A SYSTEMATIC REVIEW OF THE USE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN ONLINE EDUCATION

Shaikh Yasernihal Sajjadali
Research Scholar
DEPARTMENT OF COMPUTER SCIENCE
SUNRISE UNIVERSITY
jbhp11@gmail.com

Dr. Mahender Kumar
Research Guide
DEPARTMENT OF COMPUTER SCIENCE
SUNRISE UNIVERSITY

Abstract: *With the ever-growing quantities of data and the changing demands of higher education, such as digital education, the usage of artificial intelligence and machine learning methods across all disciplines has blossomed in the last few years. Online educational information systems also include plenty of student data. AI and machine learning can enhance digital schooling using this data. This research has two key contributions. The investigation begins with a systematic literature review. Second, the paper summarises the literature on AI-based algorithms in digital education. The research found six machine-related themes in digital education. This research found machine learning and deep learning algorithms in numerous digital learning topics. Intelligent tutors, dropout predictions, performance forecasts, adaptive and predictive learning, learning styles, analytics, group-based learning, and automation are these topics. All themes use artificial neural network, support vector machine, random forest, decision tree, naive Bayes, and logistic regression methods.*

Keywords: *AI; ML; DL; digital education; literature review; dropouts; intelligent tutors; performance prediction.*

Introduction

AI, comprising ML and DL, is a game-changer in numerous industries and sectors, including telecom, construction, transportation, healthcare, manufacturing, advertising, and education [1–3]. AI helps students to tailor learning based on their experiences and preferences, making it more significant in higher education. AI-based digital learning systems may adjust to students' knowledge, learning rates, and objectives to maximise learning. It may also assess student learning histories to detect shortcomings and recommend courses for a more customised learning experience [4,5]. AI may also minimise administrative work, freeing more time for higher education faculty to teach and research [6].

The COVID-19 epidemic increased university digitalization [7]. All universities have to teach online. Thus, educational institutions and students are discussing the post-COVID-19 repercussions of this paradigm change. AI can improve teaching and future digital education [8]. Digital education is "teaching and learning activities that employ digital technology as part of in-person, blended, and completely online learning environments" [9]. Digital education is using digital tools to educate and learn [10,11].

AI solves real-world issues using intelligent apps and machines. ML is a subset of AI that automatically learns and improves from experiences and data, whereas DL analyses multiple elements and structures like the human brain to solve complicated issues [12]. Thus, academically analysing these issues is crucial. This research examines the status of AI in higher education, including ML and DL. Two important findings are presented. The investigation begins with a systematic literature review. Second, the paper summarises the literature on AI-based algorithms in digital education. Note that the research covers higher education alone.

This paper continues as follows. Section 2 discusses related work, and Section 3 demonstrates the systematic revision process for objective and reproducible literature review. Section 4 describes the research demographics and AI in digital education topics from the literature, followed by the conclusion and future work in Section 5..

Related literature

Ten literature evaluations on AI in digital education range in technique and approach. Table 1 summarises and limits each investigation.

Murad et al. [13] provide many natural language processing-based strategies for promoting online learning systems to improve LMS design. Collaborative filtering, demographic, utilitarian, knowledge, community, and hybrid techniques are used. Content-based and collaborative filtering are the most common book and course suggestions. The report gives a preliminary investigation to develop LMS using 2013–2018 literature. Sciarrone et al. [14] provide a preliminary LMS design, implementation, and delivery research. The research introduces data-driven learning analytics. Learning analytical models were the most-cited models in the survey. These models capture data, report, forecast, act, and improve the learning environment. The paper does not explore model-compatible ML methods. Romero et al. [15] also highlight educational data mining's core ideas. Both papers summarised learning analytics and educational data mining [16,17,18].

Chen et al. [19] evaluate research on AI's effects on education. This qualitative study explores AI's main features and instructional methods. The research examines how AI affects administration, education, and learning. Guan et al. [20] examined AI topics and their progression, noting that profiling and analytics are trending. The research covers AI and deep learning in education. The research neglects ML algorithms for digital schooling. Kumar et al. [21] used educational data from a survey to construct models for increasing academic achievement and institutional effectiveness.

Most literature evaluations did not systematically evaluate the literature [14–21]. Two systematic literature reviews examined the limited literature from 2013 to 2018 [13] or predicted digital course dropouts [22]. Thus, we conducted a systematic revision to objectively and repeatable examine the AI literature on digital education. Section 3 describes methodical revision.

Research Methodology

Systematic revision research approach [23]. Systematic revision gives a consistent and impartial research perspective. Formulating research questions, searching relevant resources, data extraction after applying inclusion and exclusion criteria, and data analysis to answer research questions [23]. Figure describes this study's systematic revision technique..

Research Questions

The systematic revision began with these research questions. RQ1 addresses the study's first goal, a repeatable and objective literature review. RQ2 achieves the second goal of studying digital education algorithms.

RQ1: What themes of AI-based education exist in the literature?

RQ2: What kind of ML or DL models are currently used in digital education?

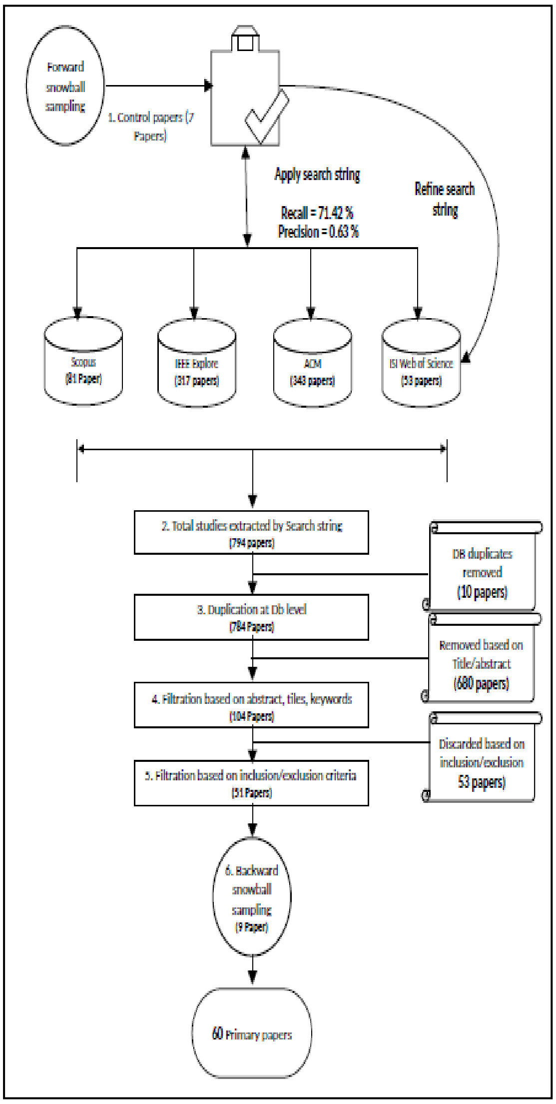

Figure . Systematic revision search process.

Search String Formulation and Performance Evaluation

This section describes the keywords and databases used to find publications relevant to this research. Three interventions form the search string:

Since keywords are generated from a small number of papers, Beyer et al. [24], Kent et al. [25], and Wohlin et al. [26] warned that the search string may overlook keywords. They presented numerous methods to avoid subjectivity in search string formulation. First, Kent et al. [25] described precision and recall in information retrieval (e.g., search string used to extract papers). Precision and recall measure information retrieval ability. Precision is the percentage of search string-relevant documents retrieved. Recall is the percentage of relevant documents recovered from the search string [25]. Beyer et al. [24] suggested an accuracy range of 0.0% to 14.3% and recall of 0% to 87% for information retrieval search strings. Second, Wohlin et al. [26] stressed the need of backward snowball sampling on the final set of research to reduce the possibility of missing studies when performing the search string query in databases. We employed backward snowball sampling to overcome the search string's missing keywords and assess its accuracy and recall (see Figure 1). First, we utilised seven control articles to assess search string accuracy and recall. The search strings used to retrieve publications have a precision (0.63%) and recall (71.42%) that are adequate for systematic revision investigations [24]. Second, we used backward snowball sampling and the search string to avoid missing key research. Thus, backward snowball sampling—scanning the reference list of 51 publications generated from the search string—found 9 more papers (see Figure 1). We used the search string to the following data sources to find relevant publications for the research (see Figure 1):

- IEEE Xplore;

- Web of Science;
- Scopus;
- ACM digital library.

Kappa Analysis and Filtration Criteria

Kappa analysis measures qualitative item inter-rater reliability for numerous raters. Kappa values range from <0 (no agreement) to 1.0 (perfect) [27]. Since several scholars used inclusion/exclusion criteria to extracted literature, we performed kappa analysis. By reaching considerable agreement, writers might objectively include or remove articles. Kappa analysis was two-step. Before applying the inclusion and exclusion criteria, we randomly picked 35 articles among papers derived from the search string. To ensure neutrality when employing the inclusion and exclusion criteria separately by the first and second authors, kappa analysis was done [28]. To assess inter-rater agreement, the first and second authors independently applied inclusion and exclusion criteria to 392 publications [28]. Second, we determined the kappa value (0.885), indicating near-perfect researcher agreement. Finally, we settled two disputes. This research included papers based on the following criteria. Articles must meet Table 2's quality standard.

Table 2. Inclusion/exclusion criteria

Inclusion Criteria	Exclusion Criteria
Studies addressing the use of AI/ML/DL in the teaching and learning.	Courses on machine learning
AI/ML/DL used on data collected from teaching and learning platforms.	Digital learning systems without the use of AI techniques.
Studies using supervised, semi-supervised, and unsupervised learning methods are included	No mention of AI/ML/DL uses in education.
Only peer-reviewed papers are included.	Articles not accessible in English.
All studies from 2000 to the present	The study is not accessible as a full text.

Data Extraction and Synthesis Strategy

The authors finalized Table 3's data extraction features for the research. To extract data from the papers, the authors produced a spreadsheet containing all Table 3 attributes. We identified themes in the data using Cruzes et alstandards .'s (see Section 4.2).

Table 3. Data extraction properties.

Data Extraction Property	Definition
General study information	Primary research ID, author(s), title, place, date, journal publishing data (volume and issue).
Type of paper	Problem identification, solution paper, survey, systematic review, experiment,

	case study
Research questions	Clear description of research question or problem under investigation.
Main aims of the Study	What were the objectives behind conducting the study?
Study outcomes	Short description of study outcomes.

Validity Threats

This section discusses systematic review validity risks and mitigation measures. Validity is the findings' dependability without the researchers' opinions [31,32]. We employed member checking to reduce researcher subjectivity. Before conducting the research, the other authors confirmed the review process created by the first author. Checking researchers' inter-rater agreement (kappa analysis) was one way to choose the correct studies for the study's scope (See Section 3.4). The study's reliability depends on the researcher's influence on data and analysis. We tried many methods to discover essential papers relevant to our systematic review investigation. Based on limited domain knowledge and existing research, the search string was created. One search string for all chosen databases risks missing main research. We measured search string accuracy and recall with seven control papers. Our search string was adjusted in all databases until it had sufficient accuracy and recall (see Section 3.3). Second, we triangulated four relevant databases to discover AI-related teaching and learning research. Third, we used backward snowball sampling to find any missing studies relevant to the topic and identified more (See Figure 1). Finally, the first two writers separately performed thematic analysis for data analysis and confirmed each other to generate common themes in the research. To guarantee data objectivity and accurate outcomes, we verified each other.

Results and Discussion

Based on data extraction qualities, the subsections below provide study distribution and qualitative analysis of extracted data.

Distribution of Studies

Figure 2 displays 60 study distributions. The vertical axis shows the number of studies, while the horizontal axis shows the year-span used in the search string to find relevant publications. Study publishing follows a linear trend. After 2015, more academics are studying the possibilities of AI/ML in education, making AI in digital education more important. Researchers investigating individualized learning tools may continue this trend. Figure 3 shows published study research methods. Most research (41) compared ML models to predict course dropouts or student achievement (see Section 4.2). This systematic revision study synthesized research information from eleven non-systematic literature reviews.

Thematic Analysis

This section used Cruzes et altheme's analysis principles [29,33]. The following processes identified six topics connected to AI in digital education research.

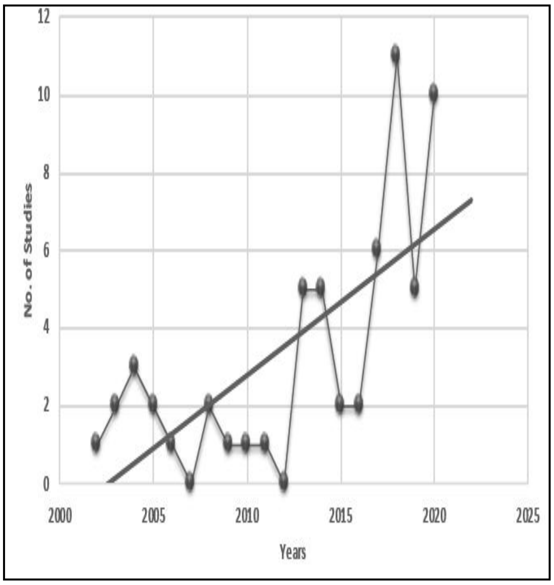

Figure 2. Number of studies published to date since 2000.

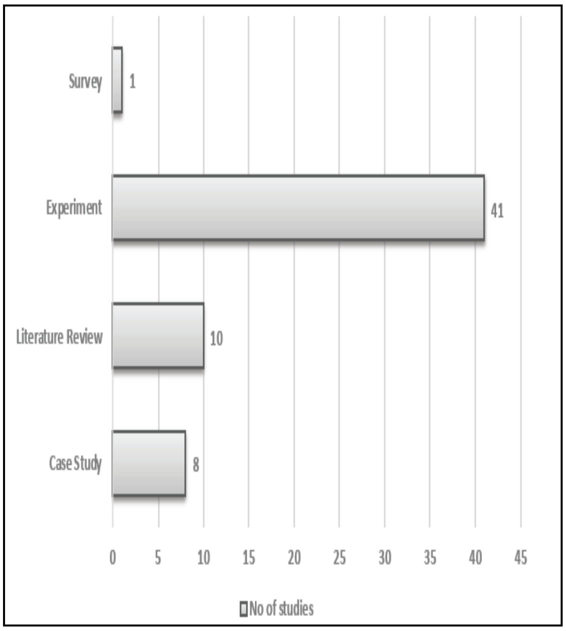

Figure 3. Research strategies used in the published studies.

Figure 4 classifies research by topics. The vertical axis depicts the six literary topics, while the horizontal axis shows the number of studies in each subject. Twelve articles were on "intelligent tutor," followed by "performance prediction," "adaptive, predictive learning, and learning styles," and "learning styles" (ten papers each). "Automation" and "analytics and evaluations and group-based learning" each included five articles.

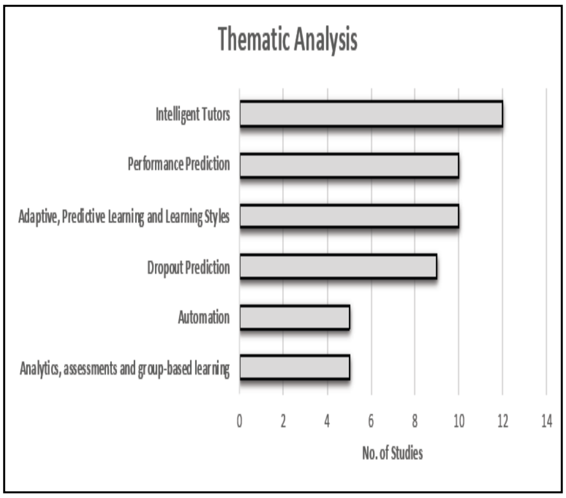

Figure 4. Classification of studies in thematic analysis.

Intelligent Tutors

Online education uses clever tutoring tools. 12 research in this area tested suggested intelligent tutors [34–45]. Butz et al. [34] introduced a web-based Bayesian intelligent teaching system (BITS). Bayesian networks advocate programming learning objectives and sequences for the tutoring system. The learner may want to study File I/O without reading all the content. BITS can assist students discover the least knowledge needed to comprehend File I/O and relate to pertinent ideas.

Suraweera et al. [35] compared KERMIT with ER tutors. The student learned entity relationship modelling utilising KERMIT and the ER-Tutor, two intelligent tutors. KERMIT models domain knowledge and generates student models using constraint-based modelling (CBM). KERMIT students outperformed ER tutors on the post-test. Alevenet et al. [36] developed cognitive tutor writing tools over six years (CTAT). CTAT has been used to develop a variety of example-tracing instructors without scripting using drag-and-drop approaches. Example-tracing tutors analyse student behaviour by flexibly comparing it to examples of right and poor problem-solving behaviours and give step-by-step advice on complicated issues while recognising numerous student tactics and preserving multiple interpretations.

Table 4. Definition of identified themes from thematic analysis.

Theme Name	Definition
Intelligent tutors	This theme refers to intelligent tutoring systems proposed or used in online education
Dropout prediction	This theme consists of studies predicting student dropouts from online courses using ML models.
Performance prediction	This theme consists of papers using different ML models to predict student performance in online courses
Adaptive and Predictive Learning and Learning Styles	This theme consists of studies that use different algorithms for adaptive and predictive learning as well as for addressing different learning styles
Analytics, assessments, and group-based learning	This theme consists of studies related to analytics, assessments, and group-based learning with the support of different algorithms.
Automation	This theme refers to the studies related to specific algorithms used for automation, whether recommendation, proficiency, classification, or for indexing in digital learning

Britt et al. [37] introduced the source apprentice intelligent feedback mechanism (SAIF), an intelligent tutor that gives students automated feedback on writing skills including plagiarism, uncited quotes, absence of citations, and restricted content integration. SAIF employs latent semantic analysis to discover and assist students to rewrite their writings for better quality.

SAIF input resulted in more explicit citations. Vijay et al. [38] presented a knowledge-based educational (KBEd) framework to capture, model, and encode laboratory teaching and evaluation procedures into AR technology. AR-trained and on-campus students performed similarly on typical experimental tasks. However, the AR tutors' limited capacity to grasp the learner's neglect caused a slight performance discrepancy between the two groups, but the tutor proved that first-year engineering students with no welding experience could transfer fundamental welding skills from AR to lab. Crowe et al. [39] performed an exploratory case study with twenty subject-matter experts programmers, instructional designers, and content experts to build a prototype knowledge-based academic writing software application for online learning. The findings revealed a Watson cloud-based application prototype was possible. Although the prototype focused on academic writing software, additional distance-learning technologies may be developed as tools and curricular applications.

Kim et al. [40] described an emotionallyaware AI smart classroom that provides real-time feedback to presenters using two modalities of an open learner model to increase presenting effectiveness, self-regulation, and non-verbal and verbal communication skills. Prominent advances, ideas, and empirical studies underpin the proposed system. Deep learning extracts a presenter's intonation, body language, and hand gestures from multimodal visual and audio data. The system also gathers audience ratings to evaluate presentations.

A prototype by Dahotre et al. [41] semi-automatically produces API instructors from open-source code. Tutors provide pupils with several training tools. This method improves student learning with high scores in less time than textbook-based teaching. Hsu et al. [42] introduced an intelligent question-answering bot called Xiao-Shih and increased its accuracy using ML. The chatbot has a 0.833 accuracy and 0.044 response rate. The random forest method outperformed NLP in accuracy. Haemaelaeinen et al. [45] examined five classification models: LR and SVM for numeric course data, NB, TAN, and BMN for categorical data. K-nearest neighbours (KNN) predicted class outcomes (pass or fail) with over 80% accuracy.

Appsamy et al. [43] proposed a content-based recommender (CBR) and collaborative filtering (CF) API tutor recommendation system. Based on requirements, the system proposes API tutors. CBR ratings outperformed CF-based recommendations. Gamboa et al. [44] suggested a Bayesian net-based intelligent tutoring system for e-learning. It has user model, knowledge base, adaption, instructional, and presentation modules. BNs analyse user preferences and expertise to provide pedagogical alternatives for the instructor.

Takeaway: Literature presents many intelligent teachers employing ML models including BN, CBR, and CF. These smart tutors advised students on learning materials based on their learning objectives and gave them feedback on their written assignments and oral presentations.

Dropout Prediction

ML algorithms predict online course dropouts on this subject. Nine articles predict online course dropouts using ML techniques [22,46–53]. Eight experimental articles and one literature review [22] were discovered. That research doesn't follow this study's systematic literature review requirements. Figure 5 displays the experimental ML models. SVM, LR, and DT are the most often used ML models to predict online course dropouts (five papers). Four publications employed random forest (RF) and gradient boosting (GB), three used KNN, and three used neural networks (NN). The dataset included online undergraduate and graduate courses in computer networks, web development, informatics, and social sciences. Studies also employed other features to train models. User characteristics (e.g., total clicks, count of time, etc.), course features (e.g., number of enrollers, start time, finish time, etc.), and demographic attributes (e.g., age, gender, work status, etc.). Appendix A lists all research characteristics (see Table A1).

Alsolami et al. [46] found a 90% dropout accuracy using the random forest model, suggesting it might be utilised in online education to predict early dropout. The model adjusts routes to assist. Cobos et al. [47] chose the Bayesian generalised linear model as the best approach since it trained faster and was more stable than NN and RF. Kotsiantis et al. [48] found no statistically significant difference between DT, NN, NB, instance-based learning methods, LR, and SVM. Gradient-boosting decision tree models by Lian et al. [49] predicted dropouts with 89% accuracy (GBDT). RF has the best accuracy (88%), according to Oliveira et al. [51]. LR had the poorest accuracy, 79%. Kostopoulos et al. [52] found a dropout predicted accuracy of 66.26% using NB based just on pre-university information (e.g., age, sex, education, employment status, etc.) and 84.56% at mid-year.

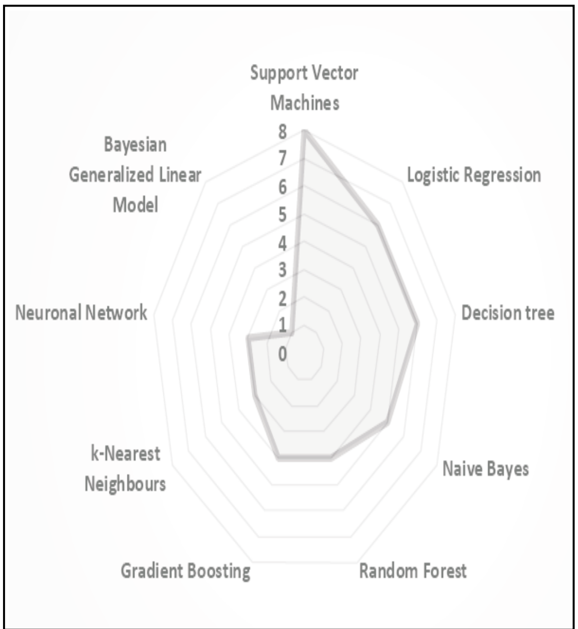

Figure 5. Algorithms used to predict students' dropout rate in the courses.

Performance Prediction

10 studies use various ML models to predict online student performance in this area. This topic has 10 experimental studies like the student dropout theme [54–63]. Figure 6 shows the number of machine models studied. SVM, LR, NB, ANN, DT, and J48 are the most often used machine models to predict student performance (e.g., grades) (four papers). Two research each employed backpropagation (BP), GB, and JRIP. One research employed KNN, LSTM, ELMs, voltera, expectation maximisation, simpleKMeans, and SGD. Appendix B lists each study's datasets and characteristics (see Table A2).

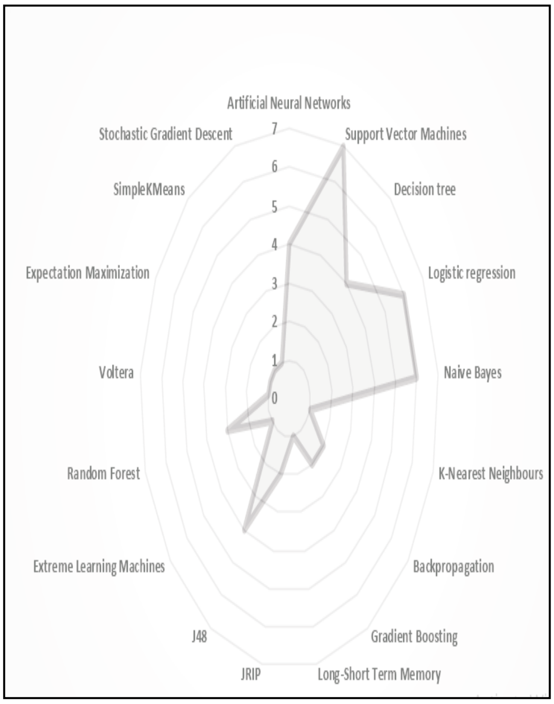

Figure 6. Algorithms used to predict students' performance.

Tomasevic et al. [54] utilised ML to predict final test outcomes using pre-exam data. ANN with engagement and prior performance data had the maximum accuracy. SVM followed ANN, with NB yielding the lowest results. BP, SVM, and GBC predicted student grades at 87.78%, 83.20%, and 82.44%, respectively, according to Sekeroglu et al. [55]. Hussain et al. [56] found that DT, J48, JRIP, and GBT were best at predicting low-engagement students in an open university exam.

De Albuquerque et al. [57] found that the MLP, an ANN, had an average accuracy of 85% and a maximum of 95% accurate classifications. Deo et al. [58] found that the ELM model outperformed the RF and Volterra models across all grades (e.g., C, F, etc.). Kotsiantis et al[59] .'s post hoc study showed that NB has the highest overall accuracy (72.48%), followed by LR (72.32%), BP (72.26%), and SVM/SMO (72.17%). Lorenzo et al. [60] predicted student video, workout, and assignment involvement using multiple ML models. SGD had the highest video engagement index (89.09%), followed by exercise (88.79%) and assignment (85.39%). Jayaprakash et al. [61] found that LR, SVM, and NBs beat J48 in recall. When sample size changes, all three algorithms behave similarly. LR, SVM, and NB are high-bias, low-variance learners.

All linear models have poor representational power and stable variance. Yoo et al. [62] found that SVM predicts student project success better than J48 and NB and is less susceptible to feature number changes. Romero et al. [63] used clustering methods with class-associated rule mining instead of classification models to identify students at risk of failing before and after the course. In all eight datasets, the EM algorithm predicts student achievement better from online discussion forum participation than the other classification systems.

Adaptive and Predictive Learning and Learning Styles

This subject includes works on adaptive and predictive learning algorithms and digital education learning styles. This subject (see Table 5) has ten papers: six experiment-based studies [64–69], three case studies [70–72], and one survey-based research [73]. ANN teachings are studied [64]. The model finds the optimal way to link known ideas to create a collection of papers for learners. The student self-defines learning objectives, and selection algorithms give the best didactic plan based on the goal and the learner's knowledge [64].

Adaptive mechanisms need learner and resource modelling [73]. Therefore, learning styles affect modelling. K-means classifies online learners' learning methods. Cluster analysis group related data into groups. The learners are goal-type, task-based, self-learning, steady, and conventional [73]. A determinantal point processes ML research samples a variety of questions for newcomers in massive open online courses (MOOC) to increase their individualised learning [65]. This strategy selects the initial majority of questions by not asking every newcomer the identical questions based on their known knowledge components.

This strategy surpasses uncertainty sampling by giving MOOC newbies relevant feedback on their strengths and weaknesses [65]. An intelligent English-teaching platform uses decision tree algorithms and neural networks to create an assessment implementation model [72]. This strategy creates a deep learning-assisted online system to enhance English language abilities and enable customised learning and instruction [72].

Bayesian nets can determine students' learning styles to distribute training materials [66]. Ten students test this method. The learning style model categorises pupils by data processing style. This research found that the Bayesian net accurately identifies student learning styles [66]. Integrating a complete digital learning style model yields an adaptive recommendation-based online learning style (AROLS) [67]. Learner clusters provide suggestions based on learning styles. Based on browsing history, the similarity matrix and connection criteria for various learning materials provide individualised suggestions [67].

[68] predicts student outcomes using the adaptive random forest classification method and compares performance. Predictive tasks include feature significance analysis. Educational data is analysed using RF and adaptive random forest (ARF) to test the system's capacity to anticipate outcomes depending on student input [68]. Another research offers individualised suggestions [69].

They use the DT technique to classify learners and offer the best learning routes based on self-perception, learning styles, and creativity [69]. Adaptive teaching uses AI [70]. The authors divide ML into three input–output categories: supervised, unsupervised, and reinforcement learning [70]. Educational data pipelines should use a grey-box approach [71]. A case study suggested a way for creating ML pipelines to predict student learning success [71]. .

Table 5. Algorithms and approaches used for adaptive and predictive learning and learning styles

Papers	**Methodology**	**Algorithms**
[64]	Experiment	Artificial neural network (ANN)
[73]	Survey	K-means
[65]	Experiment	Determinantal point processes (DPPs)
[72]	Case study	Decision tree classification, neural network
[66]	Experiment	Bayesian nets
[67]	Experiment	K-means clustering
[68]	Experiment	Random forest (RF) and adaptive random forest (ARF)
[69]	Experiment	Decision tree method
[70]	Case study	1 Supervised learning, 2. unsupervised learning, 3. reinforcement learning
[71]	Case study	Principal component analysis (PCA), support vector machine (SVM), random forest (RF), normalized root mean squared error (NRMSE)

Analytics, Assessments, and Group-Based Learning

This subject covers analytics, evaluations, and group-based learning using algorithms. Table 6 shows five experiment-based works on this subject [74–78].

Project-based learning supports group work using a multimodal learning analytics system (MMLA) [74]. This study automatically detects significant student characteristics in project-based learning settings by using instructor assistance and supervised ML and DL approaches to examine data from several sources. MMLA data is classified using neural networks and regression to predict student group performance in group-based learning settings [74]. Smart societies need a tailored ubiquitous e-teaching and e-learning framework to improve development, administration, and delivery

[75]. This framework includes a sentiment analyzer, user activity detection, user identification, and adaptive content delivery mode advisor. The system contains a naïve Bayes classifier, random forest, and deep learning artificial neural network [75].

Using the genetic algorithm (GA) to arrange students by degrees and social links improves student engagement and cooperation [76]. This research employed multiple GA models to improve auto-grouping learning. This method creates very varied groups and motivates pupils to study [76]. Deep learning technology is used to create a virtual classroom [77]. R-CNN and SVM analyse the classroom environment in real time. The research sheds light on classroom time, instructors, students, attendance, and environment [77]. E-learning system usability is evaluated using ML. Support vector machines, neural networks, decision trees, and multiple linear regression predict and find e-learning system usability by identifying the most essential usability characteristics [78].

Table 6. Algorithms and approaches used for analytics, assessments, and group-based learning.

Papers	Methodology	Algorithms
[74]	Experiment	Naive Bayesian (NB), logistic regression (LR), support vector machine with linear kernel (SVML), support vector machine for regression
[75]	Experiment	Naive Bayes classifier (NBC), random forest (RF), and deep learning artificial neural network
76]	Experiment	Genetic algorithm (GA)
[77]	Experiment	R-CNN, SVM
[78]	Experiment	Support vector machine (SVM), neural networks (NN), decision trees (DT), linear regression (LR)

Automation

This subject covers digital learning algorithms for recommendation, proficiency, categorization, and indexing. Five experiments [67,79–81] and one case study [82] support this trend.

Mabrouk et al. [82] introduce an online learning platform hybrid intelligent recommendation system. This system uses the classification and regression trees (CART) method to suggest and make learning information accessible [82]. Chen et al. [67] use K-means to create learner groups based on tailored learning style recommendations.

Hasan et al. [79] report on automated competency checking utilising characteristics from a Japanese English learner database. To aid foreign language acquisition, they collected implicit and explicit information from student data [79]. This research uses ID3, C4.5, Bayesian networks, and SVM to predict language competency using non-trivial error-related variables [79].

ANNs and LMS were used to assess accuracy, recall, and F1 value [80]. Topic hierarchies from text and audio transcripts are used to index video lectures automatically [81]. Husain and Meena [81] used semi-supervised latent Dirichlet allocation (LDA) to address the complementary strengths of slide text and audio transcript data. This method employs video slide words to train the model. The suggested method indexes video lectures effectively [81].

Digital education relies on automation.

It may streamline repetitive procedures in digital learning. Thus, to address automation in digital education, Table 7 provides an overview of techniques and AI-based algorithms utilised within this issue, whether for automated content recommendation, indexing video sequences, or language competency, which is especially crucial for globalisation of learners.

Table 7. Algorithms and approaches used for automatic recommendation, proficiency, classification, and indexing.

Papers	Methodology	Algorithms
[79]	Experiment	ID3, C4.5, Bayesian net and SVM
[80]	Experiment	ANN, least mean square (LMS)
[81]	Experiment	semi-supervised LDA algorithm
[82]	Case study	CART algorithm (classification and regression trees)
[83]	Experiment	K-means

5. Conclusions and Future Work

This article presents the findings of a thorough review of digital education literature on AI-based techniques. This research identified AI themes and ideas and which ML- or DL-based models digital education uses. Following the systematic revision criteria to thematically analyse the literature is another important addition. This paper has mostly experiments, which is intriguing. Researchers may compare algorithm outcomes utilising digital education data like student dropout or performance prediction. From 2015, ML or DL in digital education publications grew. Researchers have been using ML and DL to all disciplines. In this research, ML and DL in digital education are also growing trends.

Our findings provide policymakers, educators, researchers, and higher education institutions valuable insights into the possibilities of AI- and ML-supported digital education systems. We cover six digital education issues to help you comprehend AI and ML in higher education. These basic topics may help build and integrate AI-supported techniques into educational modules, systems, and pedagogical practises. Our findings may address and anticipate dropout rates, identify course performance difficulties, and include learning analytics and automation in such systems. Our study also helps choose AI- and ML-supported methodologies for particular intelligent instructor designs. Our study may also be used to develop AI- and ML-supported courses that reinvent course curricula and improve digitalized higher education institutions and their prospects. Our results may help digital education policymakers and instructors.

The project may investigate empirical situations to contextualise ML models and provide a design approach for practitioners to use ML models while creating digital education systems.

References

1. *Reddy, S.; Allan, S.; Coghlan, S.; Cooper, P. A governance model for the application of AI in health care. J. Am. Med. Inform. Assoc.*
2. *2019, 27, 491–497. [CrossRef]*
3. *Lee, J.; Davari, H.; Singh, J.; Pandhare, V. Industrial Artificial Intelligence for industry 4.0-based manufacturing systems. Manuf. Lett. 2018, 18, 20–23. [CrossRef]*
4. *Langer, A. Analysis and Design of Next-Generation Software Architectures: 5G, IoT, Blockchain, and Quantum Computing; Springer International Publishing: New York, NY, USA, 2020.*
5. *Kokku, R.; Sundararajan, S.; Dey, P.; Sindhgatta, R.; Nitta, S.; Sengupta, B. Augmenting classrooms with AI for personalized education. In Proceedings of the 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Calgary, AB, Canada, 15–20 April 2018; pp. 6976–6980.*
6. *Maghsudi, S.; Lan, A.; Xu, J.; van Der Schaar, M. Personalized Education in the Artificial Intelligence Era: What to Expect Next.*
7. *IEEE Signal Process. Mag. 2021, 38, 37–50. [CrossRef]*
8. *Pokrivcˇáková, S. Preparing teachers for the application of AI-powered technologies in foreign language education. J. Lang. Cult. Educ. 2019, 7, 135–153. [CrossRef]*
9. *Cone, L.; Brøgger, K.; Berghmans, M.; Decuypere, M.; Förschler, A.; Grimaldi, E.; Hartong, S.; Hillman, T.; Ideland, M.; Landri, P.; et al. Pandemic Acceleration: Covid-19 and the emergency digitalization of European education. Eur. Educ. Res. J. 2021CrossRef]*
10. *Popenici, S.A.D.; Kerr, S. Exploring the impact of artificial intelligence on teaching and learning in higher education. Res. Pract. Technol. Enhanc. Learn. 2017, 12, 22. [CrossRef]*
11. *VanLeeuwen, C.A.; Veletsianos, G.; Belikov, O.; Johnson, N. Institutional perspectives on faculty development for digital education in Canada. Can. J. Learn. Technol. 2020, 46, 2. [CrossRef]*
12. *Dillenbourg, P. The Evolution of Research on Digital Education. Int. J. Artif. Intell. Educ. 2016, 26, 544–560. [CrossRef]*
13. *Taglietti, D.; Landri, P.; Grimaldi, E. The big acceleration in digital education in Italy: The COVID-19 pandemic and the blended-school form. Eur. Educ. Res. J. 2021, 20, 423–441. [CrossRef]*
14. *Rajendran, R.; Kalidasan, A. Convergence of AI, ML, and DL for Enabling Smart Intelligence: Artificial Intelligence, Machine Learning, Deep Learning, Internet of Things. In Challenges and Opportunities for the Convergence of IoT, Big Data, and Cloud Computing; IGI Global: Hershey, PA, USA, 2021; pp. 180–195.*
15. *Murad, D.F.; Heryadi, Y.; Wijanarko, B.D.; Isa, S.M.; Budiharto, W. Recommendation system for smart LMS using machine learning: A literature review. In Proceedings of the 2018 International Conference on Computing, Engineering, and Design (ICCED), Bangkok, Thailand, 6–8 September 2018; pp. 113–118.*
16. *Sciarrone, F. Machine learning and learning analytics: Integrating data with learning. In Proceedings of the 2018 17th International Conference on Information Technology Based Higher Education and Training (ITHET), Olhao, Portugal, 26–28 April 2018; pp. 1–5.*
17. *Romero, C.; Ventura, S. Educational Data Mining: A Review of the State of the Art. IEEE Trans. Syst. Man, Cybern. Part C (Appl. Rev.) 2010, 40, 601–618.*
18. *Romero, C.; Ventura, S. Data mining in education: Data mining in education. Wiley Interdiscip. Rev. Data Min. Knowl. Discov. 2013, 3, 12–27.*
19. *Roll, I.; Wylie, R. Evolution and Revolution in Artificial Intelligence in Education. Int. J. Artif. Intell. Educ. 2016, 26, 582–599.*
20. *Moubayed, A.; Injadat, M.; Nassif, A.; Lutfiyya, H.; Shami, A. E-Learning: Challenges and Research Opportunities Using Machine Learning Data Analytics. IEEE Access 2018, 6, 39117–39138.*