Received 12 June 2025, accepted 14 July 2025, date of publication 17 July 2025, date of current version 25 July 2025.
Digital Object Identifier 10.1109/ACCESS.2025.3590134

SURVEY

Machine Learning in Education: Innovations, Impacts, and Ethical Considerations

ERSIN ELBASI[1], MUHAMMAD NADEEM[1], (Senior Member, IEEE), YEHIA IBRAHIM ALZOUBI[2], (Member, IEEE), AHMET E. TOPCU[1], (Member, IEEE), AND GREESHMA VARGHESE[1]
[1]College of Engineering and Technology, American University of the Middle East, Kuwait City 54200, Kuwait
[2]College of Business Administration, American University of the Middle East, Kuwait City 54200, Kuwait
Corresponding author: Ersin Elbasi (ersin.elbasi@aum.edu.kw)

ABSTRACT Machine Learning (ML) has recently emerged as a powerful tool with significant potential to revolutionize education, bringing about fundamental changes in pedagogy and research. Its applications span various domains within academia, including administration, instructional method enhancement, and grade prediction. This study illustrates how ML can enhance the effectiveness of research, instruction, and study strategies by adapting to student needs and leveraging new communication tools within virtual learning environments. The literature review included various research articles sourced IEEE Xplore, Scopus, Web of Science, PubMed, Google Scholar, and ScienceDirect. The inclusion criteria encompassed studies that explicitly defined Artificial Intelligence (AI) within the medical education sector and were published in English with peer review. This study delves into the potential applications of ML and its associated benefits, which can aid researchers in implementing AI-based educational systems.

INDEX TERMS Artificial intelligence, machine learning, education, personalized learning, intelligent content generation.

I. INTRODUCTION

With the introduction of modern practices in data collection and tremendous growth in the computational capability of computers, a paradigm shift towards novel learning techniques has been observed. This has led to the development of ML, which is essentially a subset of AI that enables computers to learn from data without explicit programming. Regarding education, ML has been used to analyze large datasets to make predictions and decisions, identify patterns, and personalize teaching and learning experiences. This paper explores various applications and uses of ML in education.

The global AI in education market was valued at USD 5.88 billion in 2024 and is expected to expand at a Compound Annual Growth Rate (CAGR) of 31.2% from 2025 to 2030 [1]. This growth is fueled by rising demand for personalized learning solutions, the rapid shift toward e-learning platforms (accelerated by the COVID-19 pandemic), and increasing investments in EdTech startups. By technology, ML led the market with a 64.7% revenue share in 2024, owing to its critical role in enabling personalized and adaptive learning experiences [1].

By component, the solutions segment dominated the market in 2024, accounting for 70.3% of revenue share, largely due to the widespread use of AI-powered learning management systems [1]. Meanwhile, the services segment is anticipated to grow at a significant CAGR, driven by rising demand for implementation, integration, and consulting services in AI education. In terms of deployment, the cloud-based segment held the largest revenue share (60.1% in 2024), reflecting the growing preference for cloud-based educational platforms [1]. The breakdown of AI share in the education market worldwide is given in Figure 1.

Figure 2 shows the share of AI in education in 2024. By application, the learning platform and virtual facilitators segment led the market in 2024, capturing the largest revenue share of 45.9%, driven by growing demand for

The associate editor coordinating the review of this manuscript and approving it for publication was Bhaskar P. Rimal.

digital learning environments and personalized education [1]. Virtual facilitators, such as AI-powered tutors and teaching assistants, offer real-time interaction and support to students, enhancing engagement and improving learning outcomes [2]. In terms of end use, the higher education segment dominated in 2024 with a revenue share of 44.3%, mainly due to the rising demand for innovative teaching approaches and advanced learning technologies within colleges and universities [1].

Regionally, North America held the largest share of the AI in education market in 2024, accounting for 38.0% of revenue [1]. This leadership is attributed to the region's robust technological infrastructure and substantial investments in education technology [3]. Additionally, the presence of leading EdTech firms and AI solution providers in the U.S. drives innovation and accelerates AI adoption across educational institutions [1]. The European AI in education market is projected to grow at a significant CAGR during the forecast period, supported by widespread adoption of digital learning solutions and a strong push for personalized education throughout various countries [4]. Meanwhile, the Asia Pacific market is expected to experience the fastest CAGR, fueled by increased implementation of digital learning platforms and AI technologies in countries such as China, India, and Japan, where there is a strong focus on improving educational quality and accessibility [1].

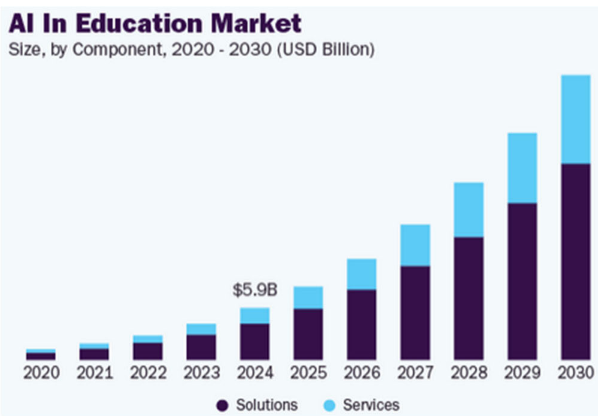


FIGURE 1. AI in education market share (Source: [1]).

Improving the effectiveness of instruction methods through personalized attention is one of the leading trends in AI education. In the past, teachers were unable to give each pupil individualized attention because of the growing administrative load. The automation of the routine duties such as class planning and grading using AI tools have offered the teachers the luxury of spending more time to concentrate on high-impact endeavors, such as mentorship, student support, and discussion facilitation [5]. They can even address customized queries from the students, thanks to the Virtual assistants with AI capabilities. It helps educators more efficiently answering student questions in a personalized way [6].

Furthermore, the field of education is being revolutionized through data-driven decision-making. The large volume of student data may be collected and analyzed using AI which

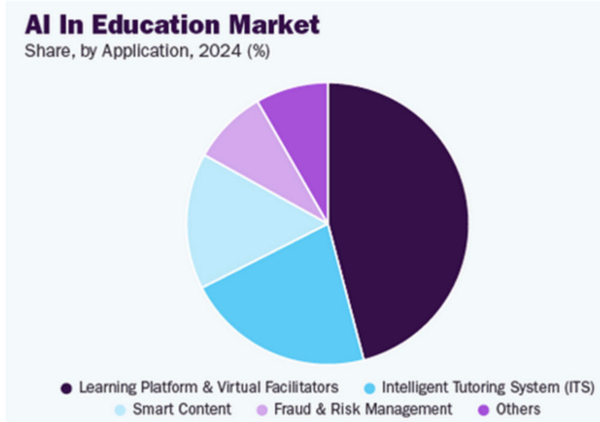


FIGURE 2. Application-wise growth of AI in education market (Source: [1]).

provides educators, administrators, and policymakers with insightful information. It is facilitating educators in developing better curriculum, allocating the resources efficiently, and enhancing teaching strategies. Now it is possible to design instructions to be more focused and efficient by recognizing trends, learning patterns, and knowledge gaps by analyzing the data. Another innovation in this field is the ML-based intelligent tutoring systems. They not only imitate human tutors but also has the ability to personalize training and provide real-time feedback without any human intervention [7]. They can also adapt to the learning preferences of the students, allowing them to pace their learning, enhancing the understanding of the concepts and fostering an enjoyable learning experience. The combination of ML with other technologies such as Augmented Reality (AR) and gaming has opened the new horizon of instruction design and other applications in education settings for meaningful learning [8], [9]. This combined with AI has helped in developing immersive and engaging learning experiences which are important for Deep Learning (DL). When amalgamated with Virtual Reality (VR) and AR, this allows students to explore historical sites, do virtual science experiments, and participate in lifelike simulations [10]. In addition, ML algorithms can also capture the footprint of student interaction style and patterns in these virtual settings, which is used to provide instant feedback and make amendments to optimize their learning experience at the same time. Also, assessing student performance is crucial component in education and the need of intelligent assessment systems is on rise as it reduces reliance on standard examination practices and gives a more accurate picture of students' achievements [11], [12]. Recently, the use of AI generative tools has gained popularity among the students making it hard to assess learning outcomes through the conventional evaluation process [13]. Therefore, there is a dire need to replace these methods with innovative and flexible ones which could analyze student responses, identify learning gaps, and generate personalized questions to gauge understanding and critical thinking skills. In short, ML technology is proving very helpful in engaging and motivating

TABLE 1. Abbreviations used in this study.

Abbreviations	Definition	Abbreviations	Definition
AI	Artificial Intelligence	LLM	Large Language Models
AR	Augmented Reality	LMS	Learning Management System
ACG	Automated Content Generation	LSTM	Long Short-Term Memory
BERT	Bidirectional Encoder Representatio ns from Transformers	ML	Machine Learning
CNN	Convolutiona l Neural Network	MOOC	Massive Open Online Course
DL	Deep Learning	NLP	Natural Language Processing
DT	Decision Tree	RNNs	Recurrent Neural Networks
GPT	Generative Pre-trained Transformer	RL	Reinforceme nt Learning
IoT	Internet of Things	SVM	Support Vector Machine
IPA	Intelligent Pedagogical Agent	VR	Virtual Reality

the students by providing them with more control over their learning experience [9]. On the other hand, it is also helping the instructors to design instructions and assessments to provide more authentic learning experiences [11]. Table 1 summarizes the abbreviations used in this study.

This review explores the ways in which ML is transforming education. It provides intuitive knowledge for scholarly research, instructional strategies, policy formation, and AI ethics. In addition to summarizing existing literature, it establishes the framework for further exploration and practical use of ML in learning environments. The potential of ML and its weaknesses, including ethical and accessibility issues, are also assessed in this study. To shape the future of AI-driven education and make sure that technology enhances learning results, stays inclusive, and morally responsible at the same time, it is imperative to understand and address these concerns.

This work also enriches the existing body of knowledge by addressing significant gaps in the literature about the deployment of ML in education, concentrating notably on the scalability of ML solutions across varied educational contexts and their applicability in low-resource settings. While much of the present research illustrates ML's potential to improve educational results, it often remains confined to narrow, well-resourced situations, which restricts its generalizability. This work advances the field by exploring how ML models can adapt to various linguistic and infrastructural settings and by proposing strategies such as lightweight model design, transfer learning, and offline functionality to enhance accessibility and effectiveness in resource-constrained environments. It helps develop more equal, inclusive, and internationally relevant educational technology corresponding to broader aims for sustainable and accessible learning systems.

This systematic review explores the role of ML in education, examining its applications, effectiveness, challenges, ethical considerations, and future research directions. This review followed a structured methodology to identify, evaluate, and synthesize research on the application of ML techniques in education. The process comprised database selection, keyword-based search, application of inclusion and exclusion criteria, and thematic analysis of selected studies. To ensure a comprehensive analysis, a thorough search was conducted across multiple academic databases, including IEEE Xplore, Scopus, Web of Science, PubMed, and Google Scholar. The search strategy combined Boolean operators (AND, OR) with relevant keywords to identify studies related to ML and its use in educational settings. The keywords used include "machine learning," "education," "student performance prediction," and "adaptive learning." Filters included the English language and publications between 2015 and 2025. Studies were selected based on clear inclusion and exclusion criteria to ensure relevance and quality:

Inclusion Criteria:

- Published in peer-reviewed journals or conference proceedings.
- Focused on ML applications in education.
- Provided empirical findings or theoretical insights on the topic.

Exclusion Criteria:

- Non-English publications.
- Studies without full-text availability.
- Articles that focused purely on the technical development of ML without an educational context.

Initially, 543 papers were identified through a keyword-based search. After title and abstract screening, 293 papers remained. Following full-text review, 218 studies were included in the final synthesis, including 144 journal articles, 62 conference papers, four book chapters, and eight relevant websites. For each study, we extracted the ML algorithm used, data characteristics, evaluation metrics (accuracy, precision, recall), and educational application type. Findings were organized thematically into categories such as performance prediction, learning analytics, and personalized tutoring. Figure 3 provides a visual representation of the structural organization of this review paper.

II. MACHINE LEARNING BASICS

ML is a subfield of AI having the ability to learn from a given dataset and classify and predict the outcomes as a result of the understanding gained in the process [14]. ML is different from the conventional computational approaches which use a sequence of programming instructions to obtain

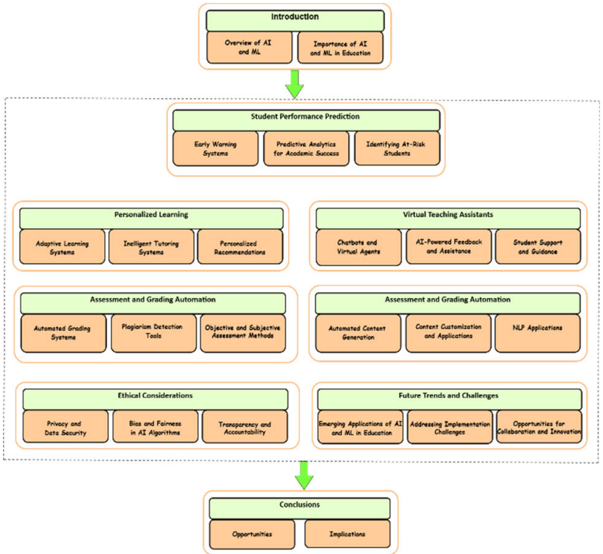


FIGURE 3. Paper structure.

the desired output. Instead, it involves computers training on data, learning from the data, and utilizing statistical techniques to compute the output [15]. The output of the trained model either performs classification or makes a prediction. The type of output expected from a given model depends on the application for which the model is being trained. ML is accustomed to analyzing large volumes of data, examining patterns, and classifying information. The analysis of large datasets enables trained models to automate the decision-making process [16]. This decision-making process may help students and academic institutions revolutionize education.

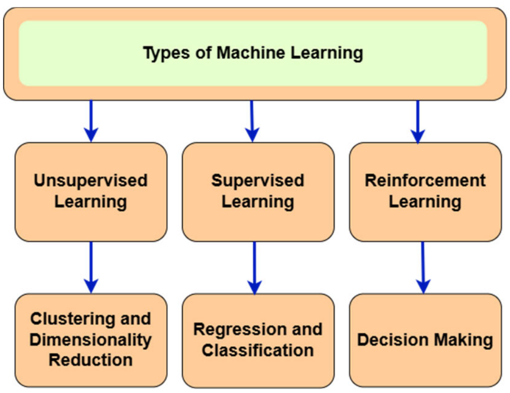


FIGURE 4. Machine learning methodologies.

A. MACHINE LEARNING METHODS

ML can be used to perform various tasks classified into different categories. There are three main types of ML: supervised, unsupervised, and Reinforcement Learning (RL). This is summarized in Figure 4. Here, we present the details of the different learning methods.

ML algorithms can be divided into three main categories [17], [18]. Frist category is supervised learning in which algorithms are trained using a labelled dataset i.e., the input data are accompanied by the correct output thus mapping new inputs to their correct outputs [19]. Supervised learning algorithms are widely used in educational systems where labeled datasets—such as student grades, test results, or engagement levels are available. The most used algorithms belonging to this category include linear regression, logistic regression, Decision Tree (DT), and neural networks [19]. They are used to predict students' learning outcomes, classify their knowledge levels (e.g., beginner, intermediate, advanced), and recommend personalized exercises. Platforms like Knewton or DreamBox Learning use supervised models to predict student performance based on quiz results, time-on-task, and prior knowledge [28]. These predictions are used to adapt the difficulty and type of content delivered in real time. In contrast to this, the algorithms are fed with unlabeled datasets in unsupervised learning which find patterns or structures within the data, without any guidance or labelled outputs. When analyzing large and complicated datasets, unsupervised learning is vital, specifically for anomaly detection, dimensionality reduction, and grouping [20]. Since it allows the development of linkages and patterns organically without the need for labels, clustering is particularly useful. These characteristics make it an effective instrument to find obscured clusters in big volumes of data [20]. They are widely used in intelligent tutoring systems to segment students based on learning behaviors, such as how they navigate content or respond to feedback.

There are many techniques that improve the effectiveness and performance of ML models [21]. One such technique is dimensionality reduction which achieves this goal by eliminating less significant features and concentrating on the most crucial ones [19]. Principal component analysis, autoencoders, and k-means clustering are some examples of dimensionality reduction often used to simplify high-dimensional learner data (e.g., time logs, question attempts) to identify key factors influencing learning progress. Association rule mining is also employed to discover common learning trajectories or difficulties across student groups. The third category is RL that relies on interaction with the environment to achieve certain goals [22]. In this approach, an agent learns over time through trial and error to provide the best results by making decisions and getting feedback in the form of rewards or penalties. This kind of learning is very popular in robotics, gaming, and autonomous driving, where systems must constantly adapt, and advance based on real-world experiences [22]. In education settings, platforms use Markov Decision Processes (MDPs) or Deep Q-Networks (DQNs) to select the next best activity, maximizing learning gains while minimizing student frustration [21]. ALEKS, for instance, uses RL to adjust the difficulty of questions in math lessons based on student performance. The game difficulty and rewards can be adapted through RL agents in real time to maintain engagement and motivation. This technique is also used to optimize tutoring strategies by learning from the student's responses over time. For instance, if a student consistently struggles with conceptual questions, the RL model

TABLE 2. ML techniques and their applications in education.

ML Techniques	Algorithms		Applications
Supervised Learning	DT & Random Forests	Used for predicting student success/failure based on multiple learning factors.	- Early dropout detection [23] - Personalized course recommendations [24] - Assessing learning outcomes [25]
	SVM	Classify students' performance levels (e.g., high, medium, low engagement).	
	Logistic Regression	Helps in predicting binary outcomes, such as whether a student will pass or fail a course.	
Unsupervised learning	Clustering (K-Means, DBSCAN, Hierarchical Clustering)	Groups students with similar learning behaviors for customized interventions.	- Student learning path optimization [26] - Identifying student engagement trends [27] - Adaptive learning systems [28]
	Principal Component Analysis (PCA)	– Reduces dimensionality in large datasets to identify key learning attributes.	
	Association rule mining (Apriori Algorithm)	Identifies patterns in student behaviors (e.g., students who struggle with algebra also struggle with trigonometry).	
DL	CNNs	Used for image-based grading, such as scanned answer sheets and handwriting recognition.	- AI-Powered essay grading [29] - Handwriting recognition for exam papers [30] - Real-time AI Feedback [31] - ClassMood trackers [32] - Emotion-aware AI tutors [33] - Student attention monitoring in online learning [34]
	RNNs	Handle text-based assessments like essay grading and AI-driven feedback.	
	Optical Character Recognition (OCR)	Extracts handwritten text from exam sheets and converts it into machine-readable format.	
	YOLO, OpenCV	Analyses student facial expressions to detect focus and engagement.	
	Speech Emotion Recognition (SER)	Uses tone and pitch analysis to determine student frustration or enthusiasm.	
	Text sentiment analysis (BERT, LSTM)	Evaluates student discussion posts to gauge sentiment towards course content.	
RL	Markov Decision Process (MDP)	Helps AI decide the next best action for personalized learning.	- AI-driven personalized learning paths [35] - Gamification in education dynamic quiz generation [36]
	Deep Q-Networks (DQN)	Reinforcement-based neural networks adjust lesson difficulty dynamically.	
	Multi-Armed Bandit Algorithms	Optimize which content to show a student next for efficient learning.	

learns to increase explanatory content or switch to simpler analogies.

B. MACHINE LEARNING TECHNIQUES IN EDUCATION

Table 2 presents a structured overview of how different ML techniques are applied in education using specific algorithms. It categorizes them into Supervised Learning, Unsupervised Learning, DL, and RL, detailing their key algorithms and practical applications in education.

A two-stage screening approach was employed to enhance transparency and minimize bias in the publication selection process. Initially, titles, keywords, and abstracts were reviewed to assess basic relevance, followed by a full-text evaluation of eligible studies. All authors conducted the screening process, and disagreements were resolved through discussion and consensus. This systematic approach ensured consistency and helped reduce selection bias. The inclusion and exclusion criteria were developed to capture a comprehensive yet focused set of studies that reflect the educational implementation of artificial intelligence, rather than only technical innovations.

Despite the breadth of this review, several limitations should be acknowledged. First, the publication search strategy was restricted to peer-reviewed articles published in English, which may have excluded valuable insights from non-English or grey literature sources, introducing potential publication bias. Second, although a structured screening protocol was applied, the inherent subjectivity in article selection could result in selection bias. Third, the included studies varied significantly in design, context, and metrics used, which limited the ability to conduct a meta-analysis or directly compare findings. Finally, the rapid advancement of AI technologies means that some tools or platforms discussed in this study may become obsolete or superseded shortly after publication, affecting the long-term generalizability of the results.

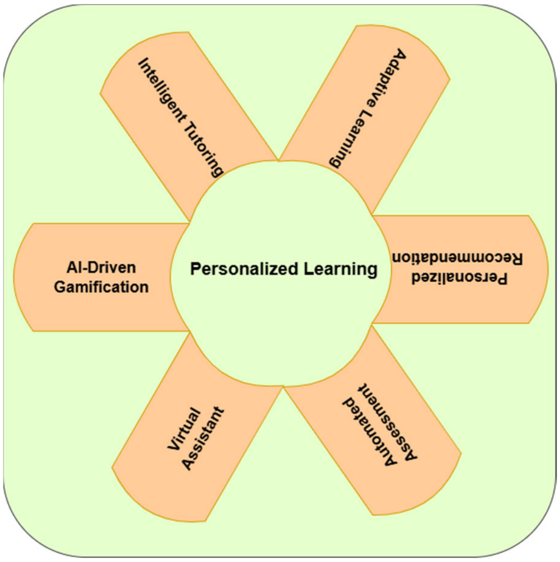


FIGURE 5. Personal learning components and techniques.

III. PERSONALIZED LEARNING

Personalized learning, powered by AI technologies such as adaptive learning systems, intelligent tutoring systems, and personalized recommendations, has the potential to revolutionize education by offering tailored, engaging, and effective learning experiences for students. Figure 5 summarizes our findings on personal learning. Table 3 summarizes how different personalized learning components may affect AI-based education.

A. ADAPTIVE LEARNING SYSTEMS

Adaptive learning systems are a cornerstone of AI-driven personalized learning. These systems dynamically adjust the content, pace, and difficulty of educational material based on a learner's performance, preferences, and learning style [28]. AI algorithms analyze student interactions, such as quiz scores, time spent on tasks, and correct or incorrect answers, to identify strengths and weaknesses. Based on this analysis, the system modifies the learning path in real-time, offering more challenging material for areas where the student excels and providing additional support or remedial content for weaker areas [26]. Platforms like Knewton and DreamBox use adaptive learning to create personalized pathways in subjects like math and language arts [28]. Additionally, ALEKS, PAT2Math, and Duolingo adapts language lessons based on a user's progress and mistakes, ensuring an engaging and appropriately challenging experience [7]. The key benefits of adaptive learning systems include individualized

TABLE 3. Summary of the benefits of personalized learning-powered by AI.

Aspect	Examples	Benefits	Study
Adaptive learning systems	Knewton, DreamBox, Duolingo	Individualized learning, engagement, data-driven insights	[26, 28]
Intelligent tutoring systems	Carnegie Learning's MATHia, Socratic by Google	Immediate feedback, self-paced learning, scalability	[7, 37]
Personalized recommendations	Coursera, edX, Khan Academy	Enhanced learning, increased autonomy	[38-40]
AI-powered virtual assistants	IBM Watson Tutor, ChatGPT for Education, Google Assistant in education	Instant support, 24/7 availability, reduces teacher workload	[41, 42]
Automated assessment & feedback	Turnitin AI, Grammarly, Gradescope, MetaTutor, ATTENDEE	Faster grading, objective feedback, helps students improve writing skills	[37, 43, 44]
AI-driven gamification	Kahoot, Prodigy, Duolingo's streak system	Increases engagement, makes learning fun and interactive	[40, 45]

attention, improved engagement, and data-driven insights that help teachers identify and address students' learning gaps effectively [26].

Adaptive learning systems harness a variety of AI algorithms to deliver personalized educational experiences by dynamically adjusting content and assessments based on individual learner performance. For instance, Bayesian networks, for example, use probabilistic relationships between variables to model a learner's knowledge state, helping to predict the likelihood of success on future tasks by dynamically adjusting the level of difficulty, as exemplified by ALEKS [46]. Similarly, items for personal assessments are selected optimally using Item Response Theory, which analyzes the probability of correct answers based on a learner's ability and the challenge of the items [47].

In addition, ML algorithms play a significant role in adaptive learning by enhancing engagement and performance through RL, which optimizes the sequence of learning activities through trial and error [48]. Collaborative filtering further supports personalization by suggesting learning materials based on the behavior and preferences of similar learners [49], while DL algorithms, using neural networks, analyze student interactions to predict performance and detect learning difficulties [50].

Adaptive learning systems also utilize DT to classify students into specific learning styles, allowing for personalized pathways [2]. In addition, knowledge tracing algorithms track the evolution of a student's knowledge over time, predicting their ability to answer future questions based on past performance [51]. These various algorithms are often combined to achieve the best learning outcomes, as each has its strengths

TABLE 4. Algorithms in adaptive learning systems.

Algorithm/ Technique	Application	Study
Bayesian Networks	Model a learner's knowledge state and predict future success, dynamically adjusting question difficulty based on inferred mastery levels.	[46]
Item Response Theory	Select optimally challenging items by analyzing the probability of a correct response based on learner ability and item difficulty, enhancing assessment efficiency.	[47]
RL	Dynamically adjust learning paths through trial-and-error, using reward signals to optimize learner engagement and performance based on real-time interactions and feedback.	[48]
Collaborative filtering	Recommend relevant learning materials by analyzing user preferences and behaviors of similar learners, thereby personalizing content suggestions.	[49]
DL	Analyze complex interaction patterns in learner data to provide personalized content recommendations, predict performance, and detect learning difficulties with high accuracy.	[21, 50]
DT	Classify students into different learning styles and generate personalized learning paths by creating data-driven rules for student segmentation.	[2]
Knowledge tracing	Monitor and predict the evolution of a learner's knowledge over time, informing the selection of future questions based on historical performance and mastery of concepts.	[51]

in specific contexts. The choice of algorithm depends on the needs of the learning environment, with the goal of maximizing efficiency, engagement, and individual success in the learning process. Table 4 presents a comparative overview of key algorithms used in adaptive learning systems. This table categorizes techniques based on their pedagogical applications, such as learner modeling, knowledge prediction, and instructional decision-making. The algorithms listed have been selected based on their frequent appearance in the reviewed literature and their relevance to the core functionalities of adaptive learning platforms.

As shown in Table 4, Bayesian networks and RL appear frequently in systems like ALEKS and PAT2Math due to their real-time adaptability. However, limited empirical validation in low-resource environments suggests further study is needed to generalize these methods across diverse educational contexts.

B. INTELLIGENT TUTORING SYSTEMS

Another form of AI-driven personalized learning is intelligent tutoring systems, which simulate one-on-one tutoring by providing real-time feedback and guidance [28]. These systems leverage AI to model students' knowledge and cognitive processes, allowing for personalized feedback and hints. Many intelligent tutoring systems incorporate NLP to create a conversational learning experience, making interactions more interactive and engaging [43]. Examples include Carnegie Learning's MATHia, ALEKS, and PAT2Math, which helps students grasp mathematical concepts through personalized exercises, and Socratic by Google, an AI-powered mobile app that assists students in understanding complex topics through guided problem-solving [7]. Other tools like MetaTutor, Guru Tutor, and Affective AutoTutor use multimodal data (e.g., facial expressions, eye tracking, biometrics) to detect emotions and adapt teaching strategies [37]. ITS provides significant advantages, including immediate feedback that helps students correct mistakes in real-time, self-paced learning that reduces peer pressure, and scalability, enabling high-quality tutoring for a vast number of learners [39].

Intelligent tutoring systems leverage a diverse array of AI algorithms to deliver personalized and adaptive instruction. These systems utilize knowledge representation and reasoning techniques—such as ontologies and semantic networks—to structure domain knowledge, model student understanding, and outline effective pedagogical strategies [52].

Rule-based systems further enhance personalization by applying if-then rules that diagnose errors and provide tailored feedback [53]. In addition to these foundational methods, intelligent tutoring systems incorporate advanced NLP and ML techniques to create interactive and responsive learning environments. Dialogue management systems interpret student inquiries to generate conversational responses [54], while sentiment analysis gauges emotional cues to refine the tutoring strategy [55].

Furthermore, ML models, such as Bayesian networks, Recurrent Neural Networks (RNNs) for knowledge tracing, RL agents, and multimodal learning approaches, enable Intelligent tutoring systems to track learning progress, optimize activity sequences, and adapt instruction in real time [51]. Affective computing, particularly emotion recognition, allows these systems to sense and respond to students' emotional states, fostering an empathetic and engaging learning experience [56]. By grounding their methods in these structured approaches, intelligent tutoring systems can dynamically adjust content to suit individual learning needs and ensure a robust framework for knowledge management. Table 5 categorizes AI techniques that underpin intelligent tutoring systems (ITS). These systems mimic human tutors, delivering real-time feedback and guidance by modeling cognitive processes and learning states.

Ontologies and semantic networks provide the structural backbone for content delivery and learner modeling. Meanwhile, reinforcement learning enhances adaptivity by adjusting pedagogical strategies based on interaction patterns.

C. PERSONALIZED RECOMMADATION

AI-powered recommendation engines further enhance personalized learning by suggesting learning resources, courses, or activities based on a student's past behavior, interests, and goals [28]. These systems operate similarly to Netflix or Amazon recommendations, using ML to analyze a student's learning history and preferences before suggesting supple-

TABLE 5. Algorithms in intelligent tutoring systems.

Algorithm/ Technique	Application	Study
Ontologies and semantic networks	Structure domain and student knowledge, model relationships between concepts, and guide the selection of appropriate pedagogical strategies.	[52]
Rule-based systems	Utilize if-then rules to diagnose student errors and provide personalized feedback and hints based on individual actions.	[53]
Dialogue management	Interpret student questions and generate appropriate conversational responses to create an engaging, interactive learning experience.	[54]
Sentiment analysis	Analyze textual inputs to assess student emotions, enabling adaptive adjustments to the tutoring strategy based on affective cues.	[55]
Knowledge tracing	Monitor the evolution of student knowledge over time, personalizing the sequence of learning activities and offering targeted feedback based on performance trends.	[51]
RL	Optimize pedagogical strategies by learning from student interactions, dynamically adapting the tutoring approach in real time to enhance engagement and performance.	[48]
Multimodal learning	Analyze diverse data (facial expressions, eye tracking, speech) to detect student emotions and adjust instructional methods accordingly.	[56]
Emotion recognition	Identify student emotions from facial expressions, speech, and physiological signals, allowing ITS to refine its tutoring strategies to better meet learners' emotional and cognitive needs.	[56]

TABLE 6. Algorithms in personalized recommendations.

Algorithm/ Technique	Application	Study
Collaborative filtering	Analyzes user-item interactions to recommend courses, videos, or articles; includes user-based and item-based approaches and evolves into hybrid collaborative filtering to address sparsity and cold-start issues.	[49]
Content-based filtering	Recommends learning resources by matching item features (e.g., keywords, topics) with learner interests; enhanced by NLP for feature extraction and knowledge graphs for improved accuracy.	[57]
Matrix factorization	Decomposes the user-item interaction matrix into latent factors, predicting user ratings and preferences; often integrated with DL and contextual information for large-scale systems.	[60]
Neural collaborative filtering & RNNs	Utilizes neural collaborative filtering, RNNs for modeling sequential behavior, and knowledge graph embeddings to provide accurate and personal recommendations; incorporates attention mechanisms.	[58]
Hybrid recommendation systems	Combines multiple techniques (e.g., collaborative filtering, content-based, and knowledge-based) using ensemble methods to deliver robust, comprehensive, and tailored recommendations.	[59]

mentary materials, such as videos, articles, or practice exercises [38]. Online learning platforms like Coursera and edX use AI to recommend courses based on previous enrollments and course completions, while Khan Academy provides personalized recommendations for instructional videos and practice exercises based on student performance. The author in [39] reported personalized video recommendations that can enhance engagement by targeting relevant topics based on learners' interests. The primary benefits of AI-driven recommendations include an enriched learning experience through exposure to tailored resources and increased learner autonomy, allowing students to explore materials aligned with their interests and career aspirations [40].

Recent advances in recommended systems have revolutionized adaptive learning by leveraging diverse algorithms to generate personalized content suggestions. Collaborative filtering analyzes user-item interactions, such as ratings and clicks, to recommend courses, videos, or articles based on similar users or items [49]. Its variants, including user-based and item-based collaborative filtering, have evolved into hybrid models that integrate content-based filtering to overcome challenges like sparsity and the cold-start problem [49]. Similarly, content-based filtering exploits item features such as keywords and topics to align recommendations with a learner's interests, with recent NLP advancements and knowledge graphs further enhancing its precision [57].

Matrix factorization techniques decompose user-item interaction matrices into latent factors that capture hidden preferences, making them vital for large-scale recommendation systems [51]. DL further augments these approaches by employing neural collaborative filtering to learn complex interaction patterns, RNNs to model sequential user behavior, and knowledge graph embeddings to understand semantic relationships between learning resources [58]. Finally, hybrid recommendation systems combine multiple techniques, merging collaborative filtering, content-based, and knowledge-based approaches through ensemble methods, to deliver more robust, accurate, and personalized recommendations that cater to individual learner needs [59]. Table 6 outlines ML algorithms that power personalized recommendation engines in online education platforms. These systems tailor content delivery to individual learner preferences and progress patterns.

Hybrid recommendation systems offer higher accuracy by combining user behavior with content metadata. DL-based recommenders using neural collaborative filtering and RNNs are emerging as powerful tools, especially in massive open online courses (MOOCs).

D. AI POWERED VIRTUAL ASSISTANCE

AI-powered virtual assistants, such as chatbots and voice assistants, are transforming the way students interact with educational content [45]. These tools provide real-time support by answering questions, offering explanations, and guiding students through learning materials [37]. For instance, IBM Watson Tutor and Google Assistant for education can help clarify complex concepts and suggest additional resources based on student queries. The key advantage of these virtual assistants is their 24/7 availability, ensuring that students receive instant help without needing to wait for a teacher's response [7]. AI systems facilitate group formation based on cognitive diversity, enabling collaborative learning environments [42]. Social constructivist approaches support metacognitive skill development through peer interaction [41]. AI contributes to the development of educational, research, and management structures, which fosters a culture of innovation and internationalization in universities [42]. Additionally, they can significantly reduce teacher workload by handling repetitive inquiries [42].

AI-powered virtual assistants in education leverage a range of NLP techniques to interpret and respond to student inquiries effectively. For instance, intent recognition algorithms classify user queries into predefined categories, such as "explain a concept" or "find a resource", ensuring that the assistant understands the learner's goals [61]. Complementing this, Named Entity Recognition (NER) extracts key information from queries [62], while question answering systems retrieve direct responses from a knowledge base [63]. Dialogue management systems then orchestrate these interactions by maintaining conversational context and managing the flow of discussion [54], and sentiment analysis gauges the emotional tone of user inputs to tailor responses appropriately [55].

Beyond NLP, ML and DL algorithms further enhance the capabilities of virtual assistants. ML models train chatbots to understand and respond to queries, often employing knowledge graphs to provide rich contextual information and clustering algorithms to group students by cognitive profiles for collaborative learning experiences [64], [65]. DL techniques, such as RNNs, Transformers, and word embeddings, process sequential data and capture semantic nuances to generate natural, coherent responses [58], [66]. Table 7 identifies the core AI and NLP techniques used in educational virtual assistants. These tools respond to learner queries and provide tutoring or feedback using voice or text interfaces.

Intent recognition and dialogue management are crucial for maintaining coherent conversation flow. Sentiment analysis enables emotional intelligence in boots, which is especially useful in student support scenarios. Transformers and knowledge graphs are increasingly integrated to enhance contextual understanding and answer generation.

TABLE 7. Algorithms in virtual assistant.

Algorithm/ Technique	Application	Study
Intent recognition	Classifies user queries into predefined intents to understand the learner's goals.	[61]
NER	Extracts and categorizes key entities from user queries for accurate response generation.	[62]
Question answering	Retrieves direct answers from a knowledge base or text corpus in response to student inquiries.	[63]
Dialogue management	Manages conversation flow and context, ensuring coherent and engaging interactions.	[54]
Sentiment analysis	Determines the emotional tone of user input, enabling the assistant to adapt its responses to the user's mood.	[55]
Knowledge graphs	Provides contextual information and reasoning by representing knowledge as networks of entities and relationships.	[64]
Clustering algorithms	Groups students based on cognitive profiles or learning styles to facilitate collaborative learning.	[65]
RNNs and Transformers	Processes sequential data to generate natural, coherent responses in conversation.	[58]
Word embeddings	Captures semantic relationships between words, improving the accuracy of various NLP tasks used in the virtual assistant.	[66]

E. AUTOMATED ASSESSMENT AND FEEDBACK

AI-driven assessment tools are revolutionizing grading and feedback mechanisms by providing instant evaluations of assignments, quizzes, and essays [43]. Platforms like Turnitin AI, Grammarly, and Gradescope use NLP to assess writing quality, detect plagiarism, and offer constructive feedback [43]. This automation speeds up the grading process and ensures objective evaluations, reducing the burden on educators [37]. Additionally, students benefit from immediate feedback, enabling them to make real-time improvements to their work [44].

Automated assessment and feedback systems in education leverage a suite of AI algorithms to analyze, evaluate, and enhance student writing and performance. NLP techniques such as text similarity and plagiarism detection [67], grammatical error detection and correction [68], automated essay scoring [67], and sentiment analysis form the foundation of these systems [55]. These methods utilize techniques like cosine similarity, n-gram analysis, and semantic similarity to detect plagiarism and compare student submissions against extensive databases [55]. Additionally, NLP models are employed to assess grammar and style, while sentiment analysis evaluates the emotional tone of the text to ensure that the feedback provided is both accurate and contextually sensitive.

Complementing NLP, ML and DL methods further refine the assessment process. ML algorithms perform feature extraction from texts, gathering essential metrics such as word counts, sentence lengths, and grammatical patterns, which are then used by regression and classification models to assign scores and detect content issues [69], [70], [71]. DL approaches, including RNNs, Transformers, and word embeddings, capture the sequential and semantic nuances of language, enhancing the accuracy of automated essay scoring

TABLE 8. Algorithms in automated assessment and feedback.

Algorithm/ Technique	Application	Study
Text similarity & plagiarism detection	Compare student text to a document database using cosine similarity, n-gram analysis, and semantic similarity to detect plagiarism and identify similar content.	[67]
Grammatical error detection and correction	Identifies and corrects grammatical errors, spelling mistakes, and style issues, providing feedback on overall writing quality.	[68]
Automated essay scoring	Analyzes essay content, structure, and language using feature extraction, regression, and DL models to assign objective scores to written assignments.	[67]
Sentiment analysis and tone detection	Evaluates the emotional tone and sentiment of text, offering feedback on the clarity and appropriateness of the writing's tone.	[55]
Feature extraction	Extracts relevant textual features (e.g., word counts, sentence length, grammatical patterns) to prepare data for further analysis and scoring.	[69]
Regression models	Predicts scores or ratings for essays based on the extracted features, enabling objective evaluation of written work.	[70]
Classification models	Categorizes text into predefined groups (e.g., plagiarism or non-plagiarism) to assess writing quality and content integrity.	[71]
RNNs and Transformers	Processes sequential text data to capture context and relationships, thereby improving the accuracy of automated essay scoring and plagiarism detection.	[58]
Word embeddings	Represents words as vectors in a high-dimensional space to capture semantic relationships, enhancing the accuracy of text similarity analyses and automated essay scoring.	[66]

and plagiarism detection [58], [66]. Table 8 summarizes AI methods used in automating assessments, particularly essay scoring, plagiarism detection, and instant feedback systems.

Transformers and DL models significantly improve scoring accuracy through contextual language understanding. NLP tools such as word embeddings and syntax analysis also improve the interpretability of results.

F. DRIVEN GAMIFICATION

Gamification, enhanced by AI, is making learning more engaging and interactive by incorporating game-like elements such as points, leaderboards, and adaptive challenges. AI-driven platforms like Kahoot, Prodigy, and Duolingo personalize the difficulty of tasks based on student performance, ensuring a balance between challenge and motivation [45]. By continuously analyzing student progress, AI can adjust game mechanics to reinforce learning without causing frustration. Gamified learning has been shown to improve knowledge retention and increase student motivation, especially in younger learners [40].

AI-driven gamification in education harnesses a variety of AI algorithms to create engaging, personalized learning experiences. RL agents adjust the difficulty of challenges in real time by analyzing student performance data and engagement metrics [48]. This dynamic adjustment helps maintain an optimal balance between challenge and motivation. In parallel, knowledge tracing models monitor the evolution of student knowledge, enabling the system to tailor challenge difficulty according to each learner's mastery level [51]. Clustering algorithms further personalize the experience by grouping students based on their learning styles, performance patterns, or engagement levels, thereby providing customized challenges and rewards [65].

Moreover, predictive modeling anticipates student performance or engagement based on past behavior, allowing the system to preemptively adjust game mechanics to reduce frustration or boredom [72]. Behavioral analytics scrutinize student interactions with the gamified platform to identify patterns and trends, thus refining the motivational strategies employed [73]. Learning analytics analyze performance data to uncover learning gaps and deliver personalized feedback, ensuring that gamified elements align with educational objectives [74]. NLP techniques generate targeted feedback and rewards [75], while recommender systems suggest personalized challenges and rewards based on student preferences and performance trends [50]. Together, these algorithms ensure that gamification not only entertains but also supports effective learning outcomes by balancing intrinsic motivation with appropriate challenge levels. Table 9 lists ML algorithms that support gamified learning experiences. These tools personalize difficulty levels, rewards, and content flow based on real-time student performance. Reinforcement learning dominates adaptive gamification due to its reward-punishment structure, mirroring game mechanics. Behavioral and learning analytics help identify engagement drop-off points, enabling designers to adjust challenges accordingly.

IV. STUDENT PERFORMANCE PREDICTION

Students struggling with their academic lives is a major concern for institutions. It is important to identify at-risk students early in the semester for effective and timely intervention to avert adverse outcomes. However, the relevant data can only be seen at the end of the course or after the midterm evaluation, which is too late to take corrective measures. Here, ML can be very useful as it can identify at-risk students by analyzing different attributes associated with students in class actions and behaviors.

To identify at-risk students in an educational setting, ML algorithms can be leveraged to predict academic performance and provide timely support [76], [77], [78], [79], [80], [81], [82], [83]. Key indicators and risk factors for identifying at-risk students include various data points such as prior academic results, demographic and financial circumstances, learning behaviors, attendance records, and online interactions [46], [76], [77], [79], [80], [81], [84], [85], [86], [87], [88]. For example, the students at risk have been identified by applying ML algorithms on the data obtained from student interaction with the virtual learning environment and

TABLE 9. Algorithms in driven gamification.

Algorithm/ Technique	Application	Study
RL	Dynamically adjusts game mechanics based on student performance and engagement metrics to maintain optimal challenge and motivation.	[48]
Knowledge tracing	Tracks the evolution of student knowledge over time to tailor challenge difficulty based on individual mastery levels.	[51]
Clustering algorithms	Groups students based on learning styles, performance patterns, or engagement levels to provide personalized challenges and rewards.	[65]
Predictive modeling	Predicts student performance or engagement, allowing adjustments to game mechanics to preempt frustration or boredom.	[72]
Behavioral analytics	Analyzes student interactions to identify patterns and trends, helping to optimize game mechanics and understand motivational factors.	[73]
Learning analytics	Analyzes performance data to identify learning gaps and personalize feedback, ensuring alignment with educational objectives.	[74]
NLP	Generates personalized feedback and rewards based on student performance, enhancing the overall engagement and learning experience.	[75]
Recommender systems	Suggests personalized challenges or rewards based on student preferences and performance trends, ensuring relevant and engaging content.	[50]

its derivative features [89], or Learning Management System (LMS) [90]. LSTM network-based approaches have also been used to identify at-risk students by extracting course data from a public dataset for training different ML algorithms [91].

There has always been the need to make prediction more accurately and ensemble-based classification models have demonstrated significant promise in predicting at-risk students with high accuracy [92]. Various ensemble strategies have been used including stacked, hybrid, and voting-based ensemble for this purpose. Stacked ensembles increase the accuracy of prediction by combining the predictions of several base models using a second-stage model [93], [94], [95]. The Hybrid ensembles model achieve higher accuracy by combining different techniques. For example, hybrid ensemble model based on Random Forest (RF) and eXtreme Gradient Boosting (XGBoost) showed high prediction accuracy of 93% and precision of 91.52% [96]. Voting-based ensemble models combine the strengths of different models to achieve higher accuracy compared to conventional classification techniques [97]. A voting ensemble integrating many algorithms was trained with academic and demographic data achieving a 94.8% accuracy [83]. These models are further optimized through hyperparameter tuning or qualitative datasets to achieve better accuracy [98].

Accuracy alone is not a reliable measure when it comes to evaluating performance of a classification model especially when the dataset is not balanced where model makes prediction based on the majority class ignoring the minority class which is equally important. The datasets can be balanced using different approaches such as SMOTE (Synthetic Minority Over-sampling Technique) to improve the performance of the model [99]. Alos, the model accuracy and dependability rely on choosing the most pertinent variables, such as behavioral, academic, and demographic data [100], [101]. Asynchronous learning activities, such the amount of time spent in online sessions and the quantity of materials downloaded, have been shown to be more reliable predictors of student risk than synchronous ones [98]. Nonetheless, there are still barriers in identifying at-risk students using ensemble learning. First, addressing class imbalance in educational data is important for enhancing the fairness and robustness of the model [102]. Second, to improve model generalization and interpretability, only the most discriminative and pertinent features must be retained by efficient feature selection [103].

Educators can detect at-risk students early in the learning cycle and provide appropriate support by integrating ML. It offers important insights into learning patterns by analyzing student behaviors, attendance records, academic background, and online interactions [77], [81], [86], [104], [105]). The most common ML techniques applied for interpreting data from online learning platforms and forecast student performance include DT, logistic regression, and random forests [46], [104], [105], [106]. Information on student interactions, engagement levels, demographics, and academic performance are among the data used by the prediction models to categorize students as either at-risk or not [105], [106]. Another problem in prediction models is the bias in grading policy arising due to imbalance dataset and these disparities must be addressed to guarantee accurate and equitable forecasts [86]. Furthermore, accuracy and efficacy are strongly influenced by the quantity and types of features employed in prediction models as well as correlations among them [91]. The use of probabilistic ML models can help in improving prediction reliability. Integrating domain information and quantifying uncertainty can increase prediction robustness and interpretability of the models [106].

Institutions can use a range of data points, such as past academic performance, demographic and financial background, learning behaviors, attendance records, and online interactions, to identify students who are at risk of academic difficulties [46], [76], [77], [78], [80], [81], [84], [85], [86], [87], [107]. These factors give teachers much needed information about student involvement and possible difficulties, enabling them to step in early and provide the assistance that students need. Simple yet powerful metrics from statistical models and social network analysis are combined in a structured at-risk identification framework to help correlate student behaviors with academic performance while reducing the need for laborious manual data collection or expert evaluation [108]. Educational institutions can better support students by implementing personalized learning interventions, early warning systems, and adaptive

TABLE 10. Methods used for identifying students at risk.

Methods	Strengths	Weaknesses
Naive Bayes, SVM, KNN	Low false negatives (Naive Bayes, SVM), Low false positives (KNN) High false positives (Naive Bayes, SVM),	High false negatives (KNN) [109]
Ensemble Models	Balanced error rates,	Improved accuracy Complexity in implementation [109]
Random Forest,	DT high accuracy (up to 95.37%)	May require large datasets for training [110]
RADAR System	Continuous monitoring, High accuracy	Implementation complexity [111]
Early Warning Systems	Timely feedback, Visualization tools	Dependence on accurate data input [111, 112]

learning experiences with the help of predictive analytics [76], [78], [80], [81]. A dynamic early alert mechanism, which continuously evaluates students' academic risk status and offers focused, real-time interventions, is one of the best options. By tackling issues before they worsen, these proactive strategies can lower dropout rates and improve student performance [96].

The application of data-driven techniques for identifying students' at-risk prediction faces many ethical issues such as responsible data usage, data security, and student privacy [78], [80], [81]. Therefore, educational institutions must make sure that predictive analytics are used in an ethical and transparent manner to benefit from the advantages offered by this technology. Careful incorporation of these tools into educational systems can establish a flexible and encouraging learning environment for promoting student achievement [76], [80], [81], [84]. Table 10 summarizes the methods used to identify students at risk,

V. INTELLIGENT CONTENT CREATION

A. AUTOMATED LEARNING SYSTEMS

Automated Content Generation (ACG) in education uses AI and ML technologies to create educational materials, assessments, and personalized learning experiences. There are several applications of AI in content generations such as [113]:

- AI based systems can analyze students' performance data to create personalized learning paths.
- AI based systems can provide customized feedback on assignments and tests, helping students understand their mistakes and learn more effectively.
- AI tools can assist educators in creating lesson plans by suggesting relevant content, activities, and resources based on the curriculum and learning objectives.
- AI based systems can generate textbooks, study guides, and supplementary materials.
- AI based translation tools can create multilingual educational materials.
- AI systems can grade assignments, quizzes, and exams, reducing the workload for educators and providing students with faster feedback.

There are several advantages of using AI technologies in the education sector, especially for content generation [114]. On the other hand, there are several negative sides which should be considered such as quality, security, fairness and privacy. To increase the quality of using AI technology in education collaboration is needed between educators, AI developers and policymakers. Figure 6 demonstrates AI content generation structure in education.

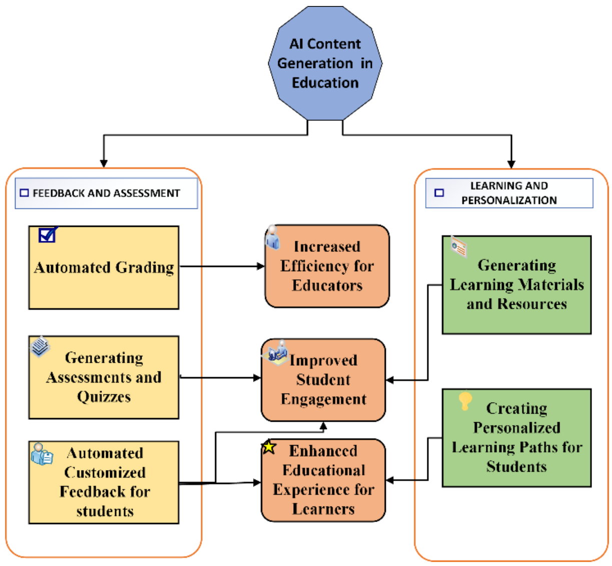


FIGURE 6. AI content generation in education.

Large Language Models (LLM) need to be implemented for educational purposes. The authors in [115] developed LLM for education to increase students' abilities in analytical thinking and content verifications. ChatGPT and other automated learning tools have high potential in educational content generation [3]. On the other hand, there are some disadvantages such as over-reliance and plagiarism. Generative AI might be used for several purposes such as healthcare, education, customer support and content generation. In [116], the authors proposed a new method for e-learning assessment. After the COVID-19 pandemic, e-learning assessment methods got importance. For fair and efficient evaluation, assessment trends move from subjective to objective methods which are mainly multiple choice-based assessment. In this work, automated generated MCQs system proposed using transformer model T5 and lexicon approach. This method has 88% accuracy using neural network method in software programming content [116].

The authors in [117] applied NLP methods to generate automated questions such as true- false, multiple-choice, blank and matching. GPT, T5, and BERT methods are applied. Experimental results show that proposed methods have more than 80% accuracy [117]. In [118], the authors examined the specific performance of LLMs in instructional

TABLE 11. Algorithms in ACG.

Study	Method	Accuracy
[115]	RNNs	Promising
[116]	Transformer based model, lexicon-based model	88%
[117]	GPT, T5, and BERT	>80%
[118]	Utilizing Generative Pretrained Transformer 4	Promising
[119]	AGV emerges tool	88.9%
[121]	Generated indirect corrective feedback and direct corrective feedback	73%
[122]	Context Sensitive Dictionary (CSD)	>80%
[123]	Semantic Web	Promising
[124]	Dynamic keyboard, automated assessment	90.53%

design to uncover their potential strengths and weaknesses. The evaluation results revealed that the teaching plans created by LLMs excel in establishing instructional objectives, identifying teaching priorities, organizing problem sequences and teaching activities, articulating subject content, and selecting methods and strategies [118]. The author in [119] analyzed automated learning in physics and mathematics using AI tools. Experiments show that using AI in content generation increases both learning and teaching abilities in mathematics and physics [119]. Several other authors including [120], [121], [122], [123], [124] proposed AI generated tools for content generation in education. Table 11 demonstrates algorithms used in ACG and their accuracy rates.

B. CONTENT CUSTOMAZATION AND ADAPTATION

Content customization and adaptation in education using ML involves tailoring educational materials and learning experiences to meet the unique needs, preferences, and learning styles of individual students. ML algorithms can analyze a student's performance, learning speed, and preferences to create customized learning paths. These paths ensure that students receive the right content at the right time, maximizing their learning potential [113], [114].

The authors in [125] introduced a novel method for detecting malicious URLs through sniffing detection using ML. This approach employs the Random Forest Classifier to identify harmful URLs effectively. In [126], the authors proposed the user identification system for home entertainment which might be used in the education sector. The proposed system can be integrated into gesture-based home entertainment systems for interface customization, content adaptation, and parental control. User attitudes toward the system were evaluated using the widely recognized technology acceptance model [126]. Based on responses from 69 participants, the results indicated a positive user attitude and a high intention to use the system [126]. The authors in [127] presented an approach to personalizing learning paths aimed at optimizing learner performance through RL based on implicit feedback, while reducing the necessity for direct interaction with the learning system during training.

C. NATURAL LANGUAGE PROCESSING APPLICATIONS

NLP algorithms can generate educational materials such as quizzes, summaries, lecture notes, and even textbooks [128]. These algorithms analyze large amounts of text data to extract and generate new content that is coherent and relevant. The authors in [129] introduced an optimized pipeline that combines PDF text extraction with advanced sequence-to-sequence models, specifically focusing on automating questions and answer generation. This system enhanced efficiency through optimized data handling and model evaluation, highlighting the importance of semantic metrics in assessing the quality of generated content [129]. Similarly, the authors in [130] explored innovative methods to integrate NLP into question generation, covering data preparation, question formulation, and evaluation processes. It emphasizes the role of transformer-based neural networks in enhancing question generation system performance. The authors in [131] generated cooking recipe using ML algorithms either from a given list of ingredients or by suggesting ingredients as well. The authors in [132] addressed the challenge of automatic multiple-choice question generation from middle-school level textbook content, aiming to assess recall of factual information. Techniques such as sentence simplification, syntactic and semantic processing, entity recognition, and neural embeddings are integrated [132].

There are several applications of NLP based intelligent content generation. Automated text summarization aims to condense large textual documents into concise summaries while retaining essential information. Extractive methods select important sentences or paragraphs, whereas abstractive methods generate new sentences to convey the main ideas [121]. NLP-driven question generation systems create questions based on textual content, facilitating educational assessments, chatbot interactions, and information retrieval [133]. These systems employ techniques such as syntactic and semantic analysis to generate contextually relevant questions [134], [135].

Content personalization leverages NLP to tailor content based on user preferences, behavior patterns, and contextual information. Recommender systems utilize collaborative filtering and natural language understanding techniques to suggest personalized content recommendations [58], [124]. NLP-powered machine translation systems enable cross-lingual communication by translating text between different languages [54], [136]. NLP models are increasingly used to generate creative content such as poetry, storytelling, and marketing copies. These models learn linguistic patterns and stylistic conventions from large corpora to produce compelling and original content [137], [138].

Opinion mining techniques analyses textual data to identify sentiments, emotions, and opinions expressed by users. These applications are crucial for social media monitoring, brand reputation management, and customer feedback analysis [139], [140]. The deployment of NLP in content generation raises ethical considerations and societal impacts, including bias mitigation, privacy concerns, and the

TABLE 12. Algorithms in NLP applications.

Application	Methodology	Study
Automated text summarization	DL, BERT	[121, 133]
Question generation and answering systems	Syntactic and semantic analysis	[134, 135]
Content personalization	Collaborative filtering	[58, 124]
Language translation and localization	Neural machine translation	[54, 136]
Opinion mining	DL frameworks such as LSTM	[139, 140]
Creative content generation	Linguistic patterns and stylistic conventions from large corpora	[137, 138]

responsible use of AI technologies [141]. Research focuses on developing fair and transparent NLP systems that uphold ethical principles and mitigate algorithmic biases [16].

In summary, NLP applications in intelligent content generation cover a wide range of tasks and industries, reshaping how information is handled, communicated, and customized in the digital age [54], [136]. Continuous research efforts are pushing the boundaries of NLP techniques, leading to advancements in AI and computational linguistics. Table 12 shows methodologies in NLP application in education. ML algorithms, especially deep neural network frequently used in NLP based solutions.

Intelligent content creation has made significant strides with the integration of generative AI tools capable of producing tailored learning materials. These systems can now generate quizzes, reading passages, writing prompts, and even multimedia content based on students' progress and performance. For example, platforms like Quizizz use adaptive algorithms to adjust question difficulty in real time, while tools like ScribeSense automate the creation and grading of assignments [137], [138]. In addition to all these advances, challenges remain in the accuracy, quality, and educational value of machine-generated content. Lack of proper oversight can lead to the creation of learning materials that miss the mark either by spreading misinformation or failing to support effective teaching. Therefore, human input and content validation remain essential components of any AI-driven content system.

VI. VIRTUAL TEACHING ASSISTANCE

A. CHATBOTS AND VIRTUAL AGENTS

AI-powered chat applications have revolutionized the way humans interact with machines, offering functionalities that range from answering simple queries to engaging in complex, context-aware conversations [142]. These chatbots, which can communicate through both text and voice, are designed to mimic human speech and improve over time using ML techniques. By analyzing past interactions, they become more adept at understanding context and generating appropriate responses [16]. Available 24/7, chatbots provide instant feedback and support, making them invaluable tools in various domains, including education. Leveraging AI and advanced conversational design, these virtual assistants can engage students across all levels of education, from elementary school to university, offering personalized assistance and fostering interactive learning environments [38]. Figure 7 shows the structure of virtual teaching assistants in the AI education system.

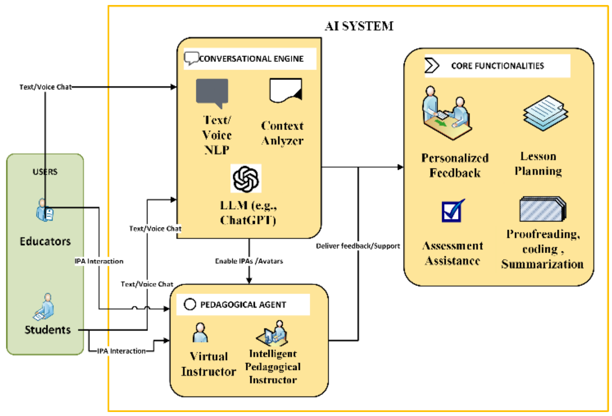


FIGURE 7. Structure of virtual teaching assistant.

In educational settings, AI chatbots are emerging as a transformative solution to enhance teaching and learning experiences [115]. They serve as virtual teaching assistants, capable of providing personalized feedback, identifying areas where students struggle, and offering tailored resources to address individual needs [63]. By enabling students to interact with course material in a conversational manner, chatbots create a more engaging and dynamic learning environment. LLM like ChatGPT further exemplify this potential, using neural networks to generate real-time responses to student inquiries, similar to having a personal tutor [52]. These AI-driven tools not only support students but also assist educators by automating tasks, allowing teachers to focus on more critical aspects of instruction [37].

The integration of AI chatbots into education holds significant promises for improving learning outcomes and the overall quality of education. By generating customized content, delivering timely feedback, and adapting to each student's unique needs, these tools help bridge gaps in understanding and keep learners motivated [84]. Moreover, their ability to perform diverse tasks-such as summarizing information, translating languages, or even composing code-makes them versatile aids in modern classrooms [40]. As AI technology continues to evolve, its application in education is likely to expand, offering innovative ways to make learning more accessible, efficient, and enjoyable for students worldwide [143].

Chatbots have found applications in various fields, and numerous studies highlight their positive impact on education [54]. Research shows that integrating this AI technology into educational settings significantly enhances students' learning outcomes, motivation, and problem-solving abilities [55].

The author in [144] highlighted that chatbots, or conversational agents, create a more personalized and intelligent learning environment tailored to meet the unique needs of individual learners. With recent advancements in AI, major companies like Google, IBM, and Amazon now offer platforms to develop chatbots specifically for educational purposes. For instance, Google DialogFlow is an example of a rule-based chatbot that is relatively simple yet effective. Most chatbots designed for educational use rely on NLP to facilitate interactions [144].

The authors in [145] examined a rule-based chatbot implemented at the Hong Kong University of Science and Technology to support the graduate teaching assistant training course offered by the Center for Education Innovation. The study highlights that commercial chatbot platforms simplify content-specific conversation creation through one-click integration [145].

The authors in [146] investigated the role of ChatGPT in enhancing student engagement and comprehension of complex concepts in undergraduate talent cultivation programs for Microelectronic Science and Engineering at the Beijing Institute of Technology, China. The findings suggest that integrating ChatGPT into undergraduate education offers valuable insights into the future of engineering education [3], [146].

The authors in [147] studied students' motivation and perceptions of AI chatbot-supported learning for climate change education. Conducted with 59 teacher education sophomores at a public university in southern China, the study addresses two key questions: how AI chatbots influence student motivation and their perspectives on chatbot-assisted learning [148]. The results confirm that chatbot interactions enhanced students' motivation, engagement, and learning attitudes. Additionally, AI technologies foster a dynamic and interactive educational environment, enabling active participation, immediate feedback, and personalized learning experiences [147].

The author in [149] explored the application of educational chatbots in foreign language learning, recommending that chatbot interactions should align with specific linguistic, speech, or socio-cultural training. The study concludes that chatbots help students practice learned language patterns, develop communication skills in social media and messaging contexts, and overcome psychological barriers in real-life foreign language communication [149].

The author in [150] examined the use of ChatGPT in teaching English for specific purposes, demonstrating its effectiveness in lesson planning, implementation, and assessment. ChatGPT facilitates personalized learning experiences by generating domain-specific texts (e.g., technical, medical, business English), creating vocabulary and grammar exercises, acting as a virtual tutor, integrating into interactive learning materials, and providing instant feedback [21], [150].

Although AI-based chatbots offer numerous advantages, their integration into education comes with ethical concerns.

TABLE 13. Chatbot methodologies and limitations.

Study	Methodology/Platform	Challenges
[145]	User-led chatbots, bot-led chatbots/Google Dialog Flow	Limited availability of well-structured and high-quality datasets for developing educational chatbots.
[3, 21, 146]	ChatGPT	It brings up ethical concerns and limitations, including issues of credibility, plagiarism, copyright violations, and potential misuse.
[147, 148]	AI powered science education chatbot using ARCS (Attention, Relevance, Confidence, and Satisfaction) motivation model	Lack of a universal solution for enhancing student learning-Technology must be tailored to students' needs and instructional goals, as no single approach works across all teaching scenarios.
[149]	The authors developed a chatbot, "Inotutor," for the social networking platform VKontakte.	Ensuring the quality of speech practice by using chatbots requires proper planning and the implementation of control and assessment measures.
[21, 150]	ChatGPT	Fine-tuning a language model demands significant computational resources and may take hours or even days to finish, depending on the dataset size and model complexity.

One of the main issues is the risk of plagiarism, as students might misuse these tools to generate content and misrepresent it as their own [146]. Moreover, data privacy and biases in AI algorithms have raised the need for clear ethical standards, transparency, and accountability in their design and application [149]. To promote their responsible use, educators must be properly trained, enabling them to utilize these tools effectively and assess their impact in the classroom [147].

Some key challenges in implementing chatbots in education, along with the methodologies used, as discussed in various studies, are summarized in table 13.

AI-based chatbots are valuable tools in education, benefiting both teachers and students by providing personalized learning experiences, instant feedback, and assistance with various tasks [151]. They have transformed online learning by allowing students to access materials anytime and enhancing engagement. Chatbots like ChatGPT help students with tasks such as searching, proofreading, organizing concepts, providing feedback, and assisting with coding and qualitative analysis [152]. In conclusion, AI chatbots enhance education by offering versatile support that improves accessibility, engagement, and academic performance [148].

Virtual agents are AI-driven systems that not only interpret user intent through NLP but also automate actions to fulfil that intent, continuously improving their performance [153]. There are primarily two types of virtual agents: those that interact with students through a chat interface and those that utilize virtual environments. Intelligent Pedagogical Agents

(IPAs) are a specific form of virtual agent designed to support learning [154]. These agents simulate human social behavior and cognition, the result of advancements in AI and network technologies. Generally, the functional modules of an agent include correspondence, mission control, an inference engine, and a knowledge library, enabling the agent to make decisions and complete tasks based on environmental information [154].

Pedagogical agents can be categorized based on their intended goals, such as tutors, mentors, assistants, or learning companions. In VR-based learning environments, these agents may take on three-dimensional representations, thus becoming pedagogical virtual agents [155]. Virtual worlds are increasingly being used in engineering education due to their visual collaboration features, authentic learning experiences, and opportunities for active learning [155]. Various types of ''virtual instructors'' or ''pedagogical agents'' have been introduced to deliver lesson content online as an alternative to human instructors [4]. As remote learning increases, these virtual instructors or pedagogical agents, offered in formats like 2D, 3D, and video-based teaching, provide a valuable alternative to real human teachers [156].

3D virtual world educational environments, such as VR, offer students diverse learning activities and have been integrated into many challenging fields and topics [156]. IPAs can be designed to enhance interaction with students and better support them in these virtual world environments [157]. In these settings, pedagogical agents appear as avatars or embodied virtual characters that support learners and fulfil various instructional roles. They can serve as learning companions, guiding students through exercises and assisting with learning activities within the virtual world [158].

The authors in [158] investigated the impact of pedagogical agents on students' engagement and learning during exercises and gamified activities. Conducted in a 3D virtual world designed to simulate real-world contexts, the study focused on environmental engineering and renewable energy topics. The virtual environment provided various learning materials and activities, with pedagogical agents integrated as avatars to assist students. These agents, controlled by scripts, guide students, offer feedback on their answers, and address errors during the learning process. The experimental results show that the presence and interaction with the agents significantly increased student engagement, making them feel more comfortable and confident, and boosting their interest in the subject [158].

The authors in [154] focused on enhancing learning through experiments using IPA in the Open Wonderland virtual world. The IPA prototype integrates multiple communication modes, including gesture generation, text chat (via NLP), and Text-to-Speech. It offers two types of feedback: corrective and supportive, while updating learner data based on performance. The system also manages learner avatar idle time, provides gestures, and allows the learner to control aspects of the experiment using natural language. The IPA boosts learner engagement and interaction by answering questions, offering demonstrations, and providing emotional support. The IPA monitors learner actions, provides corrective feedback when errors occur, and updates learner assessments accordingly [154].

The network virtual teaching model in the study by [159] utilized an Agent framework to enhance the virtual learning environment, making it more interactive and realistic for students. This model offers unlimited virtual experiences across various subjects, improving the efficiency and convenience of online learning [159].

The authors in [160] explored a web-based learning platform that uses AI-generated personas for financial literacy lessons, featuring interactive question/answer and the option to choose an instructor from a variety of personalities. The findings reveal that learners' sense of relatedness to the instructor significantly increased motivation, positive emotions, and perceived agent credibility. Goal alignment with the instructor improved learning facilitation, while admiration for the instructor correlated with perceived humanness. This interactivity mimicked a classroom dynamic and encouraged active engagement, which enriched the remote learning experience. The study highlights the value of interactive virtual instructors in remote learning but emphasizes that AI should complement human teachers, as human elements like empathy and ethical guidance remain essential [160].

B. AI POWERED FEEDBACK AND ASSISTANCE

In education, feedback refers to the process of providing learners with information about their performance, highlighting both strengths and areas for improvement. It helps students understand how they are progressing in completing assignments or mastering learning material. Feedback is part of a continuous cycle, where students are given tasks, work on them, receive feedback, and fine-tune their work based on that feedback. This process can be both informal, offering suggestions for improvement, or formal, following the completion of a learning stage with a final evaluation of their work [161]. Feedback is a vital aspect of formative assessment, serving to inform students about how well they are performing and guiding them toward the desired level of achievement. The success of an assessment approach hinges on the impact feedback has on student learning, boosting their motivation and reinforcing effective behaviors [162].

The research conducted by [163] introduced an Intelligent Feedback System designed to enhance student engagement in Digitized Physical Education through ML. The system offers remote sports learning features, collects data through log recordings for predictive analysis, and provides feedback based on assessment results, particularly targeting students with low participation. It identifies factors that influence student engagement and aims to offer personalized feedback and support [163]. By analyzing student engagement data, the system delivers feedback to students or suggests recommendations to educators. The findings highlight the significance of targeted interventions in boosting student engagement and improving academic performance. The study revealed a strong positive correlation between the length of student engagement and the frequency of interactions with the digital learning platform. Furthermore, the model demonstrated satisfactory predictive performance on the test set, achieving a final test accuracy of 81.25% [163].

A personalized English learning assistance system was proposed by [164] to create tailored learning plans for students. This system incorporated multimedia teaching resources, intelligent assessment, and a real-time feedback mechanism to enhance students' English learning and assist teachers in setting personalized teaching goals. The feature clustering-based system was specifically developed for students majoring in arts and physical education, aiming to improve learning efficiency and offer a more individualized learning experience [164]. By using feature clustering technology, students were grouped to receive more targeted and effective learning support. Multimedia teaching resources made the learning experience engaging and dynamic, while the intelligent assessment and real-time feedback mechanism enabled students to adjust their learning strategies in real time [164]. The system's integration of intelligent assessment and immediate feedback significantly supported students in mastering English effectively. Experimental results demonstrated that the system enhanced learning efficiency and provided a more personalized learning approach [164].

The authors in [165] examined the potential of using chatbots and video chat for providing feedback in education, enhancing accessibility and fostering stronger teacher-student relationships. The study reviews various methods and technologies used to organize feedback in intelligent learning systems, with a focus on ML algorithms, adaptive learning, and interactive communication tools that support personalized learning environments. The study highlights that effective feedback in intelligent tutoring systems (ITSs) requires high-quality explanations tailored to the student's level of knowledge. It also emphasizes the need for algorithms that can adapt to individual student characteristics, providing customized explanations and clear error analyses to help deepen their understanding of the material [165]. Furthermore, the research shows that immediate and regular feedback allows students to make timely adjustments, encouraging continuous progress in their learning. The integration of various multimedia formats, such as text, videos, and audio, is also found to cater to the diverse learning preferences of students. The study concludes that regular, high-quality feedback not only deepens students' understanding of educational material but also serves a motivational function, inspiring them to strive for better academic results and fostering personal development [165].

Another study by [166] examined the impact of feedback from an intelligent tutoring software, SketchTivity, on the development of sketching skills. Sketching, an essential skill for engineering design, is often under-taught in engineering education, especially in large classrooms where one-on-one feedback is limited. SketchTivity, created by researchers at Texas A&M University, was developed to provide personalized, immediate feedback on freehand sketching practice, addressing the need for more effective feedback in such environments. The study compares students who received feedback through SketchTivity with those who practiced without it, assessing their motivation, skill development, and perceptions of the software [166]. The study aims to answer three key research questions: How does personalized feedback from the intelligent tutoring software affect students' motivation to practice sketching? How does this feedback improve key sketching skills? What are students' perceptions of the intelligent tutoring software's feedback feature? Preliminary results show that students found immediate feedback on precision particularly helpful for improving their sketching skills, while both immediate and summative feedback were equally motivating for different students. The study suggests that intelligent tutoring systems like SketchTivity have the potential to overcome the challenges of teaching sketching in large classrooms by offering timely feedback that is crucial for student learning [166].

The authors in [167] discussed how AI-powered professional learning tools that offer personalized feedback to teachers have been effective in enhancing instruction and student engagement, particularly in virtual learning environments. By utilizing NLP, these tools provide formative feedback to teachers, complementing human observation and coaching, and ultimately improving instructional practices [167]. This study presents the first experimental evidence on the impact of automated feedback on focusing questions on K-12 classrooms. The results show that automated feedback significantly increases teachers' use of this high-impact instructional strategy, demonstrating its potential to enhance teacher professional development. However, the study also highlights key challenges in effectively engaging teachers with these tools, such as transcription accuracy, feedback interpretation, and time constraints. The findings stress the importance of providing teachers with targeted support, such as through instructional coaches, to maximize the benefits of automated feedback [167].

Some key challenges of AI-based feedback systems have been analyzed by [168]. The research involved students from an advanced digital design course interacting with the AI assistant. While the study showed strong student engagement and positive feedback, preliminary results indicate that AI-powered guidance can significantly enhance student participation, providing a scalable framework for fostering active learning in engineering education [168]. However, the study also highlights that, although the AI assistant was well-received, it did not offer the same level of personalized support as human teaching assistants, who provide more in-depth guidance and clarification. Additionally, the study emphasizes the need for careful management and testing of any improvements to the AI assistant to avoid the inadvertent dissemination of answers, which could undermine academic integrity. The research suggests that the AI assistant represents a promising approach to integrating AI into education, ensuring personalized learning while maintaining the integrity of the educational process [168].

To sum up, conventional evaluation methods often prove to be time-consuming and inefficient, particularly in large classrooms where quick feedback is crucial. In contrast, AI-powered evaluation tools offer a more efficient solution, providing near-instant assessments and detailed feedback on various assignments, from homework and tests to more complex tasks such as coding exercises [169]. With the integration of NLP capabilities, AI systems can quickly analyze student work, identify errors, and offer immediate corrections, significantly improving the speed and effectiveness of the evaluation process.

C. STUDENT SUPPORT AND GUIDANCE

Traditionally, academic support requires students to schedule appointments with advisors, typically instructors familiar with the curriculum. However, these sessions are limited by time constraints and may be influenced by external factors. In [170], the author emphasized the value of virtual assistants in various academic areas, including career counseling and managing the psychological challenges of student life. These AI-driven assistants help students make well-informed decisions about their career paths and prevent unnecessary career changes later in life. The introduction of career counseling chatbots aids students in navigating program choices, career assessments, and personal development within their fields [170].

The authors in [171] studied the role of AI in student mentoring, where AI-driven systems combine intelligent algorithms with ML to offer personalized guidance. Unlike human mentors, AI chatbots possess essential qualities like patience and the ability to listen without judgment, making them effective mentors. One significant advantage of AI mentoring is scalability, as AI systems can support numerous students simultaneously, helping across various time zones and regions [171]. These AI mentors also continuously learn and adapt by processing large amounts of data and incorporating real-time feedback to improve their mentoring techniques. This allows students to access diverse perspectives and explore innovative solutions to complex problems by drawing insights from multiple disciplines [171].

The authors in [172] introduced a career guidance system designed to assist students in selecting the appropriate undergraduate course. This interactive platform evaluates students' academic performance and extracurricular involvement to assess a wide range of skills relevant to various career paths [172]. The study focused on three key elements: Skill Enlightenment, Prediction, and Skill Discovery, all of which play a crucial role in helping students make informed decisions about their future academic and career trajectories [172].

Figure 8 illustrates the advantages of AI-based guidance and support, such as personalized coaching, scalability, and cross-disciplinary knowledge, which help students overcome challenges and achieve their goals.

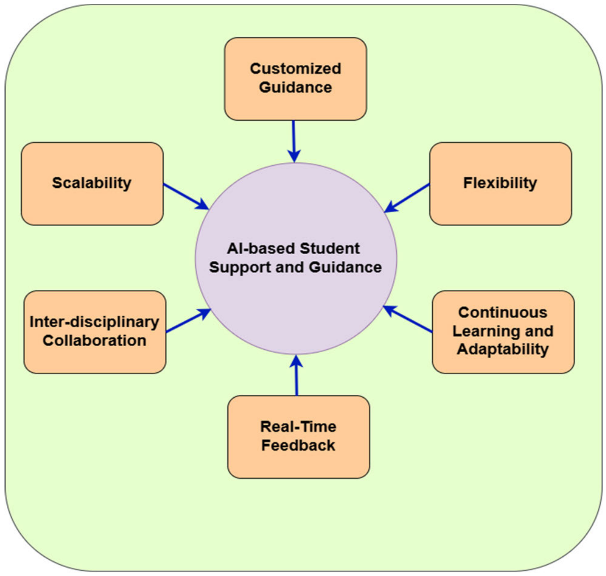


FIGURE 8. Advantages of AI based student support and guidance.

VII. ASSESSMENT AND GRADING AUTOMATION

A. AUTOMATED GRADING SYSTEM

Automated Grading Systems (AGS) methods provide a solution to speed up the assessment of grades, improve the accuracy of scores, and result in more efficient feedback [174]. Nowadays, many educational institutions or organizations provide assessment evaluation using AI-based AGS to reduce human load and enhance learning outcomes [173]. AGS can be adapted in various ways, as listed below.

AI-based solutions can evaluate written essay responses to check grammar, text quality, and sentence transitions [173], [174], [175].

- In oral examinations, AI-based systems can use speech recognition to evaluate spoken responses, pronunciation, and fluency.
- Using AI to assess code accuracy, efficiency, and technical adherence results in high success in programming languages such as Java, Python, or C++.
- Using AI models to recognize duplicated or rephrased material by contrasting submissions.
- AI-based models can automate the evaluation process of examinations such as the SAT, GRE, or Massive Open Online Course (MOOCs) for large-scale standardized testing.

Using AI-based systems, the evaluation of objective questions and short responses is automated by keyword matching for grading multiple-choice and short-answer questions [175].

Various studies have implemented AGS. For example, the authors in [176] employed the BERT model, which utilizes

TABLE 14. Algorithms in automated grading systems.

Study	Method	Accuracy
[178]	Transformer-based models	>95%
[176]	BERT	~82%
[179]	CNN and BiLSTM	~80%
[180]	Various ML algorithms	Kappa (QWK) value of 0.68
[181]	ChatGPT	Promising
[177]	BERT and NLP	Promising
[182]	LLM, GPT4	Promising

extensive unsupervised data to extract semantic, grammatical, and other properties, successfully integrating external information. Integrating BERT with the suggested Multiple Data Augmentation Strategies (MDA) and the Automatic Short Answer Scoring (ASAS) model provides substantial enhancements to the ASAS dataset compared with current methods [176]. In [177], the authors assessed the responses to open-ended questions using NLP algorithms that include BERT and linguistic aspects. In [178], the authors built a model using a transformer to detect plagiarism. Compared to BOW's dependence on word stemming, this model surpasses Bag-of-Words (BOW) by maintaining word order and context. The study shows that the method can enhance the accuracy of human evaluators and provides an implementation that can be used for educational institutions [178]. The authors in [179] developed a model utilizing DL architecture that integrates CNN and Bidirectional Long Short-Term Memory (BiLSTM) to recognize and score handwritten responses reliably, comparable to a human expert grader. The authors in [180] used various ML algorithms. This work presents an innovative automated Essay Scoring system that employs many ML methods, with XGBoost combined with Polynomial Features yielding the highest performance.

The authors in [181] indicated that GPT had a degree of accuracy and reliability for automated examination assessment. It also demonstrated its capacity to offer substantial assistance for human evaluations. Furthermore, the research in [181] revealed that the utilization of linguistic elements may enhance the precision of the score values. The findings of this study demonstrate that AI language models, such as ChatGPT, may be effectively utilized as assessment evaluation tools, suggesting that this approach can be broadly implemented in assessment and feedback writing methodologies in practice [181]. The authors in [182] employed GPT-4 evaluated whether LLM-based approaches could equal or exceed teacher dependability in grading brief astronomical writing tasks for adult learners in three MOOC courses. The findings indicate that LLM demonstrated more reliability than peer grading, both overall and for individual students, and closely aligned with teacher grades across all three online courses. LLMs may provide automatic, dependable, and scalable assessment of student science writing [182]. Table 14 summarizes the algorithms used in automated grading systems.

TABLE 15. Plagiarism detection tools.

Tool Name	Technology Used	Features
Copyscape [187]	AI and rule-based system	Detect duplicated contents
GPTZero [188]	DL, statistical analysis	Detects AI-generated content
Grammarly [189]	ML and NLP	AI writing detection, grammar check
iThenticate	ML and NLP	Feedback on academic writing plagiarism
Ouriginal [190]	ML, text mining	Detect plagiarism and improper citations
PaperRater [191]	ML and MLP	Detect plagiarism
Plagscan [192]	ML, Text Analytics	Detect similarities
Scribber [193]	ML and NLP	Paraphrasing and poor citations
Turnitin [194]	ML and NLP	AI writing detection, feedback for academic writing plagiarism

B. PLAGIARISM DETECTION TOOLS

Plagiarism detection tools are essential for fostering a fair educational environment at various levels of education and establishing accurate grading systems. These tools identify misconduct and contribute to a fair, original, and responsible learning ecosystem. These tools also assist teachers by saving time and allowing them to focus on teaching while addressing plagiarism issues [183].

Some research has been conducted to build a model and solution for detecting plagiarism. The authors in [184] investigated source code pair plagiarism detection and prediction using XGBoost. The model removes unnecessary variables and functions from the prediction assignment code. This study achieved 94% accuracy in source code analysis by eliminating redundant variables and functions [184]. In [185], the authors proposed a plagiarism detection method that extracts optimal text similarity features and constructs hyperplane equations to identify similarity cases accurately. The testing results demonstrated that the suggested system outperformed recent top-ranked systems, achieving the highest F-measure score of 92.95% [185]. The authors in [186] examined DL and ML algorithms, identifying the factors influencing the performance of algorithms viewed as black boxes through descriptive studies, including SHAP and LIME. Among the algorithms used for predictions, the 5-layer DNN method demonstrated the most effective model, achieving a success rate of 80.9% in identifying students who engaged in test copying [186]. The XGBoost model outperformed the others, attaining the highest accuracy of 97.7% [186].

On the other hand, various tools are used to detect plagiarism and verify the authenticity of text generated through different methods. Many contents are frequently repeated and reused without consideration. Identifying unique and original content can be challenging. Table 15 summarizes the current plagiarism detection solutions available on the market.

Many other plagiarism detection tools are available; we summarize the most used tools and provide a solution based on AI. Due to their comprehensive plagiarism detection and LMS integration, *Turnitin, iThenticate, Ouriginal,* and *Scribbr* are frequently used in educational institutions. *GPTZero* and *Unicheck* are designed to detect AI-generated text, making them ideal for current academic assessments. *Crossplag, PaperRater*, and *Plagscan* detect plagiarism in multiple languages.

C. OBJECTIVE AND SUBJECTIVE ASSESSMENTS METHODS

There are various objective and subjective assessment methods utilizing AI across multiple domains [195]. Numerous text analysis challenges can be addressed using AI, primarily through LLM models. As a result, AI has enhanced both objective and subjective educational assessments, making them more efficient, accurate, and tailored [196]. Objective exams evaluate factual knowledge or skills through multiple-choice, true/false, or numerical answers. Automated scoring, pattern analysis, and adaptive testing improve these evaluations with AI, which can automatically score objective questions, reducing manual effort and human errors [197].

Additionally, RL algorithms can adjust the difficulty of questions based on student performance [198]. Subjective assessments concentrate on essay-type questions that require an open-ended interpretive response, often constrained by a word limit [195]. This approach employs NLP, multimodal techniques, or transformer models as a solution that necessitates complex and contextual understanding. AI-based plagiarism detection algorithms can identify copied or repeated information in objective submissions, such as programming code plagiarism assignments. For example, MOSS and Turnitin can check answer similarities and generate a results report. As an AI tool for subjective assessment, automated essay scoring models such as GPT, BERT, and RoBERTa evaluate writing for grammar, coherence, relevance, and the strength of arguments. The ETS e-rater and Grammarly systems facilitate the automation of the writing evaluation process [199]. In short answer grading, AI models analyze written responses by comparing them to model answers or using semantic similarity metrics.

Subjective evaluations assess complex activities using advanced NLP and multimodal analysis, while objective assessments benefit from automation and scalability. These methods empower instructors and students with fair, consistent, and informative evaluations [200].

VIII. ETHICAL CONSIDERATIONS

While AI-powered personalized learning offers significant benefits, it also raises critical ethical concerns that must be addressed to ensure responsible and equitable use in education. Table 16 summarizes how different ethical concerns may affect AI-based education. By addressing these ethical challenges head-on, educators, policymakers, and technologists can ensure that AI is used responsibly and equitably in education, ultimately enhancing the learning experience for all students while safeguarding their rights and well-being.

TABLE 16. The ethical concerns of AI-based education.

Concern	Challenge	Mitigation	Study
Privacy & data security	Risk of data breaches, surveillance concerns	Encryption, anonymization, compliance with laws like GDPR, FERPA, need for transparency in AI decisions	[26, 28, 37, 42]
Bias & fairness in ai algorithms	Potential discrimination in AI decisions	Diverse datasets, bias audits, inclusive design, inclusive AI training data	[38]
Transparency & accountability	Lack of trust in AI, Limited contextual understanding, potential misinformation	Explainable AI, clear accountability measures, ongoing monitoring, training	[39, 41, 42]
Student autonomy & AI dependency	Risk of students becoming passive learners, plagiarism detection, limited understanding of creativity	Encourage critical thinking, balance AI guidance with human instruction	[40, 42]
Digital divide & accessibility	Exacerbates inequality for students in low-income regions	Develop low-resource AI solutions, expand internet accessibility	[7, 39]
Ethical AI use in student evaluations	Potential for misjudgment, bias in algorithms	Combine AI predictions with teacher evaluations	[37, 41]

A. PRIVACY AND DATA SECURITY

One of the most pressing issues is privacy and data security. Adaptive learning systems and ITS collect extensive data about students, including academic performance, learning disabilities, and personal preferences [16], [37]. In some cases, AI systems may even track emotional states using facial recognition or sentiment analysis. If not properly secured, this data could be vulnerable to breaches or unauthorized access by third parties [42]. Potential risks include data breaches leading to identity theft and surveillance concerns that may create a stifling ‘‘Big Brother’’ effect, discouraging creativity and freedom of expression [28]. Mitigation strategies include employing strong encryption methods, anonymizing data where possible, ensuring transparency regarding data collection and usage, and complying with regulations such as General Data Protection Regulation (GDPR) and (Family Educational Rights and Privacy Act) (FERPA) [26], [42].

B. BIAS AND FAIRNESS IN AI ALGORITHMS

Another significant ethical challenge is bias and fairness in AI algorithms. AI systems rely on training data, and if that data contains historical biases, the algorithms may reinforce or even amplify existing inequalities. For instance, an adaptive learning system trained on biased data might recommend fewer advanced courses to students from underrepresented backgrounds, perpetuating disparities in educational opportunities [38]. This issue poses risks such as reinforcing inequities and limiting diversity in educational content. To mitigate bias, AI models should be trained on diverse datasets that represent a wide range of backgrounds, abilities, and learning styles. Regular bias audits should be conducted to assess fairness, and inclusive design principles should be applied, involving educators, students, and ethicists from diverse backgrounds to ensure AI-driven learning systems are equitable for all [38]. Figure 9 demonstrates ethical considerations in AI education systems.

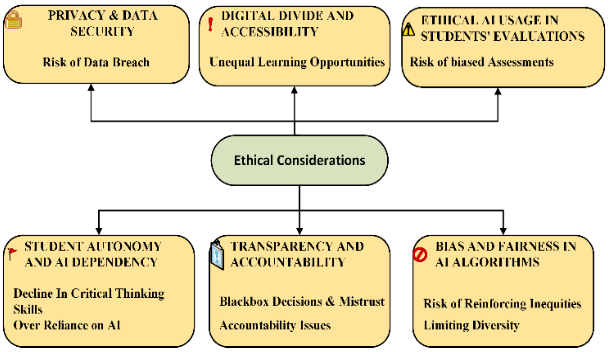


FIGURE 9. Ethical considerations in AI based education.

C. TRANSPARENCY AND ACCOUNTABILITY

Transparency and accountability remain critical concerns in AI-driven education. Many AI algorithms function as "black boxes," meaning their decision-making processes are difficult for humans to interpret [142]. This lack of transparency can lead to mistrust among educators, students, and parents who may not understand why specific recommendations or learning paths are suggested [39]. Furthermore, accountability issues arise when AI systems make mistakes, such as misclassifying a student's skill level or recommending inappropriate content [41]. Without clear responsibility, errors may go unaddressed, negatively impacting students' learning experiences. To address these challenges, AI developers should prioritize explainable AI to create systems that provide clear justifications for their decisions. Additionally, clear guidelines should be established to define accountability, ensuring that institutions, educators, or AI developers take responsibility for any errors [42]. Continuous monitoring of AI systems is essential to identify unintended consequences and make necessary adjustments to maintain fairness and effectiveness.

D. STUDENT AUTONOMY AND AI DEPENDENCY

The increasing use of AI in education raises concerns about student autonomy and the risk of over-dependence on AI-driven tools [40]. While AI can enhance efficiency by providing instant answers and personalized recommendations, excessive reliance on these tools may reduce critical thinking and problem-solving skills [142]. For example, AI-powered homework assistants like ChatGPT and Wolfram Alpha can quickly solve complex problems, but if students passively accept AI-generated answers without attempting to understand the underlying concepts, their cognitive development may suffer [42]. To mitigate this, educators should encourage students to use AI as a learning aid rather than a substitute for independent thought. Assignments that require students to explain their reasoning and engage in discussions can help balance AI support with critical thinking development [40].

E. DIGITAL DIVIDE AND ACCESSIBILITY

AI-powered personalized learning promises to expand access to high-quality education, but it also risks widening the digital divide [39]. Students in well-funded schools with reliable internet and advanced devices can fully leverage AI-driven education, while those in underprivileged areas may struggle due to limited access to technology [7]. AI-powered smart classrooms and VR-based learning experiences, for example, provide immersive and interactive education, but they remain inaccessible to many due to cost barriers. To ensure equitable learning opportunities, governments and institutions must invest in affordable AI-driven educational tools and improve digital infrastructure in low-income regions. Additionally, developing AI models that function effectively in low-resource environments, such as mobile-friendly AI tutors that work offline, can help bridge the gap in accessibility [39].

F. ETHICAL AI USAGE IN STUDENTS' EVALUATIONS

AI is increasingly being used for student evaluations, from automated grading to predictive analytics that assess a student's likelihood of success or dropout risk [37]. While these systems offer efficiency and early intervention for struggling students, they also raise ethical concerns related to fairness and bias [41]. AI-based student analytics can sometimes reflect historical inequalities, leading to unintended biases in recommendations. For example, if an AI system predicts lower performance for students from marginalized backgrounds based on past data, it may limit their access to advanced coursework or enrichment opportunities. To prevent such biases, AI models should be trained on diverse datasets that represent students from all backgrounds [37]. Regular bias audits, along with a collaborative approach where teachers review AI-generated evaluations, can ensure that assessments are fair, inclusive, and supportive of student growth [41].

IX. FUTURE TRENDS AND CHALLENGES

AI and ML transform education, so it is crucial to understand the emerging trends, challenges, and opportunities. This section discusses the future of AI and ML in education, including their growing applications, barriers to acceptance, and innovative collaboration.

A. EMERGING APPLICATIONS OF ML AND AI IN EDUCATION

AI and ML in education will provide new teaching and assessment opportunities. Some interesting new applications include (a) educational content generation, (b) personalized learning, (c) smart advising systems, (d) assessment grading automation, and (e) interactive class collaboration.

Educational Content Generation: The authors in [201] studied human evaluation of produced questions, revealing procedural quality differences and improvement areas. Additionally, the model evaluates the answers, illustrating how LLMs can effectively analyze responses, provide constructive feedback, and identify subtle comprehension issues or misunderstandings. Generative AI can reshape various educational content, such as developing higher education curricula [202]. Another work by [203] focusing on educational content discusses using LLMs in Turkish education, enabling automated production of Turkish quizzes. This study demonstrates that such models can generate coherent and meaningful quiz content. It sets a precedent for future research in the automated production of educational content in languages beyond English [203].

Personalized Learning: In [204], the authors explored how AI may improve access to education, collaborative spaces, and intelligent tutoring tools to help instructors and personalize learning. The authors in [205] discussed that AI is an innovative way for special education teachers to fulfill these responsibilities. It is used in predictive text, adaptive learning systems, and digital assistants. The authors in [144] showed that mixing technology with conventional teaching techniques improves learning. The findings include developing evidence-based Generated AI integration standards and regulations, encouraging critical thinking and digital literacy in students, and promoting responsible Generated AI use in higher education. These approaches may have a significant impact and change in education, and it is essential to evaluate the effect of changes in using AI in education. The study by [24] classified the extensive studies on AI for school customization and highlights the key themes through which an AI-driven approach structurally transforms the education system.

Smart Advising Systems: Smart advising systems are an essential use of AI and ML in education, providing students with individualized help throughout their academic experience. These systems use data analytics, predictive modeling, and NLP to make personalized suggestions about course choices, career paths, and academic performance enhancement. The authors in [206] presented a recommendation system for advisors and students that evaluates student data to create tailored study programs over several semesters. The suggested approach amalgamates concepts from graph theory, performance modeling, ML, explainable suggestions, and an intuitive user interface. The authors in [207] developed a chatbot-based academic advice system to assist students with prescriptive academic queries. The system is grounded in real-world advising situations and was designed with usability. This study includes scenario-based functional and usability criteria for the chatbot-based advising system. These solutions will help students with poor academic performance and difficulties adjusting to the educational system overcome these challenges. This will improve student academic achievement and lead to a higher-quality, more effective educational experience [207].

Assessment Grading Automation: Assessment grading automation is a critical component of AI-powered educational solutions that enable rapid, consistent, and scalable evaluation of student performance. This model overcomes the limitations of manual grading by combining ML models, NLP, and advanced analytics to ensure fairness and accuracy. Automated grading increases efficiency, reduces grading time, and gives students faster feedback. Despite the distinctions between human and AI [208] reviewed research demonstrates the ability to enhance and optimize education in face-to-face, hybrid, or virtual settings. The authors in [209] provided a modular system using transformer-based language models to generate multiple-choice questions from textual material. Another related work by [210] proposed a comprehensive AES system that provides student writers with anticipated holistic and rubric ratings while clearly outlining the scoring standards associated with each rubric. It can identify deficiencies in student essays and offer formative comments, helping students overcome the learning plateau in English writing [210].

Interactive Class Collaboration: Integrating AI with existing digital tools in classrooms has led to innovations in how students and educators interact, providing elements that promote effective learning while creating a more engaging, inclusive, and efficient educational environment [211]. AI-supported tools enhance the interaction between students and educators, making it more effective and efficient. Rather than relying on traditional automated structures during lessons, real-time interaction fosters a setting where students are more individually involved, resulting in quicker adaptations needed for learning [212]. In this way, the quality of education and the learning skills of new generations will improve through AI-supported technologies that can be more effective than monotonous traditional learning models [213]. Interactive class collaboration offers numerous advantages, including direct communication with students via NLP-based chatbots or virtual assistants. The AI-assisted educational platform utilized in [214] is named Smart-Learning Partner (SLP), which leverages AI technology to offer enhanced options for individualized learning and additional educational materials. Other activities include gamification facilitated by AI tools such as Kahoot! or Quizizz, personalized feedback through transformer-based models for group assessments, and monitoring student emotions through analyzing facial expressions, vocal tone, or text sentiment. Figure 10 demonstrate the future trends and challenges of ML in education [214].

B. ADDRESING IMPLEMENTATION CHALLENGES

Innovations in education have occurred at various times throughout human history. Some changes have been rapid, while others have been slow. These transformations have varied based on time, location, and cultural context. With the

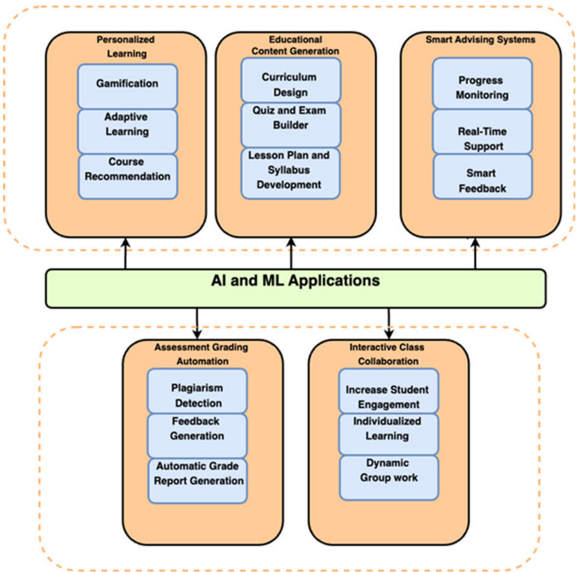


FIGURE 10. **Future trends and challenges of ML in education.**

advent of computers and the internet, access to information has become faster, leading to swift alterations in learning methods. Unlike past changes, these developments have had a global impact, prompting all countries to recognize the necessity of keeping pace with technological advancements. Concurrently, education systems have evolved to incorporate new technologies. In recent years, we have witnessed a transformation in education driven by the growth of AI. In addition to existing programs, there is a shift towards more interactive systems that enhance learning techniques. Generally, the education sector adapts at a slower pace. It is essential to assess innovations related to pedagogical and educational methods discussed by [215] and to conduct separate evaluations. Sometimes, rapid transformations are hindered by such expectations. The authors in [216] shared insights and research perspectives on AI in higher education institutions, best practices for implementation, students' understanding of AI, and their perceptions, which may evolve. The authors emphasized data privacy, reduced bias, offered teacher training, guaranteed equal access, and ensured students understood AI in an inclusive and sustainable educational environment [216].

While ethical concerns have received attention, other practical limitations of machine learning in education are also important. Many ML models require significant computing resources, which can be a barrier for institutions with limited technological infrastructure. Moreover, integrating these tools into traditional classroom settings is not always straightforward. It often involves training teachers, adjusting curricula, and overcoming resistance to change, all of which demand time, funding, and institutional support. Additionally, models trained on specific populations may not transfer well across diverse educational environments, limiting their scalability and effectiveness. These challenges underscore the importance of developing flexible, accessible, and context-sensitive ML solutions for education. Beyond ethical considerations, the practical challenges of applying machine learning in real world educational settings are significant and often underdiscussed. One major limitation is the high computational cost associated with many machine learning models, particularly those that rely on deep learning or real time data analysis. These systems often require powerful hardware, consistent internet access, and robust data infrastructure, which are not always available in public or limited resource schools. Even when cloud-based services are used to offset hardware needs, they typically involve subscription fees or usage-based pricing that can limit long-term sustainability. Additionally, concerns over data privacy, storage, and compliance with local regulations can complicate implementation, especially in regions with strict education or technology policies.

C. OPPORTUNITIES FOR COLLABORATION AND INNOVATION

LLM and Generative AI directly influence all educational activities encompassing reading, comprehension, writing, and communication, which are fundamental learning primitives. The authors in [217] examined the potential to enhance educational experiences, customize individual instruction, and foster creativity. However, it encounters several challenges, including ethical concerns, information confidentiality protection, algorithmic bias mitigation, and the redefinition of educators' roles. The authors in [218] examines ChatGPT's possible advantages, drawbacks, and solutions to mitigate the observed issues. The findings underscore the pressing necessity for more explicit regulations, standards, and procedures for the responsible integration of ChatGPT or similar applications in higher education institutions.

As discussed in Section VIII-A, new AI solutions in education introduce essential advancements, including educational content generation, personalized learning, intelligent advising systems, assessment grading automation, and interactive class collaboration. Innovative AI applications and models positively impact education, leading to the creation of more advanced tools and the enhancement of existing technologies. The primary driving forces are new AI models, performance enhancements, and data curation that expand educational categories. Consequently, various evaluation criteria have emerged, and results are analyzed through significantly different methods introduced by AI. Our study indicates that AI in education is progressing across multiple domains and evolving towards a framework that makes learning less tedious, offering practical and immediate feedback. Overall, the examinations and analyses from this study indicate that the implementation of these new AI solutions in education will have widespread effects and further accelerate change in the sector, impacting both students and teachers. Governments must revise their education policies to align with emerging technologies.

X. CONCLUSION

A. SUMMARY OF KEY FINDINGS

This paper explores the transformative role of ML in education, highlighting various applications such as intelligent tutoring systems, content creation, automated grading, adaptive learning, and smart feedback mechanisms. Key findings indicate that ML and other AI methodologies enhance personalized learning experiences by adapting content and instructional methods to individual student needs. AI-driven tools improve engagement through gamification, intelligent virtual assistants, and ACG, making education more interactive and accessible. Furthermore, ML-based predictive analytics provide early identification of at-risk students, allowing timely intervention to improve academic outcomes. Despite these advancements, the study also underscores challenges such as ethical concerns, data privacy, and algorithmic biases, which need to be addressed to ensure fair and inclusive AI-driven education.

While this review highlights the diverse and expanding role of machine learning in education, more meaningful insights can be gained by comparing these findings to existing literature. For instance, our identification of intelligent tutoring systems as a key application area is consistent with the conclusions drawn by [3] and [32], who emphasized the role of AI in delivering personalized learning experiences. Similarly, our observations regarding the use of reinforcement learning for adaptive educational pathways echo the findings in [30] and [43], where AI algorithms were shown to enhance student engagement through dynamic content delivery. However, unlike earlier reviews that focused mainly on technical implementations [13], [15], our study brings a broader, application-oriented perspective that includes ethical considerations and student support systems. This contrast underscores the importance of situating ML tools within pedagogical and institutional frameworks, not just technical domains. This contrast underscores the importance of situating ML tools within pedagogical and institutional frameworks, not just technical domains, by aligning our analysis with recent work and identifying gaps such as limited empirical evaluation in specific ML-driven platforms. We contribute to a more holistic understanding of how AI is reshaping modern education.

B. IMPLICATIONS OF THE FUTURE EDUCATION

The integration of ML into education is poised to redefine traditional teaching and learning methodologies. The use of AI-powered adaptive learning systems will continue to grow, offering students customized learning pathways that cater to their individual strengths and weaknesses. Future directions are listed as follows:

- Adaptive learning systems: Expand the use of VR and AR in adaptive tutoring systems to provide more immersive and engaging learning experiences [37]. Create teacher dashboards to assist in pedagogical practices and streamline instructional strategies [38].
- Intelligent tutoring systems: Develop intelligent tutoring systems that can detect and respond to students' affective states to improve engagement and learning outcomes [7].
- Personalized recommendations: Incorporate advanced AI techniques (e.g., ML, RNNs) to enhance personalization and adaptability in educational systems [7].
- AI-powered virtual assistants: Despite many benefits of AI on providing virtual assistants, these AI assistants still have limitations in understanding nuanced or context-heavy questions, which can lead to misinformation or incomplete explanations. To mitigate this, continuous AI training, coupled with human oversight, is essential to ensure accuracy and relevance in responses.
- Automated assessment & feedback: Despite many benefits of AI on providing automated assessment, However, these systems face challenges in accurately assessing creativity, complex reasoning, or subjective responses [38]. False positives in plagiarism detection and a lack of nuanced understanding can sometimes lead to unfair evaluations [41]. To address these issues, a hybrid approach combining AI analysis with human review is recommended to maintain fairness and accuracy in assessments [44]. Integrate neurofeedback with immersive technologies (e.g., VR) to create dynamic, responsive learning environments [41].
- Driven gamification: Despite many benefits of AI on providing driven gamification, However, excessive reliance on gamification could lead to distractions or a focus on rewards rather than DL. Educators must strike a balance by integrating gamified elements within structured learning frameworks to ensure that students remain focused on educational objectives rather than simply earning points [45].
- Develop explainable AI methods to offer transparent insights into learning outcomes and foster trust in AI systems [39].
- Offer training programs for faculty and students to improve AI literacy and adaptability, bridging the gap between proficient and less experienced users [42].
- Establish clear policies and regulations at institutional and national levels to govern the use of AI in education, addressing issues related to intellectual property, data privacy, and academic integrity [42].
- Focus future research on the long-term impacts of AI in higher education, particularly in teaching, learning, and assessment, through comparative studies across different countries and educational systems [42].
- One limitation of this literature review is the lack of an in-depth discussion regarding potential biases and experimental limitations present in the studies reviewed. While the paper aimed to provide a comprehensive synthesis of existing research, it did not thoroughly analyze how methodological differences, sample selection, or publication bias may have influenced the reported

outcomes. Future reviews could benefit from incorporating a more systematic assessment of such limitations to better contextualize the findings and strengthen the validity of the conclusions drawn.

C. CLOSING REMARKS

ML and other AI technologies have the potential to revolutionize education by enhancing personalized learning, automating routine tasks, and improving student engagement. However, to harness its full potential, it is crucial to address challenges related to data privacy, fairness, and accessibility. The future of AI in education should focus on ethical implementation, ensuring inclusivity, and promoting transparency in AI-driven decision-making.

REFERENCES

[1] GrandViewResearch. *AI in Education Market Size & Trends*. Accessed: Jun. 10, 2025. [Online]. Available: https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-education-market-report#

[2] A. Kaw, A. Yalcin, and R. Clark, "Using adaptive learning platform data in a flipped classroom for early detection and tutoring of low-performing students," *Comput. Appl. Eng. Educ.*, vol. 33, no. 2, Mar. 2025, Art. no. e70007.

[3] J. Chen, X. Zhou, J. Yao, and S.-K. Tang, "Application of machine learning in higher education to predict students' performance, learning engagement and self-efficacy: A systematic literature review," *Asian Educ. Develop. Stud.*, vol. 14, no. 2, pp. 205–240, Mar. 2025.

[4] N. Pellas, "The impact of AI-generated instructional videos on problem-based learning in science teacher education," *Educ. Sci.*, vol. 15, no. 1, p. 102, Jan. 2025.

[5] M. Nadeem, A. Chandra, A. Livirya, and S. Beryozkina, "AR-LabOr: Design and assessment of an augmented reality application for lab orientation," *Educ. Sci.*, vol. 10, no. 11, p. 316, Nov. 2020.

[6] U. H. Khan, M. H. Khan, and R. Ali, "Large language model based educational virtual assistant using RAG framework," *Proc. Comput. Sci.*, vol. 252, pp. 905–911, Jan. 2025.

[7] F. Niño-Rojas, D. Lancheros-Cuesta, M. T. P. Jiménez-Valderrama, G. Mestre, and S. Gómez, "Systematic review: Trends in intelligent tutoring systems in mathematics teaching and learning," *Int. J. Educ. Math., Sci. Technol.*, vol. 12, no. 1, pp. 203–229, Oct. 2023.

[8] M. Nadeem, M. Lal, J. Cen, and M. Sharsheer, "AR4FSM: Mobile augmented reality application in engineering education for finite-state machine understanding," *Educ. Sci.*, vol. 12, no. 8, p. 555, Aug. 2022.

[9] M. Nadeem, M. Oroszlanyova, and W. Farag, "Effect of digital game-based learning on student engagement and motivation," *Computers*, vol. 12, no. 9, p. 177, Sep. 2023.

[10] A. Zouhri and M. EL Mallahi, "Improving teaching using artificial intelligence and augmented reality," *J. Autom., Mobile Robot. Intell. Syst.*, vol. 18, no. 2, pp. 57–61, 2024.

[11] S. Akhtar, M. Nadeem, M. Rashdan, B. Hussain, E. A. Ansari, and M. H. Aslam, "Online mode of teaching and learning process in engineering discipline: Teacher perspective on challenges faced and recommendations," *Educ. Sci.*, vol. 13, no. 2, p. 200, Feb. 2023.

[12] W. A. Farag, M. Nadeem, and M. Helal, "Assessment transformation in the age of AI: Moving beyond the influence of generative tools," in *Proc. Medit. Smart Cities Conf. (MSCC)*, May 2024, pp. 1–6.

[13] R. Sajja, Y. Sermet, M. Cikmaz, D. Cwiertny, and I. Demir, "Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education," *Information*, vol. 15, no. 10, p. 596, Sep. 2024.

[14] A. E. Topcu, Y. I. Alzoubi, E. Elbasi, and E. Camalan, "Social media zero-day attack detection using TensorFlow," *Electronics*, vol. 12, no. 17, p. 3554, Aug. 2023.

[15] A. E. Topcu, E. Elbasi, and Y. I. Alzoubi, "Machine learning-based analysis and prediction of liver cirrhosis," in *Proc. 47th Int. Conf. Telecommun. Signal Process. (TSP)*, Czech Republic, Jul. 2024, pp. 191–194.

[16] Y. I. Alzoubi, A. Mishra, A. E. Topcu, and A. O. Çıbıkdiken, "Generative artificial intelligence technology for systems engineering research: Contribution and challenges," *Int. J. Ind. Eng. Manage.*, vol. 15, no. 2, pp. 169–179, Jun. 2024.

[17] I. H. Sarker, "Machine learning: Algorithms, real-world applications and research directions," *Social Netw. Comput. Sci.*, vol. 2, no. 3, p. 160, May 2021.

[18] A. E. Ezugwu, A. M. Ikotun, O. O. Oyelade, L. Abualigah, J. O. Agushaka, C. I. Eke, and A. A. Akinyelu, "A comprehensive survey of clustering algorithms: State-of-the-art machine learning applications, taxonomy, challenges, and future research prospects," *Eng. Appl. Artif. Intell.*, vol. 110, Apr. 2022, Art. no. 104743.

[19] J. Gui, T. Chen, J. Zhang, Q. Cao, Z. Sun, H. Luo, and D. Tao, "A survey on self-supervised learning: Algorithms, applications, and future trends," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 46, no. 12, pp. 9052–9071, Dec. 2024.

[20] S. Naeem, A. Ali, S. Anam, and M. M. Ahmed, "An unsupervised machine learning algorithms: Comprehensive review," *Int. J. Comput. Digit. Syst.*, vol. 13, no. 1, pp. 911–921, Apr. 2023.

[21] A. D. Samala, S. Rawas, S. Criollo-C, L. Bojic, F. Prasetya, F. Ranuharja, and R. Marta, "Emerging technologies for global education: A comprehensive exploration of trends, innovations, challenges, and future horizons," *Social Netw. Comput. Sci.*, vol. 5, no. 8, pp. 1–24, Dec. 2024.

[22] A. K. Shakya, G. Pillai, and S. Chakrabarty, "Reinforcement learning algorithms: A brief survey," *Expert Syst. Appl.*, vol. 231, Nov. 2023, Art. no. 120495.

[23] S. F. Elza and Y. D. L. Widyasari, "PRISMA-guided systematic review on machine learning for university student dropout prediction," in *Proc. 4th Int. Annu. Conf. ABEC Indonesia*, 2025, pp. 377–385.

[24] S. Maghsudi, A. Lan, J. Xu, and M. van der Schaar, "Personalized education in the artificial intelligence era: What to expect next," *IEEE Signal Process. Mag.*, vol. 38, no. 3, pp. 37–50, May 2021.

[25] M. Hooda, C. Rana, O. Dahiya, A. Rizwan, and M. S. Hossain, "Artificial intelligence for assessment and feedback to enhance student success in higher education," *Math. Problems Eng.*, vol. 2022, pp. 1–19, May 2022.

[26] I. Gligorea, M. Cioca, R. Oancea, A.-T. Gorski, H. Gorski, and P. Tudorache, "Adaptive learning using artificial intelligence in e-learning: A literature review," *Educ. Sci.*, vol. 13, no. 12, p. 1216, Dec. 2023.

[27] K. T. Chong, N. Ibrahim, S. H. Huspu, W. M. N. W. Kadir, and M. A. Isa, "A systematic review of machine learning techniques for predicting student engagement in higher education online learning," *J. Inf. Technol. Educ., Res.*, vol. 24, p. 5, Mar. 2025.

[28] W. Strielkowski, V. Grebennikova, A. Lisovskiy, G. Rakhimova, and T. Vasileva, "AI-driven adaptive learning for sustainable educational transformation," *Sustain. Develop.*, vol. 33, no. 2, pp. 1921–1947, Apr. 2025, doi: 10.1002/sd.3221.

[29] K. Seßler, M. Fürstenberg, B. Bühler, and E. Kasneci, "Can AI grade your essays? A comparative analysis of large language models and teacher ratings in multidimensional essay scoring," in *Proc. 15th Int. Learn. Anal. Knowl. Conf.*, Mar. 2025, pp. 462–472.

[30] H. A. Alhamad, M. Shehab, M. K. Y. Shambour, M. A. Abu-Hashem, A. Abuthawabeh, H. Al-Aqrabi, M. S. Daoud, and F. B. Shannaq, "Handwritten recognition techniques: A comprehensive review," *Symmetry*, vol. 16, no. 6, p. 681, Jun. 2024.

[31] U. Maier and C. Klotz, "Personalized feedback in digital learning environments: Classification framework and literature review," *Comput. Educ., Artif. Intell.*, vol. 3, Jan. 2022, Art. no. 100080.

[32] A. Dey and K. Dasgupta, "Mood recognition in online sessions using machine learning in realtime," in *Proc. 5th Int. Conf. Comput., Commun. Signal Process. (ICCCSP)*, May 2021, pp. 1–6.

[33] P. Kossack and H. Unger, "Emotion-aware Chatbots: Understanding, reacting and adapting to human emotions in text conversations," in *Advances in Real-Time and Autonomous Systems. AUTSYS 2023* (Lecture Notes in Networks and Systems), vol. 1009, H. Unger and M. Schaible, Eds., Cham, Switzerland: Springer, 2023, pp. 158–175.

[34] Z. Trabelsi, F. Alnajjar, M. M. A. Parambil, M. Gochoo, and L. Ali, "Real-time attention monitoring system for classroom: A deep learning approach for student's behavior recognition," *Big Data Cognit. Comput.*, vol. 7, no. 1, p. 48, Mar. 2023.

[35] G. P. B. Castro, A. Chiappe, D. F. B. Rodriguez, and F. G. Sepulveda, "Harnessing AI for education 4.0: Drivers of personalized learning," *Electron. J. e-Learn.*, vol. 22, no. 5, pp. 1–14, Apr. 2024.

[36] P. Anunpattana, M. N. A. Khalid, H. Iida, and W. Inchamnan, "Capturing potential impact of challenge-based gamification on gamified quizzing in the classroom," *Heliyon*, vol. 7, no. 12, Dec. 2021, Art. no. e08637.
[37] J. Fernández-Herrero, "Evaluating recent advances in affective intelligent tutoring systems: A scoping review of educational impacts and future prospects," *Educ. Sci.*, vol. 14, no. 8, p. 839, Aug. 2024.
[38] M. Afzaal, A. Zia, J. Nouri, and U. Fors, "Informative feedback and explainable AI-based recommendations to support students' self-regulation," *Technol., Knowl. Learn.*, vol. 29, no. 1, pp. 331–354, Mar. 2024.
[39] C. Halkiopoulos and E. Gkintoni, "Leveraging AI in E-learning: Personalized learning and adaptive assessment through cognitive neuropsychology—A systematic analysis," *Electronics*, vol. 13, no. 18, p. 3762, Sep. 2024.
[40] A. Ellikkal and S. Rajamohan, "AI-enabled personalized learning: Empowering management students for improving engagement and academic performance," *Vilakshan-XIMB J. Manage.*, vol. 22, no. 1, pp. 28–44, Apr. 2025, doi: 10.1108/xjm-02-2024-0023.
[41] V. Chheang, S. Sharmin, R. Márquez-Hernández, M. Patel, D. Rajasekaran, G. Caulfield, B. Kiafar, J. Li, P. Kullu, and R. L. Barmaki, "Towards anatomy education with generative AI-based virtual assistants in immersive virtual reality environments," in *Proc. IEEE Int. Conf. Artif. Intell. eXtended Virtual Reality (AIxVR)*, Jan. 2024, pp. 21–30.
[42] F. Jafari and A. Keykha, "Identifying the opportunities and challenges of artificial intelligence in higher education: A qualitative study," *J. Appl. Res. Higher Educ.*, vol. 16, no. 4, pp. 1228–1245, Jul. 2024.
[43] H. Shi and V. Aryadoust, "A systematic review of AI-based automated written feedback research," *ReCALL*, vol. 36, no. 2, pp. 187–209, May 2024.
[44] L. I. Ruiz-Rojas, L. Salvador-Ullauri, and P. Acosta-Vargas, "Collaborative working and critical thinking: Adoption of generative artificial intelligence tools in higher education," *Sustainability*, vol. 16, no. 13, p. 5367, Jun. 2024.
[45] H. Balalle, "Exploring student engagement in technology-based education in relation to gamification, online/distance learning, and other factors: A systematic literature review," *Social Sci. Humanities Open*, vol. 9, Jan. 2024, Art. no. 100870.
[46] X. Wang, V. Hoo, M. Liu, J. Li, and Y. C. Wu, "Advancing legal recommendation system with enhanced Bayesian network machine learning," *Artif. Intell. Law*, Nov. 2024, doi: 10.1007/s10506-024-09424-8.
[47] H. Tang and Y. Bao, "Self-regulated learner profiles in MOOCs: A cluster analysis based on the item response theory," *Interact. Learn. Environ.*, vol. 32, no. 5, pp. 1877–1893, 2024.
[48] L. K. Held, L. Vermeylen, D. Dignath, W. Notebaert, R. M. Krebs, and S. Braem, "Reinforcement learning of adaptive control strategies," *Commun. Psychol.*, vol. 2, no. 1, p. 8, Jan. 2024.
[49] K. Sharma, A. Nguyen, and Y. Hong, "Self-regulation and shared regulation in collaborative learning in adaptive digital learning environments: A systematic review of empirical studies," *Brit. J. Educ. Technol.*, vol. 55, no. 4, pp. 1398–1436, Jul. 2024.
[50] H. Sun, L. Shen, Q. Zhong, L. Ding, S. Chen, J. Sun, J. Li, G. Sun, and D. Tao, "AdaSAM: Boosting sharpness-aware minimization with adaptive learning rate and momentum for training deep neural networks," *Neural Netw.*, vol. 169, pp. 506–519, Jan. 2024.
[51] F. Ma, C. Zhu, P. Lei, and P. Yuan, "Enhanced learning behaviors and ability knowledge tracing," *Appl. Sci.*, vol. 15, no. 2, p. 883, Jan. 2025.
[52] H. A. A. Ghanim and L. Kovács, "Ontology supported domain knowledge module for E-tutoring system," *Acta Cybernetica*, vol. 26, no. 3, pp. 455–474, Jul. 2024.
[53] A. Vujinović, N. Luburić, J. Slivka, and A. Kovačević, "Using ChatGPT to annotate a dataset: A case study in intelligent tutoring systems," *Mach. Learn. With Appl.*, vol. 16, Jun. 2024, Art. no. 100557.
[54] R. Parikh and H. Joshi, "Intelligent chat conversation and dialogue management for Gujarati dialogue," *Social Netw. Comput. Sci.*, vol. 6, no. 1, pp. 1–14, Dec. 2024.
[55] D. Smith-Mutegi, Y. Mamo, J. Kim, H. Crompton, and M. McConnell, "Perceptions of STEM education and artificial intelligence: A Twitter (X) sentiment analysis," *Int. J. STEM Educ.*, vol. 12, no. 1, pp. 1–18, Feb. 2025.
[56] N. Khediri, M. Ben Ammar, and M. Kherallah, "A real-time multimodal intelligent tutoring emotion recognition system (MITERS)," *Multimedia Tools Appl.*, vol. 83, no. 19, pp. 57759–57783, Dec. 2023.
[57] M. Roobini, S. P. David, S. Lokeshwaran, E. Vinothini, and D. Aishwarya, "Content filtering based navigation recommendation system using NLP," in *Proc. 9th Int. Conf. Sci. Technol. Eng. Math. (ICONSTEM)*, Apr. 2024, pp. 1–8.
[58] D. Gm, R. Goudar, A. A. Kulkarni, V. N. Rathod, and G. S. Hukkeri, "A digital recommendation system for personalized learning to enhance online education: A review," *IEEE Access*, vol. 12, pp. 34019–34041, 2024.
[59] M. Mouhiha, O. A. Oualhaj, and A. Mabrouk, "Combining collaborative filtering and content based filtering for recommendation systems," in *Proc. 11th Int. Conf. Wireless Netw. Mobile Commun. (WINCOM)*, Jul. 2024, pp. 1–6.
[60] C. Mao, Z. Wu, Y. Liu, and Z. Shi, "Matrix factorization recommendation algorithm based on attention interaction," *Symmetry*, vol. 16, no. 3, p. 267, Feb. 2024.
[61] M. Jbene, A. Chehri, R. Saadane, S. Tigani, and G. Jeon, "Intent detection for task-oriented conversational agents: A comparative study of recurrent neural networks and transformer models," *Expert Syst.*, vol. 42, no. 2, Feb. 2025, Art. no. e13712.
[62] K. Tsitseklis, G. Stavropoulou, and S. Papavassiliou, "Custom named entity recognition VS ChatGPT prompting: A paleontology experiment," in *Proc. Panhellenic Conf. Electron. Telecommun. (PACET)*, Mar. 2024, pp. 1–5.
[63] K. Fatima, P. Singh, H. Amipara, and G. Chaudhary, "Accuracy of artificial intelligence-based virtual assistants in responding to frequently asked questions related to orthognathic surgery," *J. Oral Maxillofacial Surg.*, vol. 82, no. 8, pp. 916–921, Aug. 2024.
[64] E. Rajabi, A. N. George, and K. Kumar, "The role of knowledge graphs in chatbots," *Electron. Library*, vol. 42, no. 3, pp. 483–497, Jun. 2024.
[65] M. Rashmi and M. Y. Chandra, "Transforming mental health support: The role of NLP in virtual assistants," in *Proc. 22nd AIMS Int. Conf. Manage. (AIMS)*, Jan. 2025, pp. 46–58.
[66] M. Ibrahim, "CUFE@ VarDial 2025 NorSID: Multilingual BERT for Norwegian dialect identification and intent detection," in *Proc. 12th Workshop on NLP Similar Languages, Varieties Dialects*, 2025, pp. 220–223.
[67] S. Gombert, A. Fink, T. Giorgashvili, I. Jivet, D. Di Mitri, J. Yau, A. Frey, and H. Drachsler, "From the automated assessment of student essay content to highly informative feedback: A case study," *Int. J. Artif. Intell. Educ.*, vol. 34, no. 4, pp. 1378–1416, Dec. 2024.
[68] R. Shadiev and Y. Feng, "Using automated corrective feedback tools in language learning: A review study," *Interact. Learn. Environ.*, vol. 32, no. 6, pp. 2538–2566, 2024.
[69] M. Liang, "Leveraging natural language processing for automated assessment and feedback production in virtual education settings," *J. Comput. Methods Sci. Eng.*, vol. 25, no. 3, pp. 2502–2515, May 2025, doi: 10.1177/14727978251314556.
[70] A. Patel and H. Joshi, "DebugProGrade: Improving automated assessment of coding assignments with a focus on debugging," *J. Informat. Web Eng.*, vol. 4, no. 1, pp. 184–199, Feb. 2025.
[71] M. K. S. Vadla, M. A. Suresh, and V. K. Viswanathan, "Enhancing product design through AI-driven sentiment analysis of Amazon reviews using BERT," *Algorithms*, vol. 17, no. 2, p. 59, Jan. 2024.
[72] A. Yakubov, Y. Nazarov, and A. A. Rodionov, "Advancing E-learning and M-learning environments incorporating AI and gamification to boost learner motivation," in *Proc. 4th Int. Conf. Technol. Enhanced Learn. Higher Educ. (TELE)*, Jun. 2024, pp. 29–31.
[73] O. Benzizoune, "Enhancing classroom management and student engagement: The role of ClassDojo and gamification in education," *J. English Lang. Teaching Appl. Linguistics*, vol. 6, no. 3, pp. 106–114, Sep. 2024.
[74] A. Manoharan and S. Nagulapally, "Adaptive gamification algorithms for personalized learning experiences in educational platforms," *Int. Res. J. Modernization Eng. Technol. Sci.*, vol. 6, no. 3, pp. 2582–5208, 2024.
[75] E. Pearlin and S. M. G. Gandhi, "Enhancing user behavior analysis in mobile language learning apps through gamification and AI integration: A transformer-based deep learning approach," in *Proc. Int. Conf. Data Sci. Netw. Secur. (ICDSNS)*, Jul. 2024, pp. 1–6.
[76] D. Bañeres, M. E. Rodríguez, A. Guerrero-Roldán, and A. Karadeniz, "An early warning system to detect at-risk students in online higher education," *Appl. Sci.*, vol. 10, no. 13, p. 4427, Jun. 2020.
[77] L. G. Chan and Q. Y. Ng, "Using learning analytics in higher education: Assessing students' learning experience in an actuarial science course," *STEM Educ.*, vol. 4, no. 2, pp. 151–164, 2024.

[78] I. Eegdeman, I. Cornelisz, C. van Klaveren, and M. Meeter, "Computer or teacher: Who predicts dropout best?" *Frontiers Educ.*, vol. 7, Nov. 2022, Art. no. 976922.

[79] K. C. Li, B. T. Wong, and H. T. Chan, "Prediction of at-risk students using learning analytics: A literature review," in *Technology in Education. Innovative Practices for the New Normal. ICTE 2023. Communications in Computer and Information Science*, vol. 1974, S. K. S. Cheung, F. L. Wang, N. Paoprasert, P. Charnsethikul, K. C. Li, and K. Phusavat, Eds., Singapore: Springer, 2023, pp. 119–128.

[80] A. T. Remolado and D. G. Brosas, "Implementing a support vector classifier for student risk assessment in Colegio de Getafe: A machine learning approach," in *Proc. IEEE Open Conf. Electr., Electron. Inf. Sci. (eStream)*, Apr. 2024, pp. 1–6.

[81] R. Umer, T. Susnjak, A. Mathrani, and L. Suriadi, "Current stance on predictive analytics in higher education: Opportunities, challenges and future directions," *Interact. Learn. Environ.*, vol. 31, no. 6, pp. 3503–3528, Aug. 2023.

[82] M. Adnan, A. Habib, J. Ashraf, S. Mussadiq, A. A. Raza, M. Abid, M. Bashir, and S. U. Khan, "Predicting at-risk students at different percentages of course length for early intervention using machine learning models," *IEEE Access*, vol. 9, pp. 7519–7539, 2021.

[83] R. Z. Pek, S. T. Özyer, T. Elhage, T. Özyer, and R. Alhajj, "The role of machine learning in identifying students at-risk and minimizing failure," *IEEE Access*, vol. 11, pp. 1224–1243, 2023.

[84] B. Albreiki, T. Habuza, Z. Shuqfa, M. A. Serhani, N. Zaki, and S. Harous, "Customized rule-based model to identify at-risk students and propose rational remedial actions," *Big Data Cognit. Comput.*, vol. 5, no. 4, p. 71, Nov. 2021.

[85] X. Chen and X. Xu, "Mining educational big data to develop an early alert dynamic model of academically at-risk students: A proof of concept," *Innov. Educ. Teaching Int.*, vol. 2261, pp. 1–13, Aug. 2024.

[86] O. H. T. Lu, A. Y. Q. Huang, and S. J. H. Yang, "Impact of teachers' grading policy on the identification of at-risk students in learning analytics," *Comput. Educ.*, vol. 163, Apr. 2021, Art. no. 104109.

[87] S. Pongpaichet, S. Jankapor, S. Janchai, and T. Tongsanit, "Early detection at-risk students using machine learning," in *Proc. Int. Conf. Inf. Commun. Technol. Converg. (ICTC)*, Oct. 2020, pp. 283–287.

[88] R. Al-Shabandar, A. J. Hussain, P. Liatsis, and R. Keight, "Detecting at-risk students with early interventions using machine learning techniques," *IEEE Access*, vol. 7, pp. 149464–149478, 2019.

[89] E. M. Queiroga, J. L. Lopes, K. Kappel, M. Aguiar, R. M. Araújo, R. Munoz, R. Villarroel, and C. Cechinel, "A learning analytics approach to identify students at risk of dropout: A case study with a technical distance education course," *Appl. Sci.*, vol. 10, no. 11, p. 3998, Jun. 2020.

[90] A. Rahmah, "Designing early warning system for course completion using learning management system," in *Proc. 6th Int. Conf. Informat. Comput. (ICIC)*, Nov. 2021, pp. 1–5.

[91] H. Huang, S. Yuan, T. He, and R. Hou, "Use of behavior dynamics to improve early detection of at-risk students in online courses," *Mobile Netw. Appl.*, vol. 27, no. 1, pp. 441–452, Feb. 2022.

[92] S. Verma, R. K. Yadav, and K. Kholiya, "A scalable machine learning-based ensemble approach to enhance the prediction accuracy for identifying students at-risk," *Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 8, pp. 185–192, 2022.

[93] R. Alam, N. Ahmad, S. Shahab, and M. Anjum, "Prediction of dropout students in massive open online courses using ensemble learning: A pilot study in post-COVID academic session," in *Mobile Computing and Sustainable Informatics*. Singapore: Springer, 2023, pp. 549–565.

[94] E. J. M. Lauría, E. Presutti, M. Kapogiannis, and A. Kamath, "Stacking classifiers for early detection of students at risk," in *Proc. 10th Int. Conf. Comput. Supported Educ.*, 2018, pp. 390–397.

[95] A. O. Alkhamisi and R. Mehmood, "An ensemble machine and deep learning model for risk prediction in aviation systems," in *Proc. 6th Conf. Data Sci. Mach. Learn. Appl. (CDMA)*, Mar. 2020, pp. 54–59.

[96] A. C. Mary. T and A. L. Rose. P. J, "Ensemble machine learning model for university students' risk prediction and assessment of cognitive learning outcomes," *Int. J. Inf. Educ. Technol.*, vol. 13, no. 6, pp. 948–958, 2023.

[97] J. Pecuchova and M. Drlik, "Predicting students at risk of early dropping out from course using ensemble classification methods," *Proc. Comput. Sci.*, vol. 225, pp. 3223–3232, Jan. 2023.

[98] H. Karalar, C. Kapucu, and H. Gürüler, "Predicting students at risk of academic failure using ensemble model during pandemic in a distance learning system," *Int. J. Educ. Technol. Higher Educ.*, vol. 18, no. 1, p. 63, Dec. 2021.

[99] E. Mulyani, I. Hidayah, and S. Fauziati, "Dropout prediction optimization through SMOTE and ensemble learning," in *Proc. Int. Seminar Res. Inf. Technol. Intell. Syst. (ISRITI)*, Dec. 2019, pp. 516–521.

[100] E. Evangelista, "A hybrid machine learning framework for predicting students' performance in virtual learning environment," *Int. J. Emerg. Technol. Learn. (iJET)*, vol. 16, no. 24, pp. 255–272, Dec. 2021.

[101] M. Wu, G. Subramaniam, D. Zhu, C. Li, H. Ding, and Y. Zhang, "Using machine learning-based algorithms to predict academic performance—A systematic literature review," in *Proc. 4th Int. Conf. Innov. Practices Technol. Manage. (ICIPTM)*, Feb. 2024, pp. 1–8.

[102] N. Mduma, "Data balancing techniques for predicting student dropout using machine learning," *Data*, vol. 8, no. 3, p. 49, Feb. 2023.

[103] K. Janani, S. S. Mohanrasu, A. Kashkynbayev, and R. Rakkiyappan, "Ensemble feature selection via CoCoSo method extended to interval-valued intuitionistic fuzzy environment," *Math. Comput. Simul.*, vol. 229, pp. 50–77, Mar. 2025.

[104] O. Talbi, N. Chelik, A. Ouared, and N. O. Ali, "Additive explanations for student fails detected from course prerequisites," in *Proc. Int. Conf. Women Data Sci. Taif Univ. (WiDSTaif)*, Mar. 2021, pp. 1–7.

[105] R. Rozić, H. Ljubić, T. Grujić, and A. K. Skelin, "Detection of at-risk students in virtual learning environment," in *Proc. Int. Conf. Softw., Telecommun. Comput. Netw. (SoftCOM)*, Sep. 2023, pp. 1–6.

[106] E. Nimy, M. Mosia, and C. Chibaya, "Identifying at-risk students for early intervention—A probabilistic machine learning approach," *Appl. Sci.*, vol. 13, no. 6, p. 3869, Mar. 2023.

[107] A. Algarni, M. Abdullah, H. Allahiq, and A. Qahmash, "Predicting at-risk students in higher education," *Int. J. Intell. Syst. Appl. Eng.*, vol. 11, no. 3, pp. 1229–1239, 2023.

[108] T. Haig, K. Falkner, and N. Falkner, "Visualisation of learning management system usage for detecting student behaviour patterns," in *Proc. 15th Australas. Comput. Educ. Conf.*, Jan. 2013, pp. 107–115.

[109] F. Marbouti, H. A. Diefes-Dux, and K. Madhavan, "Models for early prediction of at-risk students in a course using standards-based grading," *Comput. Educ.*, vol. 103, pp. 1–15, Dec. 2016.

[110] F. Kouser, A. F. Meghji, and N. A. Mahoto, "Early detection of failure risks from students' data," in *Proc. Int. Conf. Emerg. Trends Smart Technol. (ICETST)*, Mar. 2020, pp. 1–6.

[111] O. H. Embarak and S. Hawarna, "Automated AI-driven system for early detection of at-risk students," *Proc. Comput. Sci.*, vol. 231, pp. 151–160, Jan. 2024.

[112] R. Boudjehem and Y. Lafifi, "An early warning system to predict dropouts inside e-learning environments," *Educ. Inf. Technol.*, vol. 29, no. 13, pp. 16365–16385, Sep. 2024.

[113] S. Wang, F. Wang, Z. Zhu, J. Wang, T. Tran, and Z. Du, "Artificial intelligence in education: A systematic literature review," *Expert Syst. Appl.*, vol. 252, May 2024, Art. no. 124167.

[114] M. Giannakos, R. Azevedo, P. Brusilovsky, M. Cukurova, Y. Dimitriadis, D. Hernandez-Leo, S. Järvelä, M. Mavrikis, and B. Rienties, "The promise and challenges of generative AI in education," *Behav. Inf. Technol.*, vol. 44, no. 11, pp. 2518–2544, Jul. 2025, doi: 10.1080/0144929x.2024.2394886.

[115] N. Anderson, A. McGowan, L. Galway, P. Hanna, M. Collins, and D. Cutting, "Implementing generative AI and large language models in education," in *Proc. 7th Int. Symp. Innov. Approaches Smart Technol. (ISAS)*, Nov. 2023, pp. 1–6.

[116] R. Chughtai, F. Azam, M. W. Anwar, W. H. But, and M. U. Farooq, "A lecture centric automated distractor generation for post-graduate software engineering courses," in *Proc. Int. Conf. Frontiers Inf. Technol. (FIT)*, Dec. 2022, pp. 100–105.

[117] R. M. Elshiny and A. Hamdy, "Automatic question generation using natural language processing and transformers," in *Proc. Int. Conf. Comput. Appl. (ICCA)*, Nov. 2023, pp. 1–6.

[118] B. Hu, L. Zheng, J. Zhu, L. Ding, Y. Wang, and X. Gu, "Teaching plan generation and evaluation with GPT-4: Unleashing the potential of LLM in instructional design," *IEEE Trans. Learn. Technol.*, vol. 17, pp. 1445–1459, 2024.

[119] F. L. Kock, G. A. Martins, and A. L. Dias, "Utilization of an automated guided vehicle for physics and mathematics teaching in professional and technological education," *IEEE Revista Iberoamericana de Tecnologias del Aprendizaje*, vol. 18, no. 4, pp. 344–353, Nov. 2023.

[120] L. Leppänen, A. Hellas, and J. Leinonen, "Piloting natural language generation for personalized progress feedback," in *Proc. IEEE Frontiers Educ. Conf. (FIE)*, Oct. 2022, pp. 1–8.

[121] M. Liu, Y. Li, W. Xu, and L. Liu, "Automated essay feedback generation and its impact on revision," *IEEE Trans. Learn. Technol.*, vol. 10, no. 4, pp. 502–513, Oct. 2017.

[122] V. L. Narasimhan, V. Bhargavi, and R. Prakash, "Automatic generation of context sensitive dictionary using computational linguistics approach," in *Proc. 2nd Int. Conf. Appl. Theor. Comput. Commun. Technol. (iCATccT)*, Jul. 2016, pp. 509–514.

[123] A. B. Reddy and A. Govardhan, "Resource allocation for the choice based education system using semantic web," in *Proc. IEEE Int. Conf. Comput. Intell. Comput. Res. (ICCIC)*, Dec. 2015, pp. 1–4.

[124] X. Xu, C. Sun, and X. Yu, "A personalized intelligent tutoring system for mathematics homework," in *Proc. Int. Conf. Intell. Educ. Intell. Res. (IEIR)*, Nov. 2023, pp. 1–7.

[125] M. Balamurugan, P. Vasanth, S. Grihith, and G. Youkesh, "Sniffing detection using machine learning," in *Proc. Intell. Comput. Control Eng. Bus. Syst. (ICCEBS)*, Dec. 2023, pp. 1–5.

[126] O. Mendels, H. Stern, and S. Berman, "User identification for home entertainment based on free-air hand motion signatures," *IEEE Trans. Syst. Man, Cybern. Syst.*, vol. 44, no. 11, pp. 1461–1473, Nov. 2014.

[127] S. Sarkar and M. Huber, "Personalized learning path generation in E-learning systems using reinforcement learning and generative adversarial networks," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Oct. 2021, pp. 92–99.

[128] S. Rathi, V. Pophale, P. Kutwal, S. Mishra, and A. Nadkarni, "Question and assessment generator: Deep learning approach for customizable and intelligent assessment creation," in *Proc. IEEE Int. Conf. Women Innov., Technol. Entrepreneurship (ICWITE)*, Feb. 2024, pp. 618–624.

[129] B. J. Chelliah, M. Hariharan, A. Prakash, B. Manoharan, and A. Senthilselvi, "Harnessing T5 large language model for enhanced PDF text comprehension and Q&A generation," in *Proc. Int. Conf. Comput. Data Sci. (ICCDS)*, Apr. 2024, pp. 1–6.

[130] S. Rathi, P. Wawage, and A. Kulkarni, "Automatic question generation from textual data using NLP techniques," in *Proc. Int. Conf. Emerg. Smart Comput. Informat. (ESCI)*, Mar. 2023, pp. 1–7.

[131] N.-I. Galanis and G. A. Papakostas, "An update on cooking recipe generation with machine learning and natural language processing," in *Proc. IEEE World Conf. Appl. Intell. Comput. (AIC)*, Jun. 2022, pp. 739–744.

[132] D. R. Ch and S. K. Saha, "Generation of multiple-choice questions from textbook contents of school-level subjects," *IEEE Trans. Learn. Technol.*, vol. 16, no. 1, pp. 40–52, Feb. 2023.

[133] J. A. Ali, A. H. Muse, M. K. Abdi, T. A. Ali, Y. H. Muse, and M. A. Cumar, "Machine learning-driven analysis of academic performance determinants: Geographic, socio-demographic, and subject-specific influences in Somaliland's 2022–2023 national primary examinations," *Int. J. Educ. Res. Open*, vol. 8, Jun. 2025, Art. no. 100426.

[134] A. Gašpar, A. Grubišić, and I. Šarić-Grgić, "Evaluation of a rule-based approach to automatic factual question generation using syntactic and semantic analysis," *Lang. Resour. Eval.*, vol. 57, no. 4, pp. 1431–1461, Dec. 2023.

[135] R. Chakraborty, M. Deka, and S. K. Sarma, "Syntactic category based assamese question pattern extraction using N-grams," *Proc. Comput. Sci.*, vol. 235, pp. 214–230, Jan. 2024.

[136] K. Haider, "Natural language processing in AI-powered systems: Techniques and future prospects," *Artif. Intell. Multidisciplinary J. Syst. Appl.*, vol. 1, no. 1, pp. 40–53, 2024.

[137] P. Kumar, S. Manikandan, and R. Kishore, "AI-driven text generation: A novel GPT-based approach for automated content creation," in *Proc. 2nd Int. Conf. Netw. Commun. (ICNWC)*, Apr. 2024, pp. 1–6.

[138] D. Zhao, "The impact of AI-enhanced natural language processing tools on writing proficiency: An analysis of language precision, content summarization, and creative writing facilitation," *Educ. Inf. Technol.*, vol. 30, no. 6, pp. 8055–8086, Apr. 2025, doi: 10.1007/s10639-024-13145-5.

[139] M. M. Aziz, A. A. Bakar, and M. R. Yaakub, "CoreNLP dependency parsing and pattern identification for enhanced opinion mining in aspect-based sentiment analysis," *J. King Saud Univ. Comput. Inf. Sci.*, vol. 36, no. 4, Apr. 2024, Art. no. 102035.

[140] M. M. Danyal, M. Haseeb, B. Khan, S. Ullah, and S. S. Khan, "Opinion mining on movie reviews based on deep learning models," *J. Artif. Intell.*, vol. 6, no. 1, pp. 23–42, 2024.

[141] A. K. A. Alhadrawi, S. Ezzerouali, A. R. Jawad, S. H. Albarashdi, B. K. Al-Hadrawi, and K. K. Al-Hadrawi, "Unveiling extremism: Leveraging digital data mining strategies," *J. Ecohumanism*, vol. 3, no. 7, pp. 492–502, Oct. 2024.

[142] Y. I. Alzoubi and A. Mishra, "ChatGPT technology contribution in business innovation, policy and management," *J. Sci. Technol. Policy Manage.*, Feb. 2025, doi: 10.1108/jstpm-10-2023-0173.

[143] G. Hardaker and L. E. Glenn, "Artificial intelligence for personalized learning: A systematic literature review," *Int. J. Inf. Learn. Technol.*, vol. 42, no. 1, pp. 1–14, Jan. 2025.

[144] J. Cheng, "The impact of chatbots on education," in *Proc. Congr. Comput. Sci., Comput. Eng., Appl. Comput. (CSCE)*, Jul. 2023, pp. 844–849.

[145] D. E. Gonda and B. Chu, "Chatbot as a learning resource? Creating conversational bots as a supplement for teaching assistant training course," in *Proc. IEEE Int. Conf. Eng., Technol. Educ. (TALE)*, Dec. 2019, pp. 1–5.

[146] Y. Yuan, H. Xu, and L. Si, "ChatGPT as an artificial intelligence (AI) tool for assisting undergraduate talent cultivation program in major of microelectronic science and engineering," in *Proc. Int. Conf. Microw. Millim. Wave Technol. (ICMMT)*, May 2024, pp. 1–3.

[147] H.-W. Huang and T.-S. Chang, "Students' motivation and perceptions in an AI chatbot-based climate change classroom," in *Proc. 4th Int. Symp. AI (ISAI)*, Apr. 2024, pp. 55–60.

[148] K. Mahawar and P. Rattan, "Empowering education: Harnessing ensemble machine learning approach and ACO-DT classifier for early student academic performance prediction," *Educ. Inf. Technol.*, vol. 30, no. 4, pp. 4639–4667, Mar. 2025.

[149] A. S. Shimichev and M. B. Rotanova, "Chatbot technology as an artificial intelligence tool in foreign language education," in *Proc. Int. Conf. Quality Manage., Transp. Inf. Secur., Inf. Technol. (IT&QM&IS)*, Sep. 2023, pp. 97–100.

[150] D. Kovacevic, "Use of ChatGPT in ESP teaching process," in *Proc. 22nd Int. Symp. INFOTEH-JAHORINA (INFOTEH)*, Mar. 2023, pp. 1–5.

[151] A. M. Mohamed, "Exploring the potential of an AI-based chatbot (ChatGPT) in enhancing English as a foreign language (EFL) teaching: Perceptions of EFL faculty members," *Educ. Inf. Technol.*, vol. 29, no. 3, pp. 3195–3217, Feb. 2024.

[152] D. R. Korda, E. Dapaah, and E. Akolgo, "The role of AI chatbots in education: A review," *Acad. J. Sci. Eng.*, vol. 18, no. 1, pp. 79–87, 2024.

[153] B. D. Neelima, P. R. Prasad, A. Swapna, and S. Kulkarni, "Generative AI—The revolutionizing virtual agents in health care," *Int. Res. J. Adv. Eng. Hub (IRJAEH)*, vol. 2, no. 2, pp. 231–235, Feb. 2024.

[154] M. Soliman and C. Guetl, "Implementing intelligent pedagogical agents in virtual worlds: Tutoring natural science experiments in OpenWonderland," in *Proc. IEEE Global Eng. Educ. Conf. (EDUCON)*, Mar. 2013, pp. 782–789.

[155] R. A. Aguilar, A. D. Antonio, and R. Imbert, "Pedagogical virtual agents to support training of human groups," in *Proc. Electron., Robot. Automot. Mech. Conf. (CERMA)*, Sep. 2006, pp. 149–154.

[156] K. Pahi, S. Hawlader, E. Hicks, A. Zaman, and V. Phan, "Enhancing active learning through collaboration between human teachers and generative AI," *Comput. Educ. Open*, vol. 6, Jun. 2024, Art. no. 100183.

[157] A. D. Samala, T. Govender, D. Tsoy, L. Bojic, A. G. Samala, M. P. Samala, F. Prasetya, D. T. P. Yanto, R. Zainul, and A. Fortuna, "3D visualizations in learning: An evaluation of an AR+core application for computer hardware education using the hedonic motivation system adoption model," *TEM J.*, vol. 13, no. 1, pp. 466–475, Feb. 2024.

[158] F. Grivokostopoulou, M. Paraskevas, I. Perikos, S. Nikolic, K. Kovas, and I. Hatzilygeroudis, "Examining the impact of pedagogical agents on students learning experience in virtual worlds," in *Proc. IEEE Int. Conf. Teaching, Assessment, Learn. Eng. (TALE)*, Dec. 2018, pp. 602–607.

[159] Z. Qi, Y. Yuan, and Z. Lin, "Research of the network virtual teaching model based on agent framework," in *Proc. 2nd Int. Conf. Educ. Technol. Comput.*, Jun. 2010, pp. V1–460.

[160] T. Prasongpongchai, P. Pataranutaporn, A. Lapapirojn, C. Kanapornchai, J. Leong, P. Ouppaphan, K. Winson, M. Lertsutthiwong, and P. Maes, "Effects of proactive interaction and instructor choice in AI-generated virtual instructors for financial education," in *Proc. IEEE Frontiers Educ. Conf. (FIE)*, Oct. 2024, pp. 1–9.

[161] R. Morris, T. Perry, and L. Wardle, "Formative assessment and feedback for learning in higher education: A systematic review," *Rev. Educ.*, vol. 9, no. 3, p. 3292, Oct. 2021.
[162] T. Shaik, X. Tao, Y. Li, C. Dann, J. McDonald, P. Redmond, and L. Galligan, "A review of the trends and challenges in adopting natural language processing methods for education feedback analysis," *IEEE Access*, vol. 10, pp. 56720–56739, 2022.
[163] Y. Liu, D. Lu, D. Xu, Y. Zheng, T. Zhou, N. Li, and R. Feng, "Exploring intelligent feedback systems for student engagement in digitized physical education learning through machine learning," in *Proc. Int. Conf. Artif. Intell. Future Educ.*, Nov. 2024, pp. 114–118.
[164] H. Feng, "Design of English learning assistance system for college students majoring in art and physical education based on clustering feature tree," in *Proc. IEEE 7th Eurasian Conf. Educ. Innov. (ECEI)*, Jan. 2024, pp. 144–147.
[165] N. Kerimbayev, K. Adamova, V. Jotsov, R. Shadiev, Z. Umirzakova, and A. Nurymova, "Organization of feedback in the intelligent learning systems," in *Proc. 12th Int. Conf. Intell. Syst. (IS)*, Aug. 2024, pp. 1–7.
[166] D. Jaison, M. B. Weaver, S. Ray, H. E. Merzdorf, K. A. Douglas, V. Krishnamurthy, J. Linsey, K. Watson, and T. Hammond, "WIP teaching engineers to sketch: Impacts of feedback from an intelligent tutoring software on Engineers' sketching skill development," in *Proc. IEEE Frontiers Educ. Conf. (FIE)*, Oct. 2022, pp. 1–5.
[167] D. Demszky, J. Liu, H. C. Hill, S. Sanghi, and A. Chung, "Automated feedback improves teachers' questioning quality in brick-and-mortar classrooms: Opportunities for further enhancement," *Comput. Educ.*, vol. 227, Apr. 2025, Art. no. 105183.
[168] R. Hussein, Z. Zhang, P. Amarante, N. Hancock, P. Orduna, and L. Rodriguez-Gil, "Integrating personalized AI-assisted instruction into remote laboratories: Enhancing engineering education with OpenAI's GPT models," in *Proc. IEEE Frontiers Educ. Conf. (FIE)*, USA, Oct. 2024, pp. 1–7.
[169] S. Senanayake, K. Karunanayaka, and K. V. J. P. Ekanayake, "Review on AI assistant systems for programming language learning in learning environments," in *Proc. 8th SLAAI Int. Conf. Artif. Intell. (SLAAI-ICAI)*, Dec. 2024, pp. 1–6.
[170] M. Cont, A. Ciupe, B. Orza, I. Cohut, and G. Nitu, "Career counseling chatbot using Microsoft bot Frameworks1," in *Proc. IEEE Global Eng. Educ. Conf. (EDUCON)*, Mar. 2022, pp. 1387–1392.
[171] S. Arora, S. Tiwari, N. Negi, S. Pargaien, and A. Misra, "The role of artificial intelligence in mentoring students," in *Proc. 1st Int. Conf. Circuits, Power Intell. Syst. (CCPIS)*, Sep. 2023, pp. 1–6.
[172] M. Ghuge, T. Kamble, A. Mandrawliya, A. Kumari, and V. Raikwar, "Envisioning tomorrow: AI powered career counseling," in *Proc. 3rd Int. Conf. Innov. Mech. Ind. Appl. (ICIMIA)*, Dec. 2023, pp. 377–383.
[173] M. Messer, N. C. C. Brown, M. Kölling, and M. Shi, "Automated grading and feedback tools for programming education: A systematic review," *ACM Trans. Comput. Educ.*, vol. 24, no. 1, pp. 1–43, Mar. 2024.
[174] C. Kooli and N. Yusuf, "Transforming educational assessment: Insights into the use of ChatGPT and large language models in grading," *Int. J. Hum.–Comput. Interact.*, vol. 41, no. 5, pp. 3388–3399, Apr. 2024.
[175] A. Dimari, N. Tyagi, M. Davanageri, R. Kukreti, R. Yadav, and H. Dimari, "AI-based automated grading systems for open book examination system: Implications for assessment in higher education," in *Proc. Int. Conf. Knowl. Eng. Commun. Syst. (ICKECS)*, Apr. 2024, pp. 1–7.
[176] J. Lun, J. Zhu, Y. Tang, and M. Yang, "Multiple data augmentation strategies for improving performance on automatic short answer scoring," in *Proc. AAAI Conf. Artif. Intell.*, Apr. 2020, vol. 34, no. 9, pp. 13389–13396.
[177] P. Lagakis and S. Demetriadis, "Automated essay scoring: A review of the field," in *Proc. Int. Conf. Comput., Inf. Telecommun. Syst. (CITS)*, Nov. 2021, pp. 1–6.
[178] S. Ludwig, C. Mayer, C. Hansen, K. Eilers, and S. Brandt, "Automated essay scoring using transformer models," *Psych*, vol. 3, no. 4, pp. 897–915, Dec. 2021.
[179] M. A. Rahaman and H. Mahmud, "Automated evaluation of handwritten answer script using deep learning approach," *Trans. Mach. Learn. Artif. Intell.*, vol. 10, no. 4, pp. 1–16, Aug. 2022.
[180] R. Johnsi and G. B. Kumar, "Digital essay assessment using machine learning algorithms," in *Proc. 9th Int. Conf. Sci. Technol. Eng. Math. (ICONSTEM)*, Apr. 2024, pp. 1–13.
[181] A. Mizumoto and M. Eguchi, "Exploring the potential of using an AI language model for automated essay scoring," *Res. Methods Appl. Linguistics*, vol. 2, no. 2, Aug. 2023, Art. no. 100050.
[182] C. Impey, M. Wenger, N. Garuda, S. Golchin, and S. Stamer, "Using large language models for automated grading of student writing about science," *Int. J. Artif. Intell. Educ.*, Jan. 2025, doi: 10.1007/s40593-024-00453-7.
[183] S. M. Mostofa, M. Tabassum, and S. M. Z. Ahmed, "Researchers' awareness about plagiarism and impact of plagiarism detection tools–does awareness effect the actions towards preventing plagiarism?" *Digit. Library Perspect.*, vol. 37, no. 3, pp. 257–274, Aug. 2021.
[184] N. Awale, M. Pandey, A. Dulal, and B. Timsina, "Plagiarism detection in programming assignments using machine learning," *J. Artif. Intell. Capsule Netw.*, vol. 2, no. 3, pp. 177–184, Jul. 2020.
[185] M. A. El-Rashidy, R. G. Mohamed, N. A. El-Fishawy, and M. A. Shouman, "An effective text plagiarism detection system based on feature selection and SVM techniques," *Multimedia Tools Appl.*, vol. 83, no. 1, pp. 2609–2646, Jan. 2024.
[186] B. Erdem and M. Karabatak, "Cheating detection in online exams using deep learning and machine learning," *Appl. Sci.*, vol. 15, no. 1, pp. 400–420, Jan. 2025.
[187] Copyscape. *Plagiarism Checker to Detect Duplicate Content*. Accessed: Mar. 16, 2025. [Online]. Available: https://www.copyscape.com/
[188] GPTZero. *Detecting AI-Generated Text*. Accessed: Mar. 16, 2025. [Online]. Available: https://gptzero.me
[189] Grammarly. *Plagiarism Checker Software*. Accessed: Mar. 16, 2025. [Online]. Available: https://www.grammarly.com/plagiarism-checker
[190] Ouriginal. *Originality and Plagiarism Prevention*. Accessed: Mar. 16, 2025. [Online]. Available: https://ouriginal.com
[191] PaperRater. *PaperRater: Plagiarism and Grammar Checker*. Accessed: Mar. 16, 2025. [Online]. Available: https://www.paperrater.com
[192] Plagscan. *Plagiarism Detection Software*. Accessed: Mar. 16, 2025. [Online]. Available: https://www.plagscan.com/
[193] Scribbr. *Plagiarism Checker*. Accessed: Mar. 16, 2025. [Online]. Available: https://www.scribbr.com/plagiarism-checker/
[194] Turnitin. *Plagiarism Detection Software*. Accessed: Mar. 16, 2025. [Online]. Available: https://www.turnitin.com/
[195] R. Agrawal, H. Mishra, I. Kandasamy, S. R. Terni, and W. B. Vasantha, "Revolutionizing subjective assessments: A three-pronged comprehensive approach with NLP and deep learning," *Expert Syst. Appl.*, vol. 239, Apr. 2024, Art. no. 122470.
[196] S. N. El-Tallawy, J. V. Pergolizzi, I. Vasiliu-Feltes, R. S. Ahmed, J. K. LeQuang, H. N. El-Tallawy, G. Varrassi, and M. S. Nagiub, "Incorporation of 'Artificial Intelligence' for objective pain assessment: A comprehensive review," *Pain Therapy*, vol. 13, no. 3, pp. 293–317, Jun. 2024.
[197] F. Hesse and G. Helm, "Writing with AI in and beyond teacher education: Exploring subjective training needs of student teachers across five subjects," *J. Digit. Learn. Teacher Educ.*, vol. 41, no. 1, pp. 21–36, Jan. 2025.
[198] M. W. E. Boal, D. Anastasiou, F. Tesfai, W. Ghamrawi, E. Mazomenos, N. Curtis, J. W. Collins, A. Sridhar, J. Kelly, D. Stoyanov, and N. K. Francis, "Evaluation of objective tools and artificial intelligence in robotic surgery technical skills assessment: A systematic review," *Brit. J. Surgery*, vol. 111, no. 1, Jan. 2024, Art. no. znad331.
[199] M. M. Amin, R. Mao, E. Cambria, and B. W. Schuller, "A wide evaluation of ChatGPT on affective computing tasks," *IEEE Trans. Affect. Comput.*, vol. 15, no. 4, pp. 2204–2212, Oct. 2024.
[200] M. Bevilacqua, K. Oketch, R. Qin, W. Stamey, X. Zhang, Y. Gan, K. Yang, and A. Abbasi, "When automated assessment meets automated content generation: Examining text quality in the era of GPTs," *ACM Trans. Inf. Syst.*, vol. 43, no. 2, pp. 1–36, Mar. 2025.
[201] S. Maity and A. Deroy, "The future of learning in the age of generative AI: Automated question generation and assessment with large language models," 2024, *arXiv:2410.09576*.
[202] M. U. Tariq, "Generative AI in curriculum development in higher education," in *Impacts Generative AI Creativity Higher Education*. Pennsylvania, PA, USA: IGI Global, 2024, pp. 227–258.
[203] K. Zeinalipour, Y. G. Keptiğ, M. Maggini, and M. Gori, "Automating Turkish educational quiz generation using large language models," in *Intelligent Systems and Pattern Recognition. ISPR 2024. Communications in Computer and Information Science*, vol. 2303. Cham, Switzerland: Springer, 2024, pp. 246–260.

[204] F. Pedro, M. Subosa, A. Rivas, and P. Valverde, *Artificial Intelligence in Education: Challenges and Opportunities for Sustainable Development*. Paris, France: United Nations Educational, Scientific and Cultural Organization, 2019.

[205] S. R. Goldman, J. Taylor, A. Carreon, and S. J. Smith, "Using AI to support special education teacher workload," *J. Special Educ. Technol.*, vol. 39, no. 3, pp. 434–447, Sep. 2024.

[206] S. Atalla, M. Daradkeh, A. Gawanmeh, H. Khalil, W. Mansoor, S. Miniaoui, and Y. Himeur, "An intelligent recommendation system for automating academic advising based on curriculum analysis and performance modeling," *Mathematics*, vol. 11, no. 5, p. 1098, Feb. 2023.

[207] M. A. Kuhail, H. A. Katheeri, J. Negreiros, A. Seffah, and O. Alfandi, "Engaging students with a chatbot-based academic advising system," *Int. J. Human-Comput. Interact.*, vol. 39, no. 10, pp. 2115–2141, Jun. 2022.

[208] V. G. Calatayud, M. P. P. Espinosa, and R. Roig-Vila, "Artificial intelligence for student assessment: A systematic review," *Appl. Sci.*, vol. 11, no. 12, p. 5467, Jun. 2021.

[209] A. K. Bhowmick, A. Jagmohan, A. Vempaty, P. Dey, L. A. Hall, J. Hartman, R. Kokku, and H. Maheshwari, "Automating question generation from educational text," in *Artificial Intelligence XL. SGAI 2023* (Lecture Notes in Computer Science), vol. 14381, M. Bramer and F. Stahl, Eds., Cham, Switzerland: Springer, 2023, pp. 437–450.

[210] V. S. Kumar and D. Boulanger, "Automated essay scoring and the deep learning black box: How are rubric scores determined?" *Int. J. Artif. Intell. Educ.*, vol. 31, no. 3, pp. 538–584, Sep. 2021.

[211] J. Kim, "Leading teachers' perspective on teacher-AI collaboration in education," *Educ. Inf. Technol.*, vol. 29, no. 7, pp. 8693–8724, May 2024.

[212] T.-Y. Tai and H. H.-J. Chen, "Improving elementary EFL speaking skills with generative AI chatbots: Exploring individual and paired interactions," *Comput. Educ.*, vol. 220, Oct. 2024, Art. no. 105112.

[213] V. Maanu, F. O. Boateng, and E. Larbi, "AI-assisted instructions in collaborative learning in mathematics education: A qualitative approach," *Amer. J. STEM Educ.*, vol. 7, pp. 11–36, Mar. 2025.

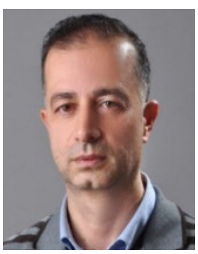
[214] S. J. Niu, J. Luo, H. Niemi, X. Li, and Y. Lu, "Teachers' and students' views of using an AI-aided educational platform for supporting teaching and learning at Chinese schools," *Educ. Sci.*, vol. 12, no. 12, p. 858, Nov. 2022.

[215] A. Alam and A. Mohanty, "Educational technology: Exploring the convergence of technology and pedagogy through mobility, interactivity, AI, and learning tools," *Cogent Eng.*, vol. 10, no. 2, Dec. 2023, Art. no. 2283282.

[216] V. Kuleto, M. Ilić, M. Dumangiu, M. Ranković, O. M. D. Martins, D. Păun, and L. Mihoreanu, "Exploring opportunities and challenges of artificial intelligence and machine learning in higher education institutions," *Sustainability*, vol. 13, no. 18, p. 10424, Sep. 2021.

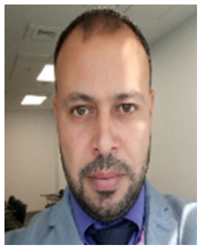
[217] R. AlAli and Y. Wardat, "Opportunities and challenges of integrating generative artificial intelligence in education," *Int. J. Religion*, vol. 5, no. 7, pp. 784–793, May 2024.

[218] R. Michel-Villarreal, E. L. Vilalta-Perdomo, D. E. Salinas-Navarro, R. Thierry-Aguilera, and F. S. Gerardou, "Challenges and opportunities of generative AI for higher education as explained by ChatGPT," *Educ. Sci.*, vol. 13, no. 9, p. 856, Aug. 2023.



ERSIN ELBASI received the M.Sc. degree in computer and information science from Syracuse University, Syracuse, NY, USA, and the M.Phil. and Ph.D. degrees in computer science from the Graduate Center, City University of New York. He is currently a Professor with the College of Engineering and Technology, American University of the Middle East, Kuwait. His research interests include multimedia security, machine learning, event mining in video sequences, and medical image processing.

MUHAMMAD NADEEM (Senior Member, IEEE) received the B.Sc. degree from the University of Engineering and Technology, Pakistan, in 1998, the M.Sc. degree from the KTH Royal Institute of Technology, Sweden, in 2004, and the Ph.D. degree from the University of Auckland, New Zealand, in 2013. With a focus on machine learning, embedded systems, the Internet of Things (IoT), and engineering education, he brings extensive research and teaching expertise. With over 20 years of experience, he has contributed to institutions, such as the University of Auckland, COMSATS University, and American University of the Middle East, Kuwait. He is currently an Associate Professor with the College of Engineering and Technology, American University of the Middle East.



YEHIA IBRAHIM ALZOUBI (Member, IEEE) received the M.Sc. degree in IT from Central Queensland University, Sydney, and the Ph.D. degree in information systems from the University of Technology, Sydney. He is currently an Associate Professor with American University of the Middle East. He has several published works in scholarly peer-reviewed international scientific journals and conferences, such as *Journal of Cleaner Production*, *Artificial Intelligence Review*, and IEEE TRANSACTIONS ON PROFESSIONAL COMMUNICATION. His research interests include agile development, cybersecurity, big data analysis, cybersecurity, machine learning, and big data analysis.

AHMET E. TOPCU (Member, IEEE) received the B.Sc. degree from the Department of Electrical and Electronics Engineering, Middle East Technical University, Ankara, Türkiye, in 1997, the M.Sc. degree in computer engineering from Syracuse University, Syracuse, NY, USA, in 2001, and the Ph.D. degree in computer science from Indiana University, Bloomington, IN, USA, in 2010. He is currently an Associate Professor with the College of Engineering and Technology, American University of the Middle East, Kuwait. His current research interests include distributed systems, machine learning, cloud computing, big data, the IoT, and blockchain.

GREESHMA VARGHESE received the M.Tech. degree in computer science and engineering from Karunya University, India. She is currently a Lab Instructor with the College of Engineering and Technology, American University of the Middle East, Kuwait. Her research interests include artificial intelligence, machine learning, and the IoT.