the most appropriate incremental machine learning technique for implementation in intelligent tutor systems. *The naïve Bayes algorithm was tested and outperformed both the K-NN and SVMs in the practical tests. It is considered a suitable incremental machine learning technique for pedagogical decision making in intelligent tutoring systems (ITSs), evaluating and comparing several incremental machine learning techniques (SVMs, K-NN, and naïve Bayes) to improve the adaptive pedagogy of intelligent tutoring systems.*
[36]	K-means clustering	K-means clustering is used to identify and cluster learners based on their learning behavior patterns, with the aim of understanding and predicting their personalities for the purpose of designing personalized online learning environments.
[37]	Learning framework "LearnFit"	Machine learning is used in this article to apply machine learning techniques within the LearnFit framework to personalize and adapt the learning paths for learners. It involves using learning style models and machine learning algorithms to analyze the learner's profile and make informed decisions on selecting and sequencing learning objects that are suitable for the learner's preferences and needs. *The algorithm involves personalizing content based on a learner's profile and preferences; this is likely a form of supervised learning, where historical data about students' interactions with learning materials informs the predictions about what content will be most effective for a given student. The use of "learning styles models" also suggests that the approach might combine traditional educational theories with machine learning techniques.*

Table 1. *Cont.*

Citation of Author(s)	Algorithm(s)/Method(s)	Usage/*Remarks*
[38]	Decision tree Rete	Both the decision tree algorithm and the Rete algorithm are utilized in the context of artificial intelligence and data mining technology to create an e-learning system that supports personalized study for learners. The decision tree algorithm is used for the classification of learners in the e-learning system. The Rete algorithm is employed in the reasoning network to handle decision support demands in the personalized learning environment based on the classified learner model. *The decision tree algorithm is used for learner classification, and the classified learner model is then sent to the reasoning network environment. The Rete algorithm is a rule-based algorithm commonly used for efficient pattern matching and inference in expert systems.*
[39]	Bayesian networks Ant colony optimization	Bayesian networks are used to infer the learner's features based on some input data (probably their interactions or preferences in the e-learning system). Once these features are understood, the system uses the 0/1 knapsack problem to select the best learning objects for the learner in the given time constraint. The ACO algorithm helps to solve this knapsack problem efficiently. The learning objects are then sequenced, probably based on some logical or pedagogical order, to ensure the learner receives a coherent learning experience.
[40]	K-means clustering	An optimized version of the K-means clustering algorithm, an unsupervised learning method, is used to efficiently cluster learners in MOOC (massive open online course) forums and aid instructors in designing personalized learning strategies. *K-means clustering is used for clustering or segmenting a dataset into groups or clusters based on their similarities.*
[41]	Ant colony optimization	The ACO algorithm has been adapted to recommend learning paths by considering factors like the students' cognitive style, knowledge base, and group preference, aiming to optimize for improved academic performance and learning efficiency. *The algorithm is a probabilistic technique used for solving computational problems which can be reduced to finding good paths through graphs.*
[42]	Multivariate K-means clustering	The multivariate K-means clustering algorithm is used within a semantic framework to address the pure cold-start problem in e-learning recommender systems. The algorithm is used to group learners with similar characteristics, enhancing the personalization of recommendations and improving the learning experience
[43]	Random forest K-Nearest neighbors Decision tree Logistic regression Support vector machine (SVM).	This study evaluates student performance using five algorithms: random forest, K-nearest neighbors, decision tree, logistic regression and SVM (support vector machine) with the aim of improving individual learning. It intends to enhance individual learning results by classifying a risk group and by offering a self-tutoring program.
[44]	Artificial neural networks (ANNs)	The ANN is likely used to recognize patterns in student interactions or navigations within the e-learning application, thus identifying unique learning styles. The patterns extracted from web usage mining serve as inputs or features for the neural network to train on and help in predicting or classifying the learning styles of individual students. *ANNs are typically used for recognizing patterns and making predictions.*

Table 1. *Cont.*

Citation of Author(s)	Algorithm(s)/Method(s)	Usage/*Remarks*
[45]	Genetic algorithm	The genetic algorithm is used to map optimal individualized learning paths for students in online courses, optimizing the ratio of the level of knowledge at course completion to time spent on the course.
[46]	Large-margin classifier (likely SVM) Random decision forests	The method employed is the application of these algorithms to classify students' performance using visual attention distributions measured via remote eye tracking. The results obtained from these machine learning approaches can guide the selection and optimization of adaptive learning environments in the context of STEM education. *Large-margin classifier: This refers to a classification algorithm that aims to maximize the margin between different classes, providing better generalization to new data points. Random forest is an ensemble learning method that combines multiple decision trees to improve accuracy and reduce overfitting.*
[47]	Reinforcement learning (RL) Conditional generative adversarial networks (cGANs)	RL is used to optimize the learning path and learning objects based on implicit feedback from the learner. The idea is to reward the system when it makes decisions that enhance the learning experience and possibly penalize it when the decisions are suboptimal. cGANs are used to adapt a model of the learner's characteristics rapidly. to simulate the learner's performance for the purpose of improving the training process. *RL is a type of machine learning where an agent learns by interacting with an environment and by receiving rewards or penalties based on the actions it takes.* *CGANs are used for generating new data samples. GANs have a generator that tries to generate data, and a discriminator that tries to distinguish between real data and the generated data.*
[48]	Naïve Bayes Recommendation systems Collaborative filtering	The proposed hybrid approach aims to improve the efficiency of e-learning systems by providing adaptive remediation tailored to each learner's needs. By using naïve Bayes for classification, the system can effectively categorize and address the identified learning difficulties, and by leveraging collaborative filtering, it can suggest appropriate remediation activities based on similar learners' experiences. This hybrid approach combines the strengths of recommendation systems and machine learning to enhance the adaptive learning experience for individual learners. The naïve Bayes algorithm is used to classify the identified errors into specific classes representing learning difficulties. *For each class (learning difficulty), a remediation strategy is planned. The collaborative filtering technique is used to recommend the most adaptive remediation activity based on the learner's identified learning difficulties.*
[49]	Genetic algorithm	The genetic algorithm is employed to search for learning activities that are optimal for learners based on their profiles, ensuring a resolution of the proposed learning problem. *Genetic algorithms are part of evolutionary algorithms, which are optimization algorithms based on the process of natural selection. They are not typically categorized strictly as supervised or unsupervised learning methods. Instead, they are a form of heuristic search and optimization technique.*

Table 1. *Cont.*

Citation of Author(s)	Algorithm(s)/Method(s)	Usage/*Remarks*
[50]	Reinforcement learning (RL)	The study uses a model-free reinforcement learning approach to optimize the learning paths for learners in an e-learning system, considering a hierarchical structure of skills. *The mentioned "model-free reinforcement learning method" belongs to the realm of reinforcement learning. In RL, an agent interacts with an environment and learns to make decisions by taking actions that maximize a reward signal.*
[51]	Graph convolutional neural network (GCN) Recurrent neural networks (RNNs)	The application of deep learning technology is used for analyzing micro-video learning resource data and providing personalized learning resource recommendations. CNNs or RNNs can learn patterns and features from the micro-video data, enabling accurate analysis and personalized recommendations based on learners' needs and interests. *A CNN is a neural network of learning graph structure, whose learning goal is to obtain the hidden state of graph perception of each node.*
[52]	Gradient-boosted tree XGBoost	The application of various data mining techniques and machine learning using algorithms to predict the probabilities of students answering questions correctly based on their interaction records with the web-based learning platform Hypocampus. *Gradient-boosted tree performed well in predicting the correctness of the student's answer. XGBoost performed well in predicting the correctness of the student's answer. XGBoost is an optimized implementation of gradient boosting.*
[53]	Recommendation engine	The recommendation engine is applied to personalize the learning process in personal learning environments (PLE). The goal is to adapt the learning environment to the needs of each individual learner, providing personalized recommendations for setting learning goals and guiding them on how to achieve those goals. By leveraging machine learning algorithms, the tool implemented can assist students in setting, evaluating, and executing their learning objectives effectively. *Recommendation engines are a type of machine learning method used to suggest items or actions to users based on their preferences, historical behavior, and other relevant data.*
[54]	Multi-granularity learning preference mining based on ant colony optimization (ACO-LPM)	The ACO-LPM algorithm is applied to address the problem of mining user's learning preferences in a personalized online learning system. The algorithm takes advantage of the hierarchical characteristics of knowledge points in the course domain and defines the equivalence relation and structure of the knowledge points quotient space. It defines functions of support, pheromone concentration, and preference on various levels to guide the learning preference mining process. By leveraging the improved ant colony optimization approach and multi-granularity data structure, the algorithm can provide personalized recommendations based on the user's preferences. *The ACO-LPM algorithm utilizes the principles of ant colony optimization and improves upon it by handling the multi-granularity data structure of the quotient space. It tackles the challenges of a large number of learning knowledge points and limited user test data in the online personalized learning system.* *The pheromone concentration in the algorithm has the characteristic of dynamic evaporation, allowing the preference patterns mined by ACO-LPM to adapt and change in real-time with the user's interest.*

Table 1. *Cont.*

Citation of Author(s)	Algorithm(s)/Method(s)	Usage/*Remarks*
[55]	Recommendation algorithm	The recommendation algorithm analyzes the user's learning history data and makes recommendations based on the user's learning level and personal preference. The system would use past data (user's learning history) to predict or recommend future resources. *Generally, recommendation algorithms can fall under supervised, unsupervised, or semisupervised learning, depending on the specific implementation.*
[56]	Logistic regression Support vector machines (SVMs) Time series forecasting (ARIMA) Deep neural networks Recurrent neural networks (RNNs)	Describes the use of both machine learning and deep learning algorithms, including logistic regression, SVM, ARIMA for time series forecasting, deep neural networks, and RNN, to improve and customize the online learning environment. *ARIMA stands for autoregressive integrated moving average. It is a forecasting algorithm based on the idea that the information in the past values of a time series can alone be used to predict the future values. RNNs are a class of neural networks where connections between units form a cycle. This creates a "memory" about the previous inputs, which is especially useful for sequence prediction problems.*
[57]	Knowledge graph Deep neural networks (DNNs)	Deep learning technology is employed in the behavior detection module. This module uses deep learning techniques to analyze student behaviors and make multidimensional and comprehensive judgments about their learning status. The framework proposed in this paper combines AI and education to create an intelligent adaptive tutoring system. The system aims to address the limitations of traditional adaptive learning systems by providing efficient algorithms for personalization recommendation, learning path, and detecting students' true learning status. *DNNs are utilized in the learning-resource recommendation module to personalize recommendations based on a knowledge graph. The deep neural networks can process complex patterns and relationships in the data to provide accurate and personalized recommendations.*
[58]	Fuzzy control matrix algorithm	The fuzzy control matrix algorithm is used for the teacher–student matching degree in the English teaching system to innovate the teacher recommendation mechanism. The goal is to match students with teachers who align well with their learning habits. *Fuzzy algorithms, in general, deal with reasoning that is approximate rather than fixed and exact, often used for situations that are inherently uncertain or ambiguous. Given the context of matching students to teachers based on a degree of suitability, it does not seem to involve labeled datasets and, thus, is likely an unsupervised method.*
[59]	Deep learning recommendation	Deep learning is combined with recommendation algorithms to design a framework to enhance the accuracy of recommendation results in personalized e-learning. *Deep learning is used alongside recommendation algorithms and it is likely employed in a supervised manner, particularly if the goal is to predict or recommend the most relevant learning resources to a user based on previous interactions.*

Table 1. *Cont.*

Citation of Author(s)	Algorithm(s)/Method(s)	Usage/*Remarks*
[60]	Real-time clustering	The overall approach involves a co-design process with teachers to identify where and how personalized instruction can be integrated, develop a mock-up of a learning analytics tool, define the explainable learning analytics scheme, and evaluate the effectiveness of the personalized learning sequences designed by using the AI algorithm. The main contributions of the study are the personalized approach for blended learning, the combination of clustering and explainable AI, and the co-design process with teachers to inform the development of a learning analytics tool. *The real-time clustering algorithms belong to unsupervised learning techniques since they group data based on inherent similarities without the need for labeled examples.*
[61]	Light gradient boosting machine (LGBM)	LGBM is used in a feature selection/extraction context to identify the learning style and to predict students' academic performance based on their learning styles and other associated features. *Gradient boosting machines (GBMs) are a popular class of machine learning algorithms that build an ensemble of decision trees in a stage-wise fashion, where each tree corrects the errors of its predecessor. LGBM is a particular implementation of the GBM that is optimized for speed and performance.*
[62]	Deep belief network for learning style detection (DBN-LIS)	Developing a model for automatic and nondeterministic learning style detection based on the traces of learner activity in adaptive learning systems. DBN-LIS is used to analyze these learning traces in learning management systems (LMSs) and detect learning styles effectively. *Deep belief networks are a type of artificial neural network with multiple layers of hidden units, capable of unsupervised learning. They are generative models, meaning they can learn to approximate the underlying probability distribution of the input data, in this case, the learner activity traces from the adaptive learning systems.*
[63]	Social bots Generative bots	It is used as a web-based model-driven framework for creating social bots. These social bots utilize deep learning technologies for providing personal feedback. *These bots work based on a predefined dataset. They usually employ pattern matching or simpler ML models to choose the most appropriate response from a set of predefined answers based on the user's input.*
[64]	Collaborative filtering (CF) Deep learning (DL)	It is used as a CF algorithm, and the method employed is the construction of a personalized learning platform based on CF. DL is used in an intelligent classroom based on AI to accurately analyze each student's learning situation and knowledge, push relevant learning materials and videos in a targeted manner, and push all materials in a differentiated, personalized, and intelligent manner, so that students of various levels can achieve the desired results. *Collaborative filtering is a method of recommender systems, which are a subset of supervised learning techniques. Collaborative filtering, in particular, recommends items by finding patterns in user–item interactions.* *The algorithm principle of DL is to input the known data whose data model is not easy to find into the input layer and obtain the output data from the output layer through the function mapping of multiple hidden layers, so as to find the real relationship between variables.*

Table 1. *Cont.*

Citation of Author(s)	Algorithm(s)/Method(s)	Usage/*Remarks*
[65]	Heterogeneous value difference metric (HVDM) Naïve Bayes classifier (NBC)	HVDM is a similarity measure used to determine the similarity between learners. By identifying similar learners, the system can provide appropriate support based on their characteristics and learning needs. NBC is used to estimate the likelihood that a learner would require additional materials for the current concept. This enables the system to dynamically recommend or provide supplementary learning materials to the learner based on their needs. HVDM and NBC are used to provide adaptive learning support in a web-based learning system. *HVDM is a similarity measure used to determine the similarity between learners. It is a distance-based metric that calculates the differences between feature values in heterogeneous datasets. NBC is a probabilistic classifier based on Bayes' theorem. It calculates the conditional probabilities of class labels given the input features and makes predictions based on the highest probability.*
[66]	Collaborative filtering (CF)	An AI algorithm that uses CF, tailored by learning style prediction, for recommending learning materials in an online portal. *Collaborative filtering is a technique used for recommendation systems. It works by finding patterns in user behavior to predict what other items might be of interest to a particular user. In this case, the model has been tailored or modified to also consider learning styles in making its recommendations.*
[67]	Genetic algorithm (GA)	The GA is utilized to generate or evolve optimal teaching paths ("teaching path generation" or TPG model) for different classes, aiming to enhance the teaching effects of instructors. It likely starts with a population of possible teaching paths and iteratively refines these paths based on some evaluation of their effectiveness or quality, until it finds or converges on an optimal (or near-optimal) solution. *Genetic algorithms are optimization and search algorithms inspired by the process of natural selection. They work by evolving a population of candidate solutions to improve them iteratively with respect to a given measure of quality.*
[68]	Multilayer perceptron (MLP)	*The purpose of using the MLP in this research is to perform a data mining task, specifically classification, within the context of a knowledge discovery in databases (KDD) process for an adaptive e-learning architecture. The classification problems analyzed in the paper were based on the classical datasets Iris (plant classification problem), Wine (wine classification problem), and Conc (stimuli arranged in a concentric way).* *Additionally, the article proposes an adaptive architecture that can be applied in adaptive e-learning systems. The MySQL database management system is used to store the neural networks as binary large objects (BLOBs).* *The modified internal functioning of the MLP involves reinitializing the internal weights of the network with random values if the MLP becomes stuck in a local minimum after a certain number of training epochs. This modification aims to prevent the MLP from converging to suboptimal solutions and helps improve its adaptability.*

Table 1. *Cont.*

Citation of Author(s)	Algorithm(s)/Method(s)	Usage/*Remarks*
[69]	Image recognition technology	Image recognition technology extracts five kinds of head movement data from student samples. Image recognition falls within the domain of computer vision, a field of AI and ML that teaches computers to interpret and make decisions based on visual data. This technique is applied to understand online learning behaviors better. *Image recognition generally falls under supervised learning when trained on labeled datasets to identify or classify visual objects. However, the abstract does not specify how the image recognition model was trained, so while it is common to train image recognition models using supervised methods, we cannot definitively state this based on the given information.*
[70]	Student learning attributes index	The concept of a "student learning attributes index" is a data structure that represents each learning attribute as a tuple with three elements: the learning attribute ID, the weight of the learning attribute among all the learning attributes, and the efficiency of the contribution to the student's learning effectiveness made by the learning attribute. *This suggests that the ML algorithm used may involve learning attributes and their weights to make decisions or predictions related to adaptive learning.*
[71]	K-means clustering Linear regression Q-learning	K-means is likely used to identify patterns or groups of learners with similar learning needs or characteristics, contributing to creating a deep learner profile. Linear regression might be used to predict certain aspects of the learner's performance or needs based on their profile data. Q-learning is employed for recommending adaptive learning paths based on the deep learner profile. A combination of unsupervised, supervised, and reinforcement learning techniques is used to create a deep learner profile and provide personalized learning path recommendations based on that profile. *Q-learning is a type of reinforcement learning algorithm. It is used to find the best action to take given the current state, in order to maximize the expected cumulative reward*
[72]	Recurrent neural networks (RNNs)	RNN is being trained to predict or recommend learning paths based on past data. It involves training an algorithm using labeled data, and given the context—learning path recommendations based on a learner's submission history—it is likely that the model is being trained on past submission histories and their corresponding outcomes to make future predictions/recommendations. *RNNs are a type of machine learning model that is particularly suited for sequential data. The unique feature of RNNs is that they can maintain a kind of "memory" of previous inputs in their hidden state. This makes them particularly suitable for tasks where the context from earlier inputs is useful in processing later inputs, such as time series prediction, natural language processing, etc.*
[73]	Deep neural network algorithm	The deep neural network algorithm is employed to make recommendations related to services on the MOOC education resource platform. *Deep neural networks (DNNs) are a subset of neural networks that fall under supervised learning techniques in machine learning. DNNs consist of multiple layers of interconnected nodes or neurons and are especially effective for complex tasks due to their ability to learn hierarchical features from data.*

Table 1. *Cont.*

Citation of Author(s)	Algorithm(s)/Method(s)	Usage/*Remarks*
[74]	Graph embedding	Graph embedding mines the relationships among users, questions, and perceptions using graph embeddings, making it more suited for recommending areas of weakness or "unknowns" for users. *Graph embeddings are used to convert nodes, edges, and their features into vector space (dense vectors), where the geometric relationships between these vectors capture certain properties of the nodes and edges in the graph.*
[75]	Decision tree Naïve Bayesian classifier k-Nearest neighbor	The machine learning algorithms are used to analyze user activity data within the e-learning system. This analysis aims to identify behavioral and activity patterns of system users during the learning process. These patterns are then used to determine learners' needs and provide them with personalized learning content and a tailored learning path. *The machine learning techniques employed in this context are utilized for predictive modeling, simulation, and forecasting, enabling the learning management system to offer unique personalized learning experiences to users. The k-nearest neighbor classifier has the best accuracy, followed by the decision tree, and the naïve Bayesian classifier has the lowest accuracy.*
[76]	Ant colony optimization Genetic algorithms	The collaborative optimization algorithm combines ant colony optimization and genetic algorithm and is used to provide learners with personalized learning paths. Ant colony optimization is used for exploration and search, while genetic algorithms contribute to refining and optimizing the personalized learning path. *ACO is used to explore and search for optimal learning object sequencing based on individual characteristics. Genetic algorithms, on the other hand, are a class of evolutionary algorithms that mimic the process of natural selection and genetic variation. They use principles such as selection, crossover, and mutation to evolve a population of solutions towards an optimal or near-optimal solution.*
[77]	Video analysis	The video analysis algorithm utilizes video analysis to detect situations of attention decrease in the e-learning environment. It uses various features such as head posture, gaze, eye closure, mouth opening, and facial expression to observe attention. These attention observation attributes are then used as inputs to machine learning classifiers. *The video analysis algorithm involves the application of machine learning classifiers to code behavior features and evaluate attention level and emotional pleasure degree.*
[78]	Fuzzy partial ordering graph Adaptive knowledge assessment	Adaptive knowledge assessment gathers genuine and current learning materials from the Internet and arranges them using a fuzzy partial ordering graph. Additionally, it employs a probabilistic function to strike a balance between assessment and recommendation during the learning journey, aiming to enhance student engagement. *The fuzzy partial ordering graph is a refined hierarchical knowledge structure with relaxed constraints, which significantly increases the density of the knowledge structure. Incorporating adaptive assessment can significantly enhance learning material recommendation in online learning.*

Table 1. *Cont.*

Citation of Author(s)	Algorithm(s)/Method(s)	Usage/*Remarks*
[79]	Wide and deep learning (WDL) Collaborative filtering ResNet (residual network)	Here, we find an improved recommendation algorithm for online education platforms. It is based on the wide and deep learning model by incorporating collaborative filtering techniques and using ResNet ideas in its deep part for better prediction and generalization. The approach aims to provide more accurate and personalized online course recommendations. *WDL is a deep learning recommendation algorithm primarily designed for click-through rate (CTR) prediction. It combines the strengths of memorization from linear models (wide) with generalization from deep learning models (deep).* *Collaborative filtering is a recommendation algorithm that makes predictions about the interest of a user by collecting preferences from many users (collaborating). Here, collaborative filtering is used to replace linear methods in the wide part of WDL.* *ResNet is a deep learning architecture that uses residual blocks, which allows for the training of deeper neural networks by creating shortcuts or skip connections. Here, it is employed to improve the deep neural network (DNN) in the deep part of the WDL model, aiming to mitigate the overfitting problem.*
[80]	Collaborative filtering Deep learning	Collaborative filtering is utilized to provide personalized recommendations to users based on the behavior and preferences of other users with similar characteristics. Deep learning is applied to process and analyze the distributed network data collected from various learning platforms. The deep learning component likely plays a role in extracting learner attribute information, learning behavior, and learning results from the large amount of data, thereby contributing to the personalized recommendation process. The hybrid intelligent recommendation engine is integrated into this structure, utilizing both collaborative filtering and deep learning techniques to achieve user-visualized personalized recommendation and customized services for learners. *Collaborative filtering is a popular recommendation technique that uses user behavior data (e.g., user–item interactions, ratings, etc.) to identify patterns and make recommendations.* *Deep learning is a subset of machine learning that uses neural networks to learn and extract patterns from large amounts of data.*
[81]	Deep reinforcement learning (DRLP) Bidirectional gated recurrent units (Bi-GRUs)	Both deep learning and reinforcement learning techniques, especially deep reinforcement learning (DRLP) and Bi-GRU, are found to develop a personalized recommendation system for programming problems, taking into account individual learner styles and a rich representation of every programming problem. *Deep reinforcement learning is an advanced technique within the realm of reinforcement learning, where agents learn to take actions in environments to maximize cumulative reward. The Bi-GRU model is used to "learn texts' contextual semantic association information from both positive and negative directions".*
[82]	Clustering Association rules Genetic algorithms Deep learning	The study applies a mix of unsupervised machine learning techniques (clustering and association rules), optimization techniques (genetic algorithms), and deep learning to develop an innovative content organization system for an English online learning platform. *Association rule learning finds interesting relations between variables in large databases.*

Table 1. *Cont.*

Citation of Author(s)	Algorithm(s)/Method(s)	Usage/*Remarks*
[83]	Two-stage Bayesian Chatbots	Two-stage Bayesian is used in a supervised manner. This means the algorithm would have been trained on labeled data to make predictions or classifications based on the input data, and functions as a recommendation system. This system provides customized learning materials based on the learner's current situation, which means it recommends certain content based on the detected needs or gaps in a learner's knowledge. This system assists in recognizing gaps in a learner's knowledge and in recommending appropriate digital materials or videos to address these gaps. The chatbot feature further enhances interactivity, providing real-time assistance to learners based on their needs. *Bayesian algorithms are statistical methods that apply probability theory to predict the likelihood of certain events based on prior knowledge.* *Chatbots are conversational agents used to address the queries and blind spots of learners during their e-learning process.*
[84]	Ant colony optimization	The specific ML method used is the modified ant colony optimization algorithm. The modification of the ACO algorithm is aimed at addressing the dynamic nature of learning scenarios (LSs), as they can be modified during the learner's learning process by inserting, deleting, and editing learning objects (LOs). The approach proposes the reallocation of "pheromones" (information about learners' behavior) and the rearrangement of old and new LOs to achieve effective learning recommendations. *This approach, based on a swarm intelligence model, effectively assists learners in reaching suitable learning objects (LOs) based on their learning styles. Furthermore, it provides benefits to tutors by helping them monitor, refine, and improve e-learning modules and courses.*
[85]	Knowledge graph Logistic regression	The algorithm analyzes data from an online learning platform to infer whether the content assigned by teachers aligns with students' readiness to learn. The knowledge graph uses the knowledge graph to determine the student's zone of proximal development, which refers to the skills that are appropriate for the student's current level of knowledge and readiness to learn. Logistic regression is used to compare student mastery outcomes based on whether they were assigned ready-to-learn skills versus unready-to-learn skills. *A knowledge graph is a structured way to represent knowledge in terms of entities and their interrelationships.*

This analysis provides an overview of the implementation, benefits, challenges, influences and best practices of integrating AI/ML into e-learning platforms for adaptive learning. Based on the above analyses, answers to the research questions can be provided in summary.

RQ1. How are AI/ML algorithms or methods currently being deployed in e-learning platforms for adaptive learning?

Answers:

- K-means clustering is used to cluster learners in MOOC forums, segment datasets based on similarity, and identify learning behavior patterns.
- Heterogeneous value difference metric (HVDM) and naïve Bayes classifier (NBC) provide adaptive learning support by measuring similarity between learners and predicting their needs.

- Reinforcement learning (RL) is employed to optimize learning paths and learning objects using implicit feedback from learners.
- Conditional generative adversarial networks (cGANs) adapt a model of the learner's characteristics to simulate performance and improve training.
- Logistic regression, SVM, ARIMA, deep neural networks, and RNNs are combined to enhance and customize the learning environment.
- Collaborative filtering (CF) constructs personalized learning platforms.
- Deep learning (DL) analyzes students' learning situations, providing targeted resources.
- Q-learning recommends adaptive learning paths.
- Genetic algorithms map optimal individualized learning paths.
- Two-stage Bayesian functions as a recommendation system, customizing learning materials.
- Light gradient boosting machine (LGBM) identifies learning styles and predicts academic performance.

In the evolving landscape of e-learning, AI/ML algorithms play a pivotal role, offering a multitude of methods from K-means clustering to light gradient boosting machines. These methodologies aid in tailoring content, predicting academic performance, mapping knowledge gaps, and offering dynamic assessments. Through this intricate web of techniques, e-learning platforms are steadily revolutionizing the educational experience, making it deeply personalized, proactive, and responsive to individual learner needs.

RQ2. What are the perceived benefits of using AI/ML to power adaptive learning in e-learning systems?

Answers:

- Personalized learning experiences and pathways.
- Dynamic recommendations of supplementary materials.
- Optimized learning paths and objects.
- Rapid adaptation of learner models.
- Enhanced recommendation systems and targeted learning material delivery.
- Efficient clustering of learners for tailored strategies.
- Identification of learning styles for improved academic predictions.

Harnessing the power of machine learning in e-learning systems unlocks a spectrum of benefits, central to which is the creation of highly personalized educational journeys. These advantages span from increased learner engagement due to tailored content, to providing educators with insightful data-driven feedback. Such integration not only enhances efficiency and flexibility but also paves the way for a transformative and optimized learning environment for diverse learners.

RQ3. What challenges or limitations do educators and developers face when integrating AI/ML into e-learning platforms for adaptive learning?

Answers:

- Cold-start problems, where systems have little initial data on learners.
- Complexity of combining multiple machine learning techniques.
- Ensuring data privacy and security.
- Integration and compatibility with existing e-learning infrastructure.
- Need for ongoing training and updates to machine learning models.
- Developing, integrating, and maintaining AI-driven systems can be expensive.
- Data privacy concerns in collecting and analyzing student data can raise privacy issues.
- Over-reliance on technology—there is a risk of neglecting the human aspect of education.

While the integration of machine learning into e-learning platforms heralds unprecedented possibilities for personalized education, this process comes with its set of challenges. From the hurdles of initial data scarcity and complexities in amalgamating AI/ML techniques, to looming concerns of data privacy and potential algorithmic biases, educators and developers must tread carefully. This intricate balance underscores the need to ensure that technology augments, rather than replaces, the essential human touch in education, all while navigating the intricacies of implementation and cost considerations.

RQ4. How does adaptive learning, driven by AI/ML, impact key metrics in education such as engagement, retention, and performance?

Answers:

- Enhances the learning experience by clustering similar learners.
- Improves personalization through targeted material delivery.
- Provides real-time assistance through chatbots.
- Focuses on optimal learning activities based on learner profiles.
- Predicts student performance using learning styles.
- Such features potentially increase engagement, retention, and performance by offering tailored content, real-time feedback, and optimal learning pathways.
- Improve test scores and overall academic performance.

Adaptive learning, powered by machine learning, profoundly reshapes the educational landscape, leading to heightened engagement, bolstered retention, and enhanced performance. By delivering tailored content and real-time feedback, and by optimizing the learning journey according to individual learner profiles, this modern pedagogical approach aligns closely with the diverse needs and styles of learners, thereby driving favorable outcomes in key educational metrics.

RQ5. What best practices can be identified for the integration and optimization of AI/ML algorithms in e-learning platforms to support adaptive learning?

Answers:

- Co-design processes with educators, like combining clustering with explainable AI.
- Use unsupervised ML techniques for clustering and association rules.
- Combining different ML techniques, like clustering and deep learning, for holistic approaches.
- Utilizing Bayesian algorithms for predictive accuracy based on prior knowledge.
- Continuous assessment and updates to the ML models to ensure relevance and accuracy.

The seamless integration and optimization of AI/ML in e-learning platforms necessitates a collaborative approach between educators and developers, with a shared focus on privacy, iterative refinement, and bias mitigation. Embracing a combination of AI/ML techniques and continuously updating models is paramount to maintaining their relevance and accuracy. Ultimately, clear communication and ethical considerations underpin these best practices, ensuring that adaptive learning remains both effective and trustworthy for users. In the realm of e-learning, the integration of AI/ML, particularly adaptive learning algorithms, stands as a pillar influencing key sectors from personalized learning experiences to intelligent recommendation systems. This co-occurrence network reinforces the intertwined relationship between contemporary e-learning platforms, learning systems, and artificial intelligence. As these systems mature, they promise a future where education is seamlessly tailored to individual student needs, optimizing both teaching methodologies and learning outcomes.

4. Discussion

4.1. Benefits of AI/ML in Adaptive e-Learning

Personalized Learning: AI/ML algorithms enable adaptive e-learning platforms to tailor the learning experience to the needs and preferences of individual learners. Personalized learning creates a more engaging and dynamic learning environment by tailoring it to individual learners' interests, needs, and skills. It allows the educator to bring more robust, practical, and varied material into the learning space [86].

Improved Learning Outcomes: Adaptive e-learning platforms powered by AI/ML algorithms can track and analyze learner performance, identify knowledge gaps, and offer remedial content or activities to address those gaps. This personalized approach helps optimize learning outcomes by focusing on areas where learners need more support and practice [87].

Real-time Feedback: AI/ML algorithms enable adaptive e-learning systems to provide instant and constructive feedback to learners. This immediate feedback helps learners understand their mistakes, make corrections, and reinforce their understanding, facilitating a more efficient learning process [88].

Enhanced Engagement: Adaptive e-learning platforms leverage AI/ML algorithms to create interactive and engaging learning experiences. These systems engage and encourage learners by adding features like gamification and tailored information, which can increase student motivation and drive, leading to improved learning outcomes [89].

4.2. Future Directions and Research Opportunities

As AI and ML algorithms continue to play a crucial role in adaptive learning, there is a growing emphasis on explainable AI. Educators and learners want to understand how algorithms make decisions and recommendations. Future developments will focus on designing AI systems that provide transparent explanations for their actions, enabling learners to comprehend the reasoning behind adaptive learning outcomes. Explainable AI aims to provide learners and educators with understandable explanations of how the algorithms make decisions, ensuring trust, accountability, and ethical use of AI technologies in e-learning. Explainable artificial intelligence mitigates to help people to understand how and why models give certain recommendations [90]. AI-powered systems can process and understand human language, enabling more advanced interactions with learners. This includes chatbots, voice assistants, and natural language-based assessment and feedback systems that can enhance conversational and personalized learning experiences.

Future directions in adaptive learning will involve integrating contextual information to further personalize the learning experience. This includes incorporating data from wearable devices, environmental sensors, or other sources to adapt content based on factors such as location, time, or learner's emotional state. Context-aware adaptation will enable adaptive e-learning systems to provide even more tailored relevant content (learning system (E-LS) must take into account the context) that is aware of learners to help them to complete their activity [91].

Adaptive e-learning is increasingly incorporating collaborative and social learning components. AI/ML algorithms can analyze learner interactions, group dynamics, and social network data to provide personalized recommendations for group projects, collaborative learning activities, and peer feedback. Interaction between students and instructors has a significant influence on students' happiness and learning results in online learning [92]. Future developments will focus on leveraging AI to enhance collaboration and foster social interactions in online learning environments.

The examination and categorization of educational tools in the tertiary education sector, which are centered around adaptive learning and the use of artificial intelligence, as highlighted in this research, come with several constraints regarding their value across various phases of educational design. Firstly, the selection of keywords to compile the publication samples may not be exhaustive, potentially missing out on pertinent studies. Moreover, there is a likelihood that not all relevant educational tools were documented in research papers listed in reference databases. Such tools might be discussed in analytical summaries, showcased in conferences, or highlighted during developer hackathons, all of which were not considered for this study. This implies that the actual array of tools may be broader and more varied than presented. Additionally, since our research query was framed exclusively in English, it inherently omits any resource published solely in other languages. Addressing these limitations could be a focus for subsequent research endeavors.

5. Conclusions

The use of adaptive learning with AI or ML in e-learning holds immense potential for revolutionizing the educational landscape. This literature review sheds light on the various aspects and benefits associated with the integration of adaptive learning techniques powered by AI and ML algorithms.

First and foremost, adaptive learning offers personalized and tailored learning experiences for students. By analyzing individual learners' strengths, weaknesses, and learning styles, AI and ML algorithms can adapt the content, the pace, and the delivery methods to optimize learning outcomes. This individualized approach enhances engagement, motivation, and knowledge retention, ultimately leading to improved academic performance.

Furthermore, adaptive learning systems provide real-time feedback and progress tracking, enabling educators to identify students' areas of struggle and intervene promptly. By leveraging AI and ML capabilities, these systems can analyze large volumes of data, identify patterns, and generate actionable insights for both students and instructors. Such data-driven decision making not only facilitates targeted interventions but also allows for continuous improvement of the e-learning environment.

Moreover, the integration of AI and ML in e-learning opens up opportunities for dynamic content generation and usage. These technologies can analyze vast repositories of educational resources, adaptively recommend relevant content based on individual learner profiles, and even generate customized learning materials. The flexibility and adaptability of content delivery ensure that students receive the most up-to-date and relevant information, making their learning experiences more meaningful and effective.

Nevertheless, it is important to acknowledge the challenges and considerations that accompany the use of adaptive learning with AI or ML in e-learning. Ethical concerns, data privacy, algorithmic bias, and the need for effective teacher–student interactions are some of the critical areas that require careful attention. As the field continues to evolve, it is essential for researchers, practitioners, and policymakers to collaborate and establish best practices, guidelines, and ethical frameworks to ensure responsible and equitable implementation of adaptive learning technologies.

In conclusion, the integration of adaptive learning with AI or ML in e-learning has the potential to reshape traditional educational paradigms. By leveraging the power of data-driven personalization, timely feedback, and dynamic content delivery, adaptive learning systems can enhance student engagement, foster self-directed learning, and improve overall learning outcomes. As the field progresses, it is crucial to address the associated challenges and ethical considerations, enabling the realization of the full potential of adaptive learning in transforming education for the better.

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