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SURVEY

A Digital Recommendation System for Personalized Learning to Enhance Online Education: A Review

DHANANJAYA. G. M.[1], **R. H. GOUDAR**[1], **ANJANABHARGAVI A. KULKARNI**[1], **VIJAYALAXMI N. RATHOD**[1], **AND GEETABAI S. HUKKERI**[2]

[1]Department of Computer Science and Engineering, Visvesvaraya Technological University, Belagavi, Karnataka 590018, India
[2]Department of Computer Science and Engineering, Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education, Manipal, Karnataka 576104, India

Corresponding author: Geetabai S. Hukkeri (geetabai.hukkeri@manipal.edu)

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ABSTRACT This review delves into using e-learning technology and personalized recommendation systems in education. It examines 60 articles from prominent databases and identifies the different methods used in recommendation systems, such as collaborative and content-based approaches with a recent shift towards machine learning. However, the current personalized recommendation system faces challenges such as a lack of understanding of the content, student discontinuity, language barriers, confusion in selecting study materials, and inadequate infrastructure and funding. The review proposes using new digital technologies to address these issues, including Fluxy AI, Twin technology, AI-powered virtual proctoring, and Alter Ego. These technologies can create a dynamic and interactive learning environment, providing tailored learning experiences for students and insights for educators to provide targeted support and guidance. The integration of these technologies can improve individualized learning, increase understanding capacity and enhance the learning experience for students with speech disorders.

INDEX TERMS Artificial intelligence, digital technologies, e-learning, online education, personalized recommendation system.

I. INTRODUCTION

Historically, the Education system highlights the rich tradition of learning and knowledge in the Universe. However, The "Gurukula" system [1] in ancient days was famous for its all-time access to teachers and abundant knowledge resources with students, living on the premises to pursue their education. Nalanda University, Takshashila was the maiden university in India, which was started in the 5th Century BC. At this time the new teaching (classroom) method was introduced [2]. This type of learning education was limited and did not have exposure across the world. Over the centuries, the education system has continued to evolve and adapt to changing times with a wide range of educational institutions offering diverse courses and programs. The country is home to several prestigious universities and institutes of national importance that are recognized globally for their academic excellence. The education system has also been instrumental in producing a large pool of highly skilled professionals in many fields, such as Engineering, Medicine, Science and Technology. Many students have also excelled in academic competitions at the international level, showcasing the country's intellectual prowess. These achievements reflect the dedication and talent of the students as well as the quality of education and support they receive. It's a testament to the nation's commitment to nurturing bright minds and fostering a culture of academic excellence. This success not only brings pride to the country but also inspires future generations to strive for greatness in their academic pursuits. The education system still faces some problems, including a lack of access to quality education in certain parts of the country, discontinuity of students, inadequate infrastructure and funding

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constraints. For example, the lack of understanding of the content can lead to the system recommending inappropriate materials for the student's knowledge level. Student discontinuity can render recommendations ineffective if users drop out of the system before receiving suitable suggestions. Language barriers can hinder personalized recommendations as the system may struggle to interpret user preferences across different languages. Confusion in selecting study materials can arise if the system fails to consider the individual preferences and the specific learning needs of each student.

Lastly, insufficient infrastructure and funding can limit the system's ability to offer high-quality personalized recommendations due to limited resources for system development and maintenance. The Government of India (GoI) has taken several programs to remove these challenges and improve the quality of education in the country [3].

Even today, it also continues to uphold its legacy of academic excellence through its various educational institutions and programs. The root of the problem was caused by some difficulties, including an outdated curriculum, a dearth of hands-on learning opportunities, a paucity of the best tutors and others [4]. However, during the last five to ten years it has been clear that the use of digital tools has advanced instructional helpfulness. An equitable approach to high-quality education has been facilitated through e-learning. It has achieved this by providing limitless chances for Teaching and also learning [5], [6] as well as greatly enhancing student learning outcomes, participation and pedagogical creativity.

The majority of students hold online or internet+ education in high regard due to the substantial improvement in education information technology [7]. Online education addresses the shortcomings of traditional education, which is constrained by time, geography, and environment allowing for share and salvaging of excellent education assets on a broader rule [8]. e-learning often known as online learning, increases both the effectiveness and efficiency of learning while also boosting student enthusiasm and knowledge retention. Learning resources are being offered at an accelerated rate due to the sharp increase in the number of people using online learning. Learners are forced to identify the data they essential from the large ocean of education learning capitals as a result, which offers obstacles like "information burden" and "learning difficulty" in the progression of education [9]. To solve these types of learning problems researchers introducing a recommendation system for education.

A recommendation system for education is introduced to provide personalized learning experiences, suggest relevant educational resources and assist in matching students with suitable courses or materials. It aims to enhance student engagement, improve learning outcomes and cater to individual learning needs. Using document recommender system approaches has proven to be a successful way to deal with the weight of overloaded information [10]. Users of e-learning often receive a range of offerings and information to ensure a positive user experience, making personalization a crucial strategy. This recommender system category is essential in numerous Web applications like e-learning websites and the necessity to provide learners with precise information is among the challenges in e-learning.

Students should have access to a centralised e-learning platform that has been developed over a duration with the aid of instructional ideas [11]. Remote learning offers students a multitude of benefits in education. Institutions, universities, companies and organizations worldwide offer distance learning courses, online certificates and degrees to promote e-learning. Numerous online courses and certifications are offered and announced by MIT(Massachusetts Institute of Technology) Open Courseware, Learndirect.com, NPTEL(National Programme on Technology Enhanced Learning) and MOOC(Massive Open Online Course) [12]. Education systems may go beyond the amount of data or resources students need to use before they can recognize their needs as a result of this customisation. One way to decrease the amount of information is to use a recommendation system. These systems leverage data analysis, machine learning and user behaviour modelling to offer tailored recommendations for educational content, courses, learning materials and activities. The primary goals of recommendation systems in education are to enhance student engagement, support individualized learning paths, and facilitate the discovery of relevant and high-quality educational resources [6]. They can be implemented in various educational settings, including K-12 schools, higher education institutions, online learning platforms and corporate training programs. Recommendation systems for education play a crucial role in promoting adaptive learning, improving learning outcomes and optimizing the educational experience for learners of all ages and backgrounds [13]. When adopting a recommendation system, each learner has a unique capacity for handling complexity, learning speed and the integration of large amounts of information with suitable correlation. The use of a personalized recommendation system can improve individualised learning, improve the understanding percentage and identify the complete problem of learning individually in various educational contexts [14].

The traditional teaching paradigm has many elements that make it difficult for students to learn. The initial instruction mode is "Teacher-Centred", it is an old-style inner-space teaching approach, that fails to take into account differences in students' knowledge levels, learning capacities and learning styles [15]. This can lead to some students losing motivation and developing a negative attitude towards education. Additionally, the timing and physical environment affect learning[16]. Educational resources are unevenly distributed, leading to variations in teaching quality, resources and instructional technology across different regions in China [17].

That's why concentrating on a "Learner-Centred" personalized education and chosen learning model has taken the place of the conventional "Teacher-Centred" paradigm as a result of the development of contemporary educational technology [18]. By monitoring their students' online learning, teachers can deliver tailored instruction. Students can utilize the internet to access resources shared by experts, join communities that cater to their learning needs and interact with fellow community members to leverage their unique learning styles, preferences and other individual qualities [19]. The flaws of past educational strategies have been changed, the instructional strategy has been switched around and the concepts of ''instruction according to the resources or materials'' and ''personalized instruction'' have been accomplished [20]. The ''13th Five-Year Plan of Education Information'' from the Indian Ministry of Education introduces a novel concept called ''Internet + Education'' to support the growth of educational information technology. For information technology to be entirely and broadly applied in the sphere of education and the goal of education informatization must be accomplished effectively [1].

Personalized recommendation systems like MOOCs (Massive Open Online Courses), Netease Open Classes and Coursera as well as individual e-learning classes, have emerged to achieve the suggestion of personalized teaching and learning resources and the revolutionary idea of ''Internet+'' knowledgeable Education [21]. Students can accomplish individual, group and customized learning tasks using mobile devices autonomously, according to their schedules and needs. The educational platform, which has been in use for many years, contains a substantial number of educational resources and instructional materials. It also utilizes educational data mining to analyze students' learning preferences, proficiency levels, teaching and learning habits to identify issues and risks in the learning process. The data obtained throughout the learning progression is logically recycled to determine learning capitals that meet each student's unique personality and attributes to address the difficulties of carelessness and unsuitable resources in the examination for learning resources [20].

The innovation of this work lies in the proposal to address the challenges faced by personalized recommendation systems in education by integrating new digital technologies. The review suggests the use of Fluxy AI, Twin technology, AI-powered virtual proctoring and Alter Ego to create a dynamic and interactive learning environment. These technologies are aimed at providing tailored learning experiences for students and offering insights for educators to provide targeted support and guidance. By integrating these technologies, the work aims to improve individualized learning, enhance understanding capacity and create a more enriching learning experience, particularly for students with speech disorders. Overall, the innovation lies in leveraging advanced digital tools to overcome existing challenges and enhance the effectiveness of personalized recommendation systems in education.

This review study's goal is to analyse the work done on recommending systems that lead educational practises to gather data on the different types of educational recommendations and subjects or interest areas that deal with the improvement strategy employed and the recommending elements, as well as to identify research gaps in this area. An extensive review was conducted that covered 60(N) number of research articles from a total of 3003 articles found in major databases like IEEE, Springer, ACM, Scopus, BERA, Science Direct, Web of science, Multidisciplinary Digital Publishing Institute and many more see in Figure 1.

It was able to be determined that the majority of these research articles indicate the educational resources recommendation for students or learners as well as teachers of the regular education systems.

The main methods used in recommendation systems are the collaborative technique, the content-based technique and the hybrid filtering technique. With a recent trend towards the use of machine learning (ML) in the last two to four years [24], [33]. Finally, potential directions for research surveys and the need for development in this area are offered by Digital technology (DT) including Artificial Intelligence (AI) and other new technologies. The following are the parts of this survey: The review of e-learning technology is presented in the II literature review, the next section provides a III discussion about this survey and while in the next section IV provides a resolution about this survey using some digital technologies to enhance the personalized recommendation system in the educational environment and in the next section V gives the pre-defined results and advantages of enhancing the personalized recommendation system with digital technologies.

II. LITERATURE REVIEW

In this section offers a thorough analysis of educational expert recommender systems with a focus on high-quality education-oriented recommendations. Recommender systems come in a variety of shapes and sizes and are intended to aid both students and teachers' learning. However, the advantages of customized recommender systems for various academic fields and levels within the organisations will be the main emphasis of this research.

Tables summarize and classify into several groups according to their common methodology or findings. Majorly classified into six groups, Group 1: contains Artificial Intelligence, Machine learning and Deep learning techniques, Group 2: contains Hybrid filtering for Educational Recommendations, Group 3: Ontology-Based Hybrid Recommendation Systems for Personalized Learning, Group 4: Content-Based Educational Recommendation Systems, Group 5: Collaborative Filtering Techniques for Personalized Recommendations and Group 6: Group-Based Educational Recommendation Systems.

Table 1 summarizes various AI, ML and DL techniques used in distance learning and education. It includes the purpose of each technique, the number of users involved in the study, and key insights, contributions, and future work for each approach. Additionally, future work is provided for each technique, highlighting the potential for further

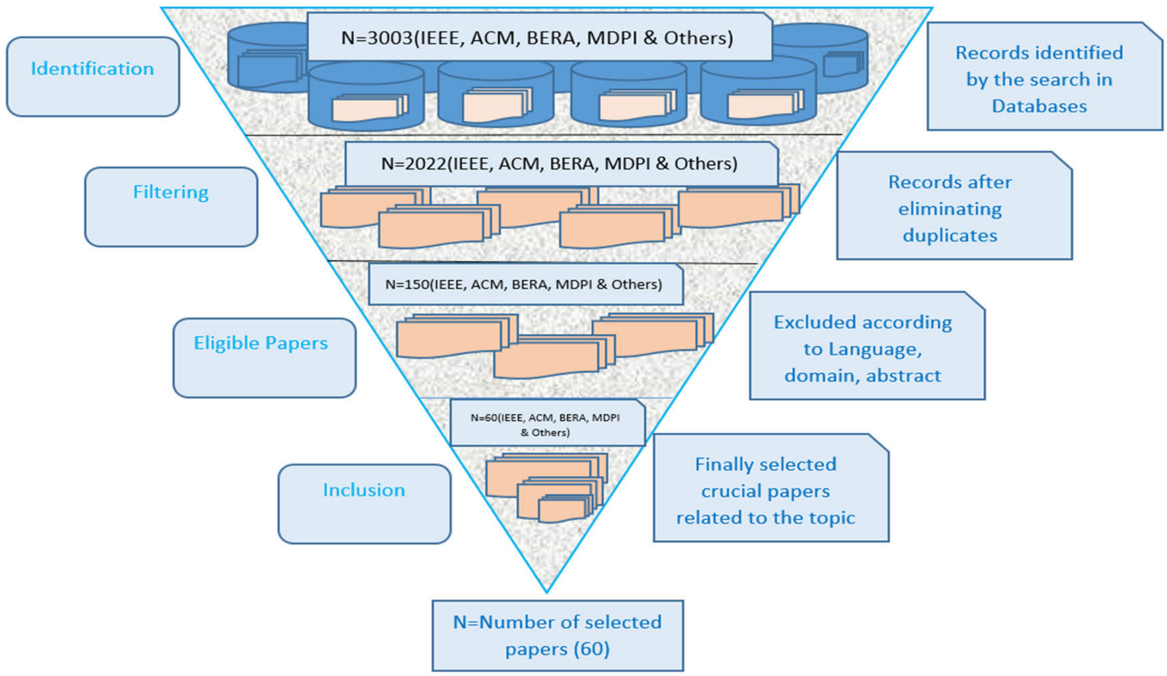

FIGURE 1. Articles are chosen for review study from reputable repositories.

advancements and improvements in the field of AI, ML and DL for distance learning. Based on this future enhancement propose some digital technologies to improve the recommendation system for improve the learning efficiency of learners and provide suitable learning paths and recourses for effective learning.

In Table 1 many authors used many techniques like AI, ML, DL [17], [34], [68] but they do not include some of the AI new applications like Fluxy AI and Twin technology. That's why strongly recommended to include this type of application for better personalized recommendations. The inclusion of new AI applications like Fluxy AI and Twin technology in the context of personalized recommendation systems. It's important to consider the latest advancements in AI and ML techniques to enhance the effectiveness of personalized recommendations. Including these new applications can contribute to a more comprehensive and up-to-date analysis of the techniques used in the field.

Table 2 summarizes various hybrid Filtering methodologies and techniques used in the context of educational recommendation systems. It includes the purpose of each technique, the number of users involved in the study, and key insights, contributions, and future work for each approach. Additionally, key insights, contributions, and future work are provided for each technique, highlighting the potential for further advancements and improvements in the field of hybrid filtering for educational recommendation systems.

Table 3 summarizes various ontology-based hybrid recommendation systems and their applications in personalized learning. It includes the purpose of each technique, the number of users involved in the study, and key insights, contributions, and future work for each approach. Highlighting the potential for further advancements and improvements in the field of ontology-based hybrid recommendation systems for personalized learning. From this table investigate the application of our approach in informal e-learning environments, where the absence of a structured curriculum makes it challenging for students to select appropriate learning materials also and lack of interconnectivity of learning paths. For this purpose we recommend digital technologies like Fluxy AI and Other AI technologies to create a trajectory for students based on knowledge.

Table 4 covers a range of innovative content-based educational recommendation systems and their applications in personalized learning. It includes various content-based recommendation techniques, such as integrating with TF-IDF, personalized learning strategies, and the use of deep learning and ML techniques for intelligent content-based recommendation systems. Additionally, key insights, contributions, and future work are provided for each approach, highlighting the potential for further advancements and improvements in the field of content-based educational recommendation systems for personalized learning.

Table 5 encompasses a variety of innovative collaborative filtering techniques and their applications in personalized recommendations. It includes collaborative filtering algorithms, item-based recommendation systems, and the use of meta-learning techniques and intelligent systems for recommendation purposes. Additionally, key insights, contributions, and future work are provided for each approach,

TABLE 1. Important articles based on the innovative AI/ML/DL techniques for education.

Ref. No	Methodologies/ Techniques	Purpose & No. of Users	Key insights, contributions and Future work
[22]	Multi-criteria decision-making (MCDM) was designed using a weighted matrix	Learners (327)	The goal of this study is to analyze and identify the correlation between various criteria that influence distance learning. By utilizing a multi-criteria decision-making model to assign weights to alternatives, we aim to determine the best-scored alternative. This alternative will then be passed through a recommendation model. To enhance analytics and predict the efficiency of online learning, it may be useful to integrate machine learning with MCDM.
[23]	Genetic algorithm with 1-point crossover modification.	Learners (60)	A genetic algorithm was implemented for group formation by modifying 1-point and 2-point crossover and gene crossover. The algorithm efficiency was tested in two group formation cases. The algorithm will need to be improved to reduce the execution time and resource required for it.
[24]	Integrating stereotype method with fuzzy inference rules	Learner (primary school)	To represent the learner model author integrates relevant information such as pertinent data, including learning style, domain-related, and assessment-related, it addresses the issue of managing the uncertainty of particular parameters, and it has benefits in terms of precision. Work on recognizing learners' emotions and how to include this technique in the learning system's personalization and recommendation
[25]	Deep reinforcement learning	Learner (1709)	This study introduces a dynamic multi-objective sequence-wise recommendation framework called DMoSwR-DRL. The framework utilizes deep reinforcement learning to automatically select the most suitable exercises for each student. By leveraging skillfully designed domain-objective rewards, the framework aims to maximize the utilization of valuable information obtained from e-learning platforms. To enhance the current reinforcement learning method, one approach could be to explore improvements in high exploration methods, such as hierarchical RL and random network distillation. By manipulating these methods, it is possible to enhance the exploration capabilities within the reinforcement learning framework. This can potentially lead to improved learning and decision-making processes.
[26]	Deep Learning	Learner (335)	The study creates the Top-enhanced Recommender Distillation framework (TERD), a fully adaptable recommendation paradigm. To be more precise, the suggested TERD injects knowledge from a teacher network into a carefully thought-out student network. The state and action space of the learners' system is more defined using the prior knowledge provided by the instructor network, including student exercise embedding. Need to introduce the state-of-art DRL technique for improving recommendation accuracy. And need to apply a multi-objective optimization method for a redesign.
[27]	Integrating Bigdata and deep learning	Learner (632)	This work focuses on a personalized recommendation approach for Massive Open Online Course (MOOC) systems. The approach integrates deep learning and big data techniques, utilizing various methods based on the Bidirectional Encoder Representations from Transformers (BERT) model. After pre-processing, the author presents a framework for the recommendation model, which incorporates the BERT model and a self-attention mechanism. This framework aims to improve the accuracy and effectiveness of personalized recommendations in MOOC systems. Need theoretical verification and dataset for experiments should be increased
[33]	Machine learning	Learner (Users No. are not mentioned)	The paper reviews recent e-learning recommendation system developments and advancements. They provide the taxonomy of recommendation systems along with machine learning algorithms, and evaluation metrics and highlight the challenges like data scarcity and cold start problems in recommendation systems. For result enhancement in support vector machine (SVM) and neural network incorporating the machine learning techniques in clustering. And also improving the latency and scalability of recommender systems with new emerging technology.
[34]	Deep learning with implicit feedback	Learner (Users No. are not mentioned)	The study proposes a personalized conceptual framework for recommending materials to school students based on their characteristics, utilizing deep learning algorithms and implicit feedback. The framework aims to improve student engagement, performance, and knowledge. One proposed future work is to test the effectiveness of the personalized framework by involving teachers and students in Malaysian high schools. This testing will help determine how well the framework assists students in their e-learning. The study also suggests that data collection through survey forms and interviews with students and teachers can be used to enhance the proposed framework and gain insights into the actual needs and preferences of the users.
[37]	AI(recommended)	Learner (Users No. are not mentioned)	This article intends to present research on e-learning innovations, a literature analysis of currently employed intelligent strategies, and an examination of their prospective advantages. According to the review, AI-supported solutions can assist both teachers and learners by suggesting resources and grading contributions. Need to design an environment that can satisfy all the demands and requirements of learners, and determine the optimal combination of strategies that could be applied in a single e-learning system by using artificial intelligence techniques.
[42]	Uses the Felder-Silverman Learning Style Model (FSLSM), Neighbors users based on Pearson correlation	Students (Users No. are not mentioned)	The research paper proposes a new algorithm for recommending learning objects based on the Felder-Silverman Learning Style Model (FSLSM). The algorithm considers students' learning styles and historical ratings to provide personalized recommendations for course learning objects. The aim is to enhance prediction accuracy and address challenges like cold-start problems and sparse ratings. The algorithm is evaluated using a real student dataset, and the study presents experimental results and analysis to validate its effectiveness. The study acknowledges that the dataset used in the research was relatively small and suggests that a larger dataset would provide more robust results and address scalability issues in recommendation systems. The study highlights the importance of addressing such challenges to ensure the effectiveness and practicality of recommendation systems in real-world applications.

TABLE 1. ***(Continued.)*** **Important articles based on the innovative AI/ML/DL techniques for education.**

[51]	Bayesian Model, Adaptive Learning Management System	learner's (Users No. are not mentioned)	Construction of adaptive learning management systems, modelling personalized e-learning environments, consideration of learner's characteristics for tailored instruction Further refinement of adaptive systems, exploring the integration of more factors for enhanced personalization
[52]	Reinforcement Learning Integration	Users (Users No. are not mentioned)	Combine reinforcement learning with similarity measures to refine recommendation accuracy. Enhance recommendation accuracy, Investigate advanced reinforcement learning techniques and algorithms to further enhance recommendation quality.
[53]	Machine Learning-Based Personalization, Natural Language Processing (NLP)	Learners (Users No. are not mentioned)	Customized learning for students, Enhanced language proficiency, Efficient learning environment Enhance the model's ability to understand the context in content creation, Refine model's understanding of subject-specific terminology
[54]	Machine Learning-Based Personalize recommendation system.	Students, Teachers. The number of users is not mentioned.	The key insights include the development of a personalized recommender system tailored for e-Learning, which has the potential to enhance the learning experience for users. The contributions of the study involve the implementation and evaluation of the recommender system in an e-Learning environment. Future work may involve further refinement of the system based on user feedback and the exploration of additional features to improve its effectiveness
[55]	ChatGPT Tool	Users (Users No. are not mentioned)	Application of ChatGPT tool to ameliorate education system, Explore the relationship between physical appearance and academic performance Explore additional factors influencing student performance, such as socioeconomic background Conduct longitudinal studies to assess the long-term effects of teaching mode on student outcomes
[56]	Machine leaning	Learners (Users No. are not mentioned)	Response retrieval inspired by recommendation systems, Facilitates collective decision tasks Continuous Scale Ratings, Pairwise Comparisons, Continuous Scale Ratings, Binary Choice Surveys Explore hybrid survey methods combining pairwise comparisons and continuous scales, Investigate methods to improve the predictive accuracy of aggregate assessments using matrix factorization
[59]	AI technologies and online tools	Users (Users No. are not mentioned)	Explore interdisciplinary collaborations between technology experts, social workers, and ethicists to develop holistic solutions Develop educational resources and training programs for professionals on the ethical use of AI in domestic violence interventions
[60]	Artificial Intelligence (AI) Applications	Users (Users No. are not mentioned)	Literature-based study of AI applications in marketing, use of AI-based technologies in addressing domestic violence, Collaborate with cybersecurity experts to enhance the security of AI-based solutions Develop strategies to counteract the technological capabilities of perpetrators and ensure the effectiveness of protective technologies
[61]	Point Process, Hawkes Process, Hierarchical Poisson Factorization	Users (Users No. are not mentioned)	Point process-based time-sensitive personalized recommendation, Implement a customised initial intensity estimation based on Incorporate dynamic activity patterns Explore techniques to mitigate issues related to data sparsity and cold start problems in personalized recommendations, Develop techniques to enhance the scalability and efficiency of the framework for larger datasets and real-time applications.
[63]	Dual Process Theory, Scenario-Based Surveys, Lab Experiments, AI-based recommendation systems.	Users 500	Understanding the psychological factors influencing travelers' adoption intentions towards AI-based recommendation systems. Conducted two studies comprising scenario-based surveys and lab experiments, involving a total of 500 participants from different travel contexts Enhancing the effectiveness of AI recommendations. Explore the adoption behaviour over an extended timeframe to assess the long-term sustainability of trust-based AI adoption. Collaborate with industry partners to implement the study's insights into the design and marketing of AI-powered travel planning platforms.
[67]	Machine Learning, Ontology	Learners (Users No. are not mentioned)	Exploring the landscape of modern educational systems and their shift towards E-Learning and M-Learning. Focusing on the development of a Personalized Self-Directed Learning Recommendation System (PSDLR). Examining the shift in educational paradigms towards E-Learning and M-Learning, To enhance engagement and motivation in self-directed learning. Collaborate with educational researchers to conduct longitudinal studies assessing the long-term impact of the PSDLR system on learners' SDL skills and competencies.
[68]	Machine learning and AI	Learners (Users No. are not mentioned)	Response retrieval inspired by recommendation systems, Facilitates collective decision tasks Continuous Scale Ratings, Pairwise Comparisons, Continuous Scale Ratings, Binary Choice Surveys Explore hybrid survey methods combining pairwise comparisons and continuous scales, Investigate methods to improve the predictive accuracy of aggregate assessments using matrix factorization

highlighting the potential for further advancements and improvements in the field of collaborative filtering techniques for personalized recommendations.

The Table 6 encompasses a range of innovative group-based educational recommendation systems and their applications in personalized learning. It includes group-based recommendation methodologies, self-organization theory, and the use of meta-learning techniques and intelligent systems for recommendation purposes. Additionally, key insights, contributions, and future work are provided for each approach, highlighting the potential for further advancements and improvements in the field of group-based educational recommendation systems for personalized learning.

III. DISCUSSION

The above tables reveal some of the research gaps in the "future work" column, these gaps are considered as problems and these problems are necessary to update the personal-

TABLE 2. The important articles based on hybrid techniques for educational recommendations.

Ref. No.	Methodologies/ Techniques	Purpose & No. of Users	Key insights, contributions and Future work
[28]	Hybrid method	Learner (30)	This hybrid approach aims to leverage the strengths of both methods to provide more accurate and diverse recommendations The content-based approach uses the domain model to recommend learning activities that are similar to the ones the learner has already engaged with, while the collaborative filtering approach uses the learner model to recommend learning actions that are common among learners with similar characteristics. Overall, the paper describes the execution of the proposed TEL recommender system as using ontological representation, a hybrid recommendation strategy This system relies on a limited set of learner characteristics, and the accuracy and relevance of recommendations could potentially be improved by incorporating additional characteristics. Furthermore, the system could be extended to support social recommendations, which take into account the preferences and behaviour patterns of the user's social network. This could lead to more relevant and personalized recommendations, as social influence can play a significant role in decision-making processes.
[35]	Hybrid model Learner Influence Model (LIM)	Learners. (Users No. are not mentioned)	The key insights and contributions include the proposal of a hybrid filtering recommendation approach (SI - IFL) that combines LIM, SOB recommendation strategy, and SPM for recommending learning objects to learners. Future work could involve further optimization of the proposed approach and its application in different e-learning scenarios.
[36]	Hybrid filtering (CB+CF)		A new recommender system was proposed with content-based, collaborative, and hybrid filtering components. The suggested recommender system makes better recommendations for discussion groups by using the tagging features. With the help of the WordNet lexical database, the semantic importance of tags is extracted for this purpose, and the tags are then arranged in a hierarchical structure according to this semantic relevance. Not specified.
[38]	Hybrid filtering method	Learners. (Users No. are not mentioned)	The article provides an overview of the approaches used to create individualized learning routes in this document, along with each approach's benefits and drawbacks. Additionally, the primary criteria for tailoring learning routes are outlined. Additionally suggesting strategies for assessing path personalization techniques. While implementing the MOOC-based e-learning platforms because of the rapidly expanding trend.
[49]	Highly used labels: algorithm, weighted hybrid strategy, social tagging, sequential pattern mining.	Learners (Users No. are not mentioned)	The paper emphasizes the incorporation of communication and information technology in teaching, conducting a literature review that investigates the factors affecting teachers' adoption and integration of ICT in their instructional practices. It provides insights into the challenges and opportunities associated with ICT integration and offers recommendations for future research and practice. Throughout the years, Recommendation Systems have been extremely popular as a result of the development of various well-liked systems and the introduction of numerous innovative, cutting-edge techniques. Nevertheless, RS still has to be improved to make recommendation strategies more successful across a wider range of applications. As collaborative tagging systems gain in popularity, tags may develop into intriguing data that may be used to improve RS algorithms. Along with assisting consumers
[50]	Fuzzy tree matching method, neighbour users based on cosine similarity and fuzzy set strategy and Knowledge representation, collaborative filtering and fuzzy logic	Users (Users No. are not mentioned)	The paper suggests a technique termed KCP-ER for exercise recommendation in a learning system. Depending on how well pupils have mastered the principles, the objective is to provide tasks that are appropriate for them. The Knowledge Concept Prediction (KCP) layer and the Exercise Set Filtering layer are the two primary parts of the technique. Recurrent neural networks (RNNs) are employed in the KCP layer to forecast the knowledge topic coverage in exercises. The model makes predictions about the likelihood that each knowledge topic will be successfully answered by looking at the students' exercise answer records. Based on the projected knowledge concept coverage and the predicted level of knowledge concept mastery, the exercise set filtering layer sorts the exercise bank. A final list of suggested candidates is created by this filtering procedure. There are a few potential paths for further research in the area of exercise advice based on knowledge concept prediction, based on the findings and limitations addressed in the paper: Enhanced Recommendation Algorithms: The KCP-ER method's recommendation algorithms can still be enhanced. Improve the precision and efficacy of the workout suggestions, this can entail investigating various machine-learning approaches, optimizing model topologies, and fine-tuning hyper parameters. Textual Analysis is Incorporated: The paper's main goal is to predict knowledge topic coverage and mastery using exercise answer records. Future research might examine how to use text analysis methods to extract more data from activity descriptions or question texts, which could enhance the recommendation process for exercises.
[65]	Hybrid filtering and Machine learning	Users (Users No. are not mentioned)	Identified the focus of recommendation systems in education, emphasizing the importance of relevant educational resources for enhancing the student learning experience. Explored the prevalent approaches used, including collaborative, content-based, and hybrid approaches, with a recent trend towards integrating machine learning. Identified gaps in the current research landscape to guide future research directions. Investigate the integration of emerging technologies (e.g., natural language processing, deep learning) in educational recommendation systems and their potential benefits. Collaborate with educators to validate the effectiveness of recommendation systems in real-world educational settings. Explore the potential of personalized recommendations based on individual learning styles and preferences.

TABLE 3. The important articles on ontology-based hybrid recommendation systems.

Ref. No.	Methodologies/ Techniques	Purpose & No. of Users	Key insights, contributions and Future work
[31]	Ontology-based Hybrid recommendation system(CB+CF)	Learner (300)	Ontology-based e-learning recommender system addresses the cold-start problem with a hybrid approach for personalized recommendations. The system generates personalized recommendations for new users by utilizing semantic user profiles and an ontology-based content representation. To achieve better performance emphasize more on learners' behaviour by integrating machine learning and deep learning technologies.
[32]	Ontology and Fuzzy based systems	Learner (Users No. are not mentioned)	The paper analyzes prior studies on content recommenders in online learning, focusing on personalized and adaptive learning environments between 2015 and 2020. It categorizes various recommendation methodologies, data inputs, algorithms, similarity metrics, and assessment metrics used in these studies. The paper also highlights recent advancements in the recommendation process. Integrating deep learning and machine learning into the existing methodology. And alleviating cold start problems by analyzing the different learner characteristics and learner behaviour in the learning management system.
[40]	Ontology/knowledge-based systems	Learner (Users No. are not mentioned)	The review topics include recommender evaluations ontology use, recommender trends, recommender processes, and recommender techniques. Discovered that the process for LP recommendations is semi-dynamic and dynamic at the moment. Semi-dynamic learning paths begin with a predetermined course, whereas dynamic learning paths are adjustable from the very first step and are meant for individual application. This review is restricted to English hence it needs to extend to other languages to improve the accuracy.
[41]	Neighbour users based on cosine similarities, Generalized Pattern algorithm resources	Candidates (Users No. are not mentioned)	This paper presents a thorough analysis of works on ontology-based recommender systems for e-learning in this paper. These research accomplishments in the field of ontology-based recommendation categories the types of e-learning resources that ontology-based recommenders suggest. To enhance the quality of recommendations in ontology-based recommendation for e-learning, future research will concentrate more on the hybridization of recommendation and knowledge representation techniques.
[46]	Mixed concept mapping and immune algorithm and knowledge representation and heuristic methods	Learners (Users No. are not mentioned)	In this research, we address the growing importance of enhancing the diversity and adaptability of reinforcement systems, particularly in the rapidly evolving online learning environment. We propose a LO's self-organization-based recommendation strategy for e-learning. This strategy integrates a learner-focused content-based (CB) recommender system with a LO-oriented recommendation mechanism. To represent the state of the LO, we expand the relevant metadata and model LOs as intelligent entities. By combining these approaches, we aim to improve the effectiveness and personalization of recommendations in e-learning. In future work, our focus will be on enhancing the performance of the algorithm and exploring suitable knowledge representation methods. Additionally, we plan to investigate the application of our approach in informal e-learning environments, where the absence of a structured curriculum makes it challenging for students to select appropriate learning materials
[57]	Ontology-based and MLTeqnique	Students (679).	Proposed method for predicting student final grades using performance data in the current semester. Assisted students in analyzing the effort needed to obtain desired grades and helped instructors identify student types for better support. Clustered students based on experience points (XP) and balanced clusters by generating virtual students. Early and continuous feedback is effective for student retention in higher education. Method outperformed other approaches, showing potential for effectively predicting final grades. Future work-Exploration of additional factors that may impact student performance. Integration of the method with existing student support systems for real-time intervention.
[62]	Knowledge Association	Learners (Users No. are not mentioned)	Study on personalized recommendation algorithm based on knowledge association Explore methods to improve interpretability and explainability of the recommendation process to enhance user trust,
[66]	Link prediction based on bipartite graph and optimized SVD++	Users (Users No. are not mentioned)	Developing an effective link prediction-based recommendation system to address the information overload problem using bipartite graphs. Applied to the Movie Lens dataset for evaluation. Investigate the integration of additional data sources, such as user feedback and reviews, to enhance recommendation quality and user satisfaction. Explore the potential of incorporating real-time updates to the recommendation model to adapt to users' changing preferences. Collaborate with e-commerce platforms to implement the proposed system for personalized product recommendations.

ized recommendation system for effective education. These are explained with solutions one by one in the below paragraphs,

Continuous Monitoring: Traditional methods may not provide real-time insights into students' progress, making it challenging to identify areas where students may be struggling or excelling. This problem is solved with AI-powered Virtual Proctoring and AI-enabled cameras and sensors can enable continuous monitoring of students' engagement, behaviour and progress, providing real-time insights to edu-

TABLE 4. The important articles based on Content-based recommendation.

Ref. No	Methodologies/ Techniques	Purpose & No. of Users	Key insights, contributions and Future work
[24]	Content-based recommendation	Learner (161 adults)	The research examines the impact of a teaching professional development program that incorporates a personalized learning system on in-service teachers' technological pedagogical and content knowledge (TPACK). To gain a better understanding of how these variations may impact outcomes, further research in other fields is recommended. Additionally, comparisons between trainees who have received training in andragogy and/or personalized learning systems and those who have not should be conducted.
[29]	Content-based recommendation integrating with(TF-IDF) Term frequency and Inverse document frequency	Learner (290)	The study designs a unique framework for an e-learning (ICRS) Intelligent Content-Based Recommendation System which combines deep and ML techniques with semantic analysis of e-content to help learners choose the best e-learning resources. To construct the structure of the context-based graph, the system utilizes textual electronic content and extracts representative terms and their semantic associations to create a meaningful representation of the textual knowledge. The e-content is semantically represented using the learner's terms, which are expanded using the ConceptNet semantic network. This process aims to create a more accurate and comprehensive representation of the e-content, which can then be used to provide personalized and relevant recommendations to the learner.. The authors propose that additional issues could be addressed to further improve the system. For example, exploring the relationships among user profile features and updating the semantic matrix's values based on each user's actions could enhance the accuracy of the recommendations. Additionally, fuzzy logic could be incorporated to more accurately reflect the real world. By addressing these issues, the system could potentially provide even more personalized and relevant recommendations to users.
[30]	Quasi-experimental design using a quantitative approach	Learner (292)	This study used a personalized learning strategy to help students receive the right learning paths and content in line with their learning preferences. It also integrated self-regulated online learning into the physics classroom. By employing a quantitative methodology and a quasi-experimental design to assess the efficacy of the suggested learning environment. The current study relied only on Science learning to diagnose so it can be extended to other subjects by adding course features in a hierarchal manner.

cators. Firstly, there is no cognitive performance assessment, so need for effective technology that can accurately assess students' cognitive performance. For this problem-solving purpose, the Neurosky EEG Biosensor can be used to measure brainwave activity, providing insights into students' cognitive performance, attention, and engagement.

There are no quick and accurate responses, so providing quick and accurate responses to students' queries and assessments is essential for maintaining engagement. For this Fluxy AI can be used to provide quick responses to student queries and assessments, enhancing engagement and addressing learning gaps.

Problems in real-time feedback and intervention, so providing immediate feedback and intervention based on students' performance can enhance the learning process. For this AI-powered systems can analyze student performance in real time and provide automated feedback, while educators can use this data to intervene when necessary.

There is no proper customized learning paths based on student interest or knowledge. Tailoring learning paths to individual students' needs is important for optimizing the learning experience. The solution is for this problem- Alter Ego and Twin Technology can support personalized learning paths by adapting content and resources to individual student needs and learning styles.

Personalized content delivery is very important for every student. Each student's level of understanding and interests can enhance engagement and knowledge retention. Easily solve this problem with the solution of AI-powered recommendation systems that can analyze student preferences and performance to deliver personalized content and learning materials.

Flexible Learning is very important for every learner, so offering flexible learning options that accommodate different learning paces, schedules, and preferences can improve accessibility. The solution for this problem is to use Fluxy AI and resource recommendation system can enable access to learning materials and resources flexibly and efficiently, accommodating diverse learning needs.

Problem for comprehensive subjects ensuring that the curriculum covers a wide range of subjects is important for students' overall development. The solution to this problem is to use AI-powered curriculum planning tools that can help educators design comprehensive and well-rounded curricula that cover a wide range of subjects.

An interactive chat environment needs to be adopted for creating an interactive chat environment that can facilitate collaborative learning and peer interaction. The solution for this problem is to use AI-powered chatbots, Fluxy AI and communication tools can create interactive chat environments that support collaborative learning and immediate access to support.

Providing opportunities for additional learning, enrichment, and exploration can foster a love for learning. The solution for this problem is to use Emerging technologies such as virtual reality (VR) and augmented reality (AR) can

TABLE 5. The below table shows the important articles based Collaborative filtering method for personalized recommendations.

Ref. No	Methodologies/ Techniques	Purpose & No. of Users	Key insights, contributions and Future work
[39]	Collaborative filtering method	Learners (Users No. are not mentioned)	This study suggests a user-interest-based algorithm. Additionally, this paper combines user behaviour data to derive the user interest model from the user's historical interest model. It then calculates how similar the candidate items are to the user and recommends TOP-N based on the similarity calculation results. Not specified
[47]	Item-based recommendation, Mahout machine learning library.	Students (Users No. are not mentioned)	The primary outcome of this paper is to provide recommendations for elective courses to students based on their grade points in subjects. This study can be utilized by educational institutions such as schools, colleges, or universities to suggest alternative elective courses to students. By leveraging the recommendations generated from this study, institutions can assist students in making informed decisions about their elective course selections, enhancing their educational experience and academic success. To further enhance the accuracy of the suggestion, they want to adopt a hybrid model-based recommendation system in the future. Based on certain historical data of students from past batches, we also want to employ recommender systems to make job recommendations to college students.
[58]	Collaborative Filtering Algorithms, Similarity Measures, Matrix Reduction	E-commerce Users(Users No. are not mentioned)	Examination of collaborative filtering algorithms for clothing recommendation, Develop and apply three similarity Refine and optimize the matrix reduction method for various dataset sizes and characteristics, Experiment with other similarity measures and metrics to fine-tune recommendation algorithms
[69]	Collaborative Filtering	Learners (Users No. are not mentioned)	To improve collaborative filtering recommendation systems by addressing data sparsity and cold-start problems. Experimental evaluation shows that both measures outperform existing methods, with producing lower error values. The contribution to education has the potential to enhance recommendation system accuracy for a wide range of users. Key insights highlight the importance of cognitive features in similarity calculation. Future research could focus on refining measures, exploring applicability to different systems, and integrating advanced cognitive features for improved accuracy
[70]	Meta-learning techniques and intelligent systems	Users (Users No. are not mentioned)	Examination of collaborative filtering algorithms for clothing recommendation, Develop and apply three similarity Refine and optimize the matrix reduction method for various dataset sizes and characteristics, Experiment with other similarity measures and metrics to fine-tune recommendation algorithms

offer immersive additional learning opportunities that engage students in new ways. Communication Support for Individuals with Speech Disorders: Offering effective communication support for individuals with speech disorders is crucial for ensuring equal access to education. The solution to this problem is to use AI-powered speech recognition EEG Biosensors and communication tools that can provide effective support for individuals with speech disorders, enabling them to participate fully in educational activities.

These are the problems identified in the literature survey and then suggested solving them using some new Digital Technologies (DT). These innovative technological solutions have the potential to transform education by addressing the identified challenges and enhancing the learning experience for students. It is approached and delivered very effective manner to all the learners and Teachers. So adopt some new digital technologies to improve the personalized recommendation system, as explained in the next section.

IV. DIGITAL TECHNOLOGIES TO ENHANCE THE PERSONALIZED RECOMMENDATION SYSTEM IN THE EDUCATIONAL ENVIRONMENT

Enhance personalized recommendation systems by leveraging adaptive new technologies. These technologies can also play a pivotal role in enhancing conventional educational institutions through digital advancements. The integration of these technologies has the prospective to significantly improve both student knowledge and teacher guidance. By incorporating emerging technologies into the traditional personalized recommendation system, we can introduce a new paradigm to conventional educational establishments.

Some of the transformative technologies that can be inculcated into the education recommendation system, like the Neurosky EEG Biosensor, AI-powered Virtual Proctoring, AI-enabled cameras and sensors, Fluxy AI, Alter Ego, Twin Technology for organizational enhancement, RFID and NFC Technology. These innovations collectively contribute to creating lively and interactive learning that adapts to the needs of each student while supporting educators in their teaching endeavors see in Figure 7.

Through this approach, students can benefit from personalized learning experiences that cater to their unique learning styles and pace. Teachers, on the other hand, can harness these technologies to gain insights into students' progress and challenges, enabling them to provide targeted guidance and support. The integration of these technologies not only modernizes the educational landscape but also equips students and educators with the tools necessary to excel in an increasingly technologically driven world. These adaptive

FIGURE 2. **Neurosky EEG biosensor.**

new technologies are helpful to improve student knowledge as well as helpful to teachers for guiding the students to add to the traditional personalized recommendation system and then we can introduce them to conventional institutions for all the students are getting the opportunity to use this tremendous personalized recommendation system.

A. NEUROSKY EEG BIOSENSOR

In the current education system, Teachers are taking online/offline classes and facing the problem of whether students are getting the concepts or not. All teachers can get an acknowledgement in the form of facial expressions or gestures of students to know whether the students are attentive or not. And also, in these pandemic days classes are online. Even the learners are facing problems like network issues, mismatch in audio (delay time) etc. Since students or learners are facing these problems, teachers may not know what's going on during online classes. During classes, some concepts will be understood by the students and a few may not. So teachers may not know which points are not clear to students or which part of the syllabus has not been understood.

The Neurosky EEG Biosensor is substantially possible for enhancing student education and personalized recommendation systems in the field of education. By utilizing the brain's electrical activity, as measured by EEG, this technology can provide valuable insights into students' cognitive states, thereby enabling more effective learning experiences and tailored educational approaches as shown in Figure 2. The forehead sensor and ear clip electrodes detect electrical signals from the brain, which are processed by the device's microcontroller. The AAA battery provides power to the device, and the power switch and LED power indicator are used to control and display the device's power status.

The foam pad helps to improve signal quality and provide comfort for the user. The aim is to create a system which helps teachers to monitor the students continuously and to know which part of the syllabus is difficult to understand by one/all the students so that teachers can take suitable pedagogical measures [71], [72] and then take extra classes for them. Neurosky EEG biosensors can potentially identify students' cognitive strengths by measuring and analyzing their brainwave patterns. The biosensors can detect electrical activity in the brain, such as levels of attention, meditation, and cognitive workload. By analyzing these patterns, educators and researchers can gain insights into students' cognitive processes, including their attention span, engagement levels and cognitive workload learning tasks.

Creating a personalized learning path based on this data involves using the insights gained from the EEG biosensors to tailor educational experiences to individual students. For example, if the biosensors indicate that a student has difficulty maintaining focus during certain types of tasks, educators can adjust the learning materials or teaching methods to better suit the student's needs. This might involve providing additional support, adapting the pace of learning, or offering alternative learning resources to address the student's specific cognitive strengths and weaknesses [72].

The data collected from the EEG biosensors can be used to develop personalized learning algorithms that adapt in real-time to students' cognitive states, providing them with individualized challenges and support as needed. This approach can help optimize the learning process for each student based on their unique cognitive strengths and learning preferences.

1) ADVANTAGES

Enhancing student learning and engagement: The Neurosky EEG Biosensor can monitor brainwaves, such as beta waves associated with problem-solving and decision-making. By analyzing these brainwave patterns, educators can gain insights into students' levels of engagement, focus, and cognitive processing during different learning activities. This info can be used to adapt teaching strategies and content delivery in real-time, ensuring that students remain engaged and challenged throughout their learning journey.

Personalized Learning Paths: The data collected from the Neurosky EEG Biosensor can be utilized to create personalized learning paths for individual students. By identifying the cognitive strengths and weaknesses of each student, educators can tailor educational materials and activities to match their preferred learning styles and optimize their academic progress

Cognitive Performance Assessment: EEG-based analysis can provide valuable insights into students' cognitive performance, helping educators assess factors such as attention levels, memory retention, and cognitive load [81]. This information can aid in identifying areas where students may need additional support or where content delivery may need to be adjusted for optimal learning outcomes.

TABLE 6. The important articles based on Group-based recommendation methodology.

Ref. No	Methodologies/ Techniques	Purpose & No. of Users	Key insights, contributions and Future work
[43]	Self-organization theory	Students, Teachers (Users No. are not mentioned)	Study proposes Self approach to improve e-learning recommendations by incorporating learning mechanism for adaptability and diversity. The approach simulates Learning Objectives as intelligent entities that can receive, transmit, and move information and an environment perception module captures and perceives learners' preference drifts. Based on learners' explicit requirements and implicit preference drifts. The authors of the study intend to conduct additional case studies to validate the effectiveness of the proposed approach, particularly in Massive Open Online Courses (MOOCs). They also plan to explore recommender systems based on learners' self-organization behaviors.
[44]	Group based methods	Learners (Users No. are not mentioned)	This research study aimed to understand how to measure the success of a recommender system from the users' perspective. A recommender system is a type of software that provides personalized recommendations to users based on their preferences and behavior. The study developed a framework called ResQue (Recommender systems' Quality of user experience) to evaluate the quality of recommended items, the usability and usefulness of the system, as well as users' satisfaction and behavioral intentions. The study used psychometric methods to validate the framework and found that it consists of 32 questions and 15 constructs, which can help practitioners and scholars evaluate the success of a recommender system and identify areas that need improvement.
[45]	Group-based recommendation methodology meta-learning techniques	Users (Users No. are not mentioned)	The paper introduces a model for searching, selecting, and rating learning objects (LOs) in user groups. This model was tested within the DELPHOS hybrid recommendation system. The evaluation of 11 rating aggregation methods using Top-1 Frequency and Average Ranking measures revealed that the Average method performed the best when considering data from all groups. This finding suggests that the Average method is effective for aggregating ratings and can contribute to improving the recommendation system's performance. In the experiment conducted by the authors, the AGORA repository was used exclusively for testing purposes, meaning that only LOs from this repository were searched. However, DELPHOS, the hybrid recommendation system, allows for expanded search capabilities through federated search with other repositories. It is important to note that the compressibility and acceptability of group recommendations pose limitations. Currently, DELPHOS does not explain how the best aggregation strategy is utilized to generate the final rating.
[48]	Group-based recommendation methodology meta-learning techniques	Learners (Users No. are not mentioned)	Teacher-oriented educational resource recommender system suggests learning materials based on pedagogical aims. The abundance of educational resources has resulted in information overload, and digitization and multimedia have created new means to transmit knowledge in the teaching and learning process. The usage of big data has pushed data analysis from the expert to the user level.
[64]	Group-Based Trust Model, Hybrid Personal Trust (HPT) Model, Machine Learning	Users (Users No. are not mentioned)	Demonstrated through experiments that the method outperforms other trust-based recommendation methods, enhancing prediction accuracy and recommendation quality. Updating the trust model to account for changing team dynamics and user interactions.

Real-time Feedback and Intervention**:** The Neurosky EEG Biosensor can offer real-time feedback to both students and educators. If a student's brainwave patterns indicate a decreased level of focus or engagement, educators can intervene with appropriate strategies to re-engage the student and optimize their learning experience.

Improving Study Habits and Stress Management**:** EEG-based insights can help students understand their cognitive processes and stress levels. With this self-awareness, students can develop effective study habits, stress management techniques, and mindfulness practices tailored to their needs and cognitive states.

Personalized Recommendations**:** The data collected from the Neurosky EEG Biosensor can contribute to building a personalized recommendation system for education. This system could suggest learning materials, study techniques, and resources based on an individual student's cognitive patterns, helping them achieve optimal learning outcomes.

The Neurosky EEG Biosensor has the potential to revolutionize student education by providing real-time insights into cognitive states and enabling personalized learning experiences [72]. It can enhance engagement, optimize content delivery, and contribute to the improvement of more effective and efficient educational strategies.

B. AI-DRIVEN APPLICATIONS

AI-driven technology has the potential to reform the education sector by providing personalized and adaptive learning experiences for students, automating administrative tasks and improving educational outcomes. The development of AI technologies for education is rapidly expanding and shows no signs of slowing down. As we look forward to the potential of AI in education, it's important to ensure that these tools are crafted with thoughtfulness and purpose. If AI to have a positive and useful impact on students' learning and engagement in classrooms [73]. Figure 3 shows here are some of how AI-driven technology can be important for education:

Intelligent tutoring system: It is a computer program that provides personalized instruction or feedback to students based on their individual needs and progress.

Automated grading and assessment**:** A system automatically grades and assesses student work such as assignments, quizzes and tests or exams. The system can use some techniques such as machine learning (ML) and natural language processing (NLP) to analyze student responses and provide feedback.

Chatbots and virtual assistants: In the context of a student education recommendation system, chatbots and virtual assistants can provide personalized assistance to students such as answering questions, providing feedback, and suggesting learning resources.

Curriculum planning: It is the process of designing a course of study for students. In the context of a student education recommendation system, curriculum planning can be automated ML algorithms that analyze student data to identify the most effective sequence of learning activities.

Content recommendations: It is a system that recommends learning a variety of resources such as books, videos, and articles based on student preferences and learning goals. The system can use two techniques such as collaborative filtering and content-based filtering to suggest relevant resources.

Language learning: It is the process of acquiring a new language. In the context of a student education recommendation system, language learning can be facilitated using personalized instruction, feedback, and resources tailored to the student's level, interests, and goals as described in Figure 3.

C. AI-POWERED VIRTUAL PROCTORING

AI-powered Virtual Proctoring offers several benefits to students in education, enhancing the learning experience and providing personalized support. Here's how AI-powered Virtual Proctoring can help identify the students are physically present or not when they are attending the classes and writing the exams. The approach integrates various technologies to create a comprehensive system for test monitoring without the need for physical proctoring. By utilizing a multi-modal system that combines video capture from webcams with active window capture, you've established a method to observe the test environment and the test taker's actions. Key elements such as facial recognition and emotion analysis provide insights into the test taker's state of mind, allowing for the anticipation of emotions that could hint at potential malpractice

Detection of external elements like phones, books, or the presence of another person adds another layer to this system, allowing for the identification of potential cheating indicators. The amalgamation of these models into an intelligent, rule-based inference system enhances the capability to identify instances of malpractice or suspicious behaviour during an examination. This approach presents a promising strategy to maintain test integrity without the necessity of physical proctoring. [74].

AI-driven tools and technologies possess the potential to overhaul the educational landscape, spanning from tailored learning experiences to automated grading and assessment. Through the analysis of student behaviors, learning preferences, and performance metrics, AI aids educators in delivering instruction that is not only more effective but also more efficient, resulting in enhanced learning outcomes and heightened student contentment. Additionally, AI can revolutionize educational research and analytics by enabling researchers to swiftly and accurately gather and analyze vast quantities of data, surpassing previous capabilities. This can provide valuable insights into student learning, teacher effectiveness and overall Learning efficiency [75].

AI holds significant potential in enhancing educational performance, particularly in analyzing student learning outcomes. Through AI-powered algorithms, data on student behaviour, such as task duration, challenging question types, and learning material interactions, can be collected. This information allows for the identification of patterns that inform the refinement of teaching methodologies and curriculum design. Moreover, AI can elevate teacher performance by analyzing teacher-student interactions and student outcomes, offering insights into effective teaching methods and areas necessitating further support. This empowers educational institutions to tailor professional development programs to meet specific teacher needs. Additionally, AI aids educational research by analyzing data from online learning platforms, leveraging the wealth of information available on student engagement and the efficacy of online materials. This analysis can pinpoint the most effective resources for diverse learner profiles and suggest optimizations to improve overall student outcomes.

1) ADVANTAGES

Secure and Convenient Assessments: AI-powered Virtual Proctoring ensures the integrity of online assessments by detecting and preventing cheating behaviours. It monitors students during exams, using facial recognition and behaviour analysis to identify suspicious activities [78]. This creates a secure and controlled testing environment while allowing students to take exams conveniently from their own locations.

Flexibility and Accessibility: Virtual Proctoring allows students to take exams remotely, providing flexibility for those who may have scheduling constraints or are unable to physically attend an exam location. This accessibility promotes inclusivity and accommodates diverse student needs.

Reduced Stress: Traditional in-person proctoring can create stress and anxiety for some students. AI-powered Virtual

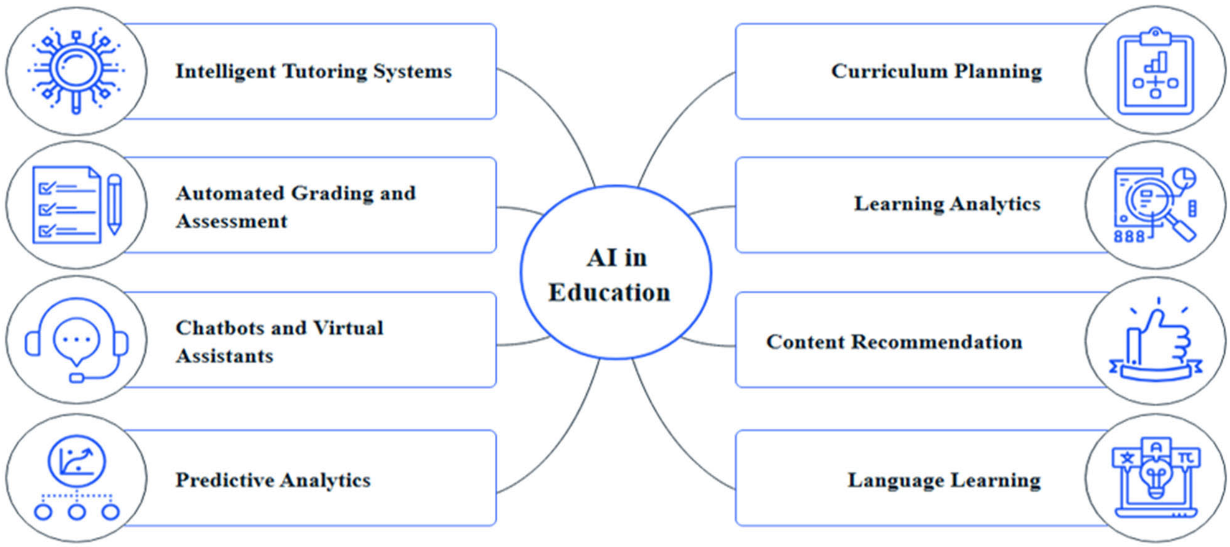

FIGURE 3. Benefits of AI in education.

Proctoring offers a less intrusive and more relaxed exam environment, potentially leading to better test performance.

Immediate Feedback: Some AI-powered proctoring systems provide real-time feedback during exams, alerting students if they engage in behaviours that could be flagged as cheating. This instant feedback helps students correct unintentional actions and maintain test integrity.

Privacy and Data Security: Virtual Proctoring systems often prioritize student privacy and data security. They are designed to comply with data protection regulations and ensure that student information remains confidential.

Customized Learning Paths**:** AI-powered systems can analyse student performance data to identify strengths and weaknesses. This info can be used to recommend targeted learning resources and materials, helping students focus their efforts on areas that need improvement.

Individualized Support**:** Virtual Proctoring systems can track students' interactions and behaviours during exams, enabling educators to offer personalized guidance and support based on their performance. This tailored feedback helps students enhance their understanding and skills.

Adaptive Assessments**:** AI-powered systems can analyse student responses and adapt the difficulty of questions based on their performance. This ensures that students are challenged appropriately and provides a more accurate assessment of their knowledge and skills.

Efficient Grading and Feedback: AI-powered systems can automate the grading process, providing faster and more consistent evaluation of assignments and exams. This efficiency allows educators to focus on providing detailed feedback to support student learning.

AI-powered Virtual Proctoring is indeed revolutionizing the assessment process in education. By utilizing AI technologies such as personalized or individual learning, smart tutoring systems, NLP (natural language processing), gamification and automatic grading, educational universities or institutions can offer students a more tailored and engaging learning experience. This personalized support enhances student understanding and retention of the material, ultimately helping them achieve their educational goals. Moreover, AI-powered Virtual Proctoring ensures a secure and convenient testing environment. It enables remote proctoring, eliminating the need for physical test centers and allowing students to take exams from anywhere at any time. This flexibility benefits students who may have scheduling conflicts or geographical limitations. Additionally, AI can alleviate the load of teaching faculties and instructors, enabling them to focus on mentoring and guiding students. Automated grading systems save time and effort, providing prompt feedback to students while reducing manual grading tasks for educators.

Overall, AI-powered Virtual Proctoring is transforming education by promoting individualized learning, improving assessment processes, and empowering both students and teachers.

Strengths: AI-powered virtual proctoring provides remote monitoring and supervision during online exams or assessments. It uses AI algorithms to detect suspicious behavior, plagiarism, or cheating attempts, ensuring exam integrity.

Characteristics: AI-powered virtual proctoring utilizes techniques like facial recognition, gaze tracking, and behavioral analysis to identify irregularities and potential violations.

Scope of Application: AI-powered virtual proctoring is primarily used in online education, remote learning, and certification programs that require secure and monitored assessments.

Limitations and Implementation Challenges: Challenges may include privacy concerns related to the collection and storage of biometric data, false positives or negatives in behavior detection, and the need for reliable internet connectivity and robust algorithmic models.

D. ALTER EGO

AlterEgo, a novel technology developed at the MIT Media Lab, holds promising potential for personalized learning in education. By allowing users to communicate and interact with computers using their internal speech mechanisms, this peripheral neural interface enables natural language communication between humans and machines, artificial intelligence (AI) assistants, services, and even other people, all without the need for audible speech or observable movements. The device allows users to articulate words internally and the feedback is provided through audio using bone conduction, creating a closed-loop interface that maintains the user's usual auditory perception. One of the key features of AlterEgo is its ability to capture and interpret neural signals generated by internal speech articulators when a user silently vocalizes words or phrases. These signals, derived from neuromuscular activity in the lower face and neck, are processed by the device to reconstruct the user's intended speech see in Figure 4. This approach enables a discreet and seamless conversation between the user and a computing device, AI assistants or other communication targets [76].

The primary goal of AlterEgo is to support communication, particularly for individuals with speech disorders such as ALS (amyotrophic lateral sclerosis) and MS (multiple sclerosis). Beyond aiding individuals with speech impairments, AlterEgo holds the potential to transform human-computer interaction. By allowing users to interface naturally with computers and technology, it aims to make computing, the internet, and AI an integrated part of daily life—a "second self" that augments cognition and abilities. AlterEgo operates based on silent speech, which involves subtle neuro-muscular movements of internal speech organs without actually vocalizing words. Users can communicate with the system internally, sending and receiving information without overt actions or observable behaviour. The device reads and processes the neural signals associated with silent speech and provides auditory output through bone-conduction headphones, facilitating seamless interaction. The AlterEgo system consists of several components, including a peripheral interface for capturing silent speech input, hardware and software for processing electrophysiological signals, an intelligent system for generating responses, and bone conduction output for audio information delivery. It will not put any pressure on students however, to address concerns about potential pressure from monitoring technologies like Alter Ego, it's important to implement balanced and supportive monitoring, prioritize student well-being, uphold ethical standards, and involve students in decision-making. Open communication, education about the benefits, and student participation can help minimize negative impacts and empower students within the learning environment [77].

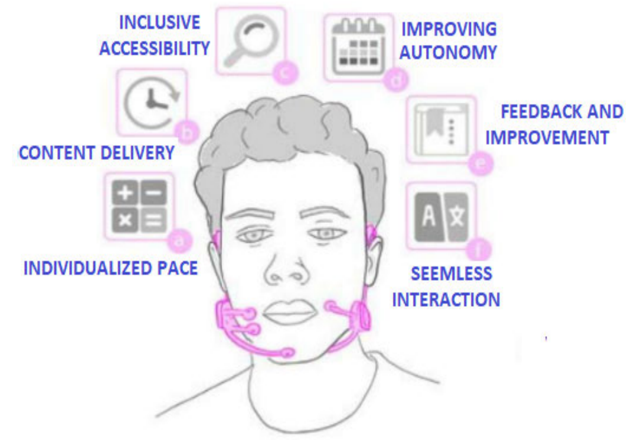

FIGURE 4. AlterEgo for speak without words.

1) ALTEREGO OFFERS SEVERAL ADVANTAGES THAT CAN ENHANCE PERSONALIZED LEARNING EXPERIENCES

Seamless Interaction: AlterEgo enables students to interact with educational content and resources using their internal thoughts and speech, eliminating the need for physical input devices like keyboards or touchscreens. This seamless interaction can enhance the accessibility and convenience of personalized learning materials.

Personalized Content Delivery: The technology's ability to detect and interpret internal speech allows it to understand a student's preferences, interests, and learning needs. This info can be used to deliver tailored educational content, resources, and exercises that align with each student's learning style and pace.

Adaptive Learning by Alter Ego**:** AlterEgo's real-time monitoring of students' cognitive responses can help educators gauge their comprehension and engagement levels. This info can be used to adapt learning materials on-the-fly, providing additional explanations or challenges based on the student's cognitive state [77].

Enhanced Engagement: By enabling students to interconnect with the educational system using their thoughts, AlterEgo can make a more immersive and engaging learning environment. This engagement can lead to increased motivation and active participation in the learning process and is also helpful in getting information about student interests.

Individualized Pace: Just as personalized learning allows students to learn at their own pace, AlterEgo can support this approach by adjusting the delivery of content based on a student's cognitive responses. This ensures that each student can progress comfortably and confidently through their learning journey.

Feedback and Improvement: AlterEgo's ability to track cognitive responses provides valuable data that educators can

Feedback and Improvement: AlterEgo's ability to track cognitive responses provides valuable data that educators can use to assess students' progress and areas of development. This feedback loop allows for the continuous refinement of personalized learning strategies.

Inclusive Accessibility: For students with physical disabilities or challenges that limit their use of traditional input methods, AlterEgo offers an inclusive and accessible way to engage with educational content. It breaks down barriers and provides equal opportunities for all students to participate in personalized learning.

Empowering Autonomy: Personalized learning with AlterEgo empowers students to take control of their learning experiences. They can actively navigate through learning materials, ask questions, and explore subjects of interest using their own thoughts and speech. Incorporating AlterEgo into educational settings can revolutionize the way students interact with learning materials and educators.

By binding the power of internal speech and cognitive responses, this technology has the potential to create truly personalized and engaging learning environments that cater to the unique needs and preferences of each student as depicted in Figure 4.

Strengths: Alter Ego is a technology that enables communication and interaction between humans and machines by interpreting internal speech and muscle signals. It provides a hands-free and seamless interface for controlling devices or accessing information.

Characteristics: Alter Ego uses electrodes or sensors to detect neuromuscular signals and interpret them into commands or responses.

Scope of Application: Alter Ego has potential applications in areas such as human-computer interaction, assistive technologies for individuals with physical disabilities, and augmented reality/virtual reality (AR/VR) interfaces.

Limitations and Implementation Challenges: Challenges may include the accuracy and reliability of interpreting internal speech and muscle signals, user training and adaptation, and the need for lightweight, non-intrusive wearable devices.

E. FLUXY AI

Fluxy AI is an innovative platform designed to improve learning capabilities by providing students with the tools they want to excel in their studies. With Fluxy AI, students can access a range of features that make learning more convenient, efficient, and engaging. Fluxy offers personalized learning tailored to their needs. It understands students or their strengths and weaknesses, then provides targeted assistance to help them overcome challenges and build on their strengths. It adapts its explanations and examples to match the learning style, ensuring that students grasp the concepts effectively. With FluxyAI's scientifically proven personalized learning approach, they will have a deeper understanding of concepts. A better understanding of concepts translates to a higher retention rate, which in turn leads to improved overall scores in all their exams. Pedagogy has to change with every new technology. Modern technology, when combined with new approaches, results in innovative ways of learning. Incorporate FluxyAI [78] into daily traditional learning approaches to enhance their creativity through cross-referencing learning from one subject to another.

Learn anytime and anywhere. There are no fixed schedules, learn at their own pace and convenience and get insights across various subjects and disciplines. Explore topics beyond traditional education settings and learn anything to become a subject matter expert. Fluxy provides instant responses. Receive real-time clarification on concepts, problems, and guidance. Fluxy is helpful in adapting to a personalized learning style. It provides tailored explanations, examples, and resources. Hence enhancing students' understanding and retention in an exam. In addition to traditional subjects, Fluxy also offers language learning, guidance on essay writing, interview preparation, scholarship SOP (Sscholarship Statement of Purpose) writing and much more.

Key features and benefits of Fluxy AI include:

Cheaper Learning: Fluxy AI offers an affordable learning solution compared to traditional paid tuition. This makes quality education accessible to a broader audience.

Flexible Learning: Students can learn anytime and anywhere, as Fluxy AI does not adhere to fixed schedules. This flexibility accommodates various learning preferences and lifestyles.

Comprehensive Subjects: Fluxy AI covers a wide range of subjects and disciplines, permitting students to explore topics beyond traditional education settings. This promotes holistic learning and expertise development.

24/7 Availability: Fluxy AI provides instant responses and real-time clarification on concepts and problems. Whether they're an early riser or a night owl, Fluxy AI is available around the clock to support learning.

Personalized Learning: Fluxy AI adapts to each student's learning style, offering tailored explanations, examples, and resources. This personalized approach enhances effective understanding and retention of overall knowledge.

Safe and Non-Judgmental Environment: Fluxy AI creates a safe space for students to learn without judgment. Students can ask questions without hesitation and receive the provision they want to succeed.

Interactive Chat Environment: Students can learn through an interactive chat environment, engaging in conversations and discussions to enhance their understanding of various subjects.

Additional Learning Opportunities**:** Beyond traditional subjects, Fluxy AI offers language learning, guidance on essay writing, interview preparation, and even assistance with scholarship Statement of Purpose (SOP) writing.

Fluxy AI aims to revolutionize the way students learn by leveraging advanced technologies to provide accessible, engaging, and effective educational experiences. With its user-friendly interface, personalized learning approach, and diverse learning opportunities, Fluxy AI [78] has the probable to shape the future of education and empower students to achieve their academic goals. Fluxy combines human creativity with AI brilliance to help them learn better. Fluxy AI offers a range of strengths that make it a valuable tool for personalized language learning. Its use of artificial intelligence and machine learning algorithms enables it to provide customized learning experiences by tailoring content, feedback, and interactive exercises to individual learners. By analyzing learner data, Fluxy AI can track progress effectively and adapt recommendations to suit learners' proficiency levels and specific needs. This personalized approach enhances language learning outcomes by addressing learners' unique strengths and weaknesses. Fluxy AI's application is versatile, making it suitable for integration into self-study platforms, online language courses, and language tutoring programs.

However, Fluxy AI does have a few limitations and implementation challenges to consider. Ensuring the accuracy of language comprehension and recommendations can be a challenge, as language learning involves nuanced understanding and interpretation. Fluxy AI must account for the diverse preferences and learning styles of its users to provide truly personalized experiences. Additionally, data privacy and security are important considerations, as Fluxy AI relies on collecting and analyzing learner data. Overcoming these limitations and addressing implementation challenges will be crucial to maximizing the effectiveness and user satisfaction of Fluxy AI in language learning contexts

F. TWIN TECHNOLOGY FOR ORGANIZATIONAL ENHANCEMENT

Digital Twin technology is indeed a promising tool for enhancing education. Its virtual representation of physical products or processes can provide innovative and engaging learning experiences for students. The use of DT can start from curriculum design and extend to various aspects of teaching and learning. It can help keep content up-to-date and create useful simulation models based on course requirements. Simulation-based learning has been shown to increase motivation, self-responsibility for learning, facilitate peer learning, and improve overall learning activity. From the teacher's perspective, DT can enhance content delivery, improve the use of technology for teaching, ease demonstration, and assist in student assessment [79]. Additionally, it can help recreate the communal classroom experience with more improvised classroom engagements. In the context of education, Digital Twin technology can revolutionize the learning environment in several ways as described in Figure 5.

Hybrid Classrooms and Lifelong Learning: Digital Twin technology supports the concept of "Hybrid classrooms," where students have lifelong access to new knowledge and skills. This technology facilitates continuous learning and knowledge acquisition, enabling students to engage with educational content beyond traditional classroom settings.

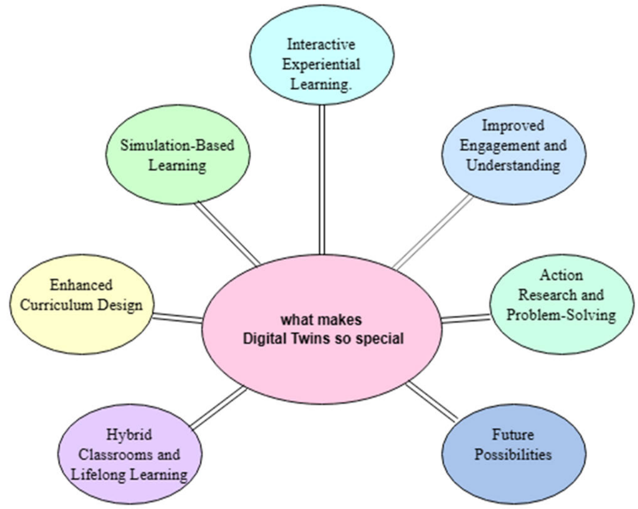

FIGURE 5. Benefits of digital twins in education.

Enhanced Curriculum Design: Educators can leverage Digital Twin technology in curriculum design to ensure up-to-date content and create simulation models based on course requirements.

This approach enhances curriculum relevance and allows students to interact with real-world scenarios, making learning more engaging and applicable. In the context of education, Digital Twin technology can revolutionize the learning environment in several ways as described in Figure 5.

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Enhanced Curriculum Design: Educators can leverage Digital Twin technology in curriculum design to ensure up-to-date content and create simulation models based on course requirements. This dynamic approach enhances curriculum relevance and allows students to interact with real-world scenarios, making learning more engaging and applicable.

Simulation-Based Learning: Digital Twin technology enables simulation-based learning, where students can explore and interact with virtual models of systems, processes, and equipment. This hands-on approach increases motivation, self-responsibility for learning, peer collaboration, and overall learning activity.

Interactive Experiential Learning: Digital Twins facilitate interactive and experiential learning experiences. Students can engage with virtual representations of complex systems, exploring their behaviour and limitations under various conditions. This approach helps students understand system dynamics, failure modes, and sensitivities in a controlled and engaging environment.

Improved Engagement and Understanding: Through Digital Twins, students can bridge the gap between the digital and physical worlds, gaining timely access to real-time data from physical systems. This technology helps students explore and understand system behaviour, answer queries, and comprehend failure modes more effectively, resulting in enhanced classroom engagement and learning outcomes.

Action Research and Problem-Solving: Digital Twins support action research by allowing students to simulate system behaviour under various conditions. This enables students to identify failure modes, test hypotheses, and develop solutions in a risk-free environment. By manipulating virtual representations, students can gain insights into system sensitivities and optimize system performance.

Future Possibilities: As the future of education evolves, Digital Twin technology holds the potential to transform traditional teaching methodologies into more interactive and experiential learning processes.

Incorporating Digital Twin technology into education can bridge the gap between theoretical concepts and practical applications, offering students a unique and immersive learning experience that enhances their understanding, critical thinking skills, and overall educational journey [79].

Strengths: Twin technology, also known as digital twins, enables the creation of virtual representations of physical objects or systems, allowing for real-time monitoring, analysis, and optimization. Its strengths lie in its ability to enhance predictive maintenance, improve operational efficiency, and support decision-making processes.

Characteristics: Twin technology integrates IoT (Internet of Things) devices, data analytics, and simulation models to create virtual replicas that mirror the behavior and performance of physical assets or systems.

Scope of Application: Twin technology finds applications in various industries, including manufacturing, healthcare, transportation, and energy, for tasks such as predictive maintenance, process optimization, and simulation-based training.

Limitations and Implementation Challenges: Challenges may include data integration and synchronization, model accuracy, scalability, and the need for comprehensive and accurate real-time data collection.

G. RFID AND NFC TECHNOLOGY

RFID (Radio Frequency Identification) and NFC (Near-Field Communication) technologies offer several benefits that can significantly enhance the educational experience for students. These technologies can be adopted into educational institutions' systems and processes to streamline various tasks and provide a more efficient and secure learning environs. Here, proposed some ways in which RFID and NFC technology [80] can be helpful for students' education.

Automated Attendance Tracking: RFID chips or NFC tags can be embedded in students' ID cards, enabling automated attendance tracking. An RFID reader placed at the entrance of a classroom or school can instantly record students' presence as they enter. This reduce the need of manual attendance taking and ensures accurate attendance records. Teachers can focus more on teaching, and students can use their time more effectively.

Enhanced Security: RFID-embedded ID cards or NFC tags can be used to track students' movement within the campus. This ensures greater security and safety for students, as parents and school administrators can monitor their whereabouts. In case of any unusual activity, alerts can be sent to parents, providing them with peace of mind and an increased sense of comfort regarding their child's safety.

Efficient Library Management: Libraries can benefit from RFID and NFC technology by incorporating it into book checkout systems. Students can use their ID cards or NFC-enabled devices to check out books seamlessly. RFID/NFC-enabled library systems help track book availability, overdue books, and prevent theft. This technology streamlines the process of borrowing and returning books, making it more convenient for students and library staff.

Interactive Learning Materials: NFC technology can be combined into teaching and study materials, allowing students to access additional digital content, such as videos, interactive quizzes, and online resources. By simply tapping their NFC-enabled devices on designated tags, students can access supplementary learning materials that complement their studies and provide a more engaging learning experience.

Real-time Communication with Parents: NFC-enabled devices can facilitate real-time communication between schools and parents. Schools can use NFC tags to share important announcements, event details, and academic progress with parents. This direct communication channel helps parents stay informed and engaged in their child's education.

Mobile Learning Enhancements: NFC technology can enable seamless resource sharing between mobile devices and digital displays within the classroom. Students can tap their NFC-enabled devices to access presentations, assignments, and learning materials, promoting interactive and collaborative learning experiences. Incorporating RFID and NFC technology into education can lead to increased efficiency, enhanced security and improved engagement for students. These technologies have the potential to transform traditional educational processes and create a more dynamic and interactive learning environment as shown in Figure 6.

V. PRE-DEFINED RESULTS AND ADVANTAGES OF ENHANCING THE PERSONALIZED RECOMMENDATION SYSTEM WITH DIGITAL TECHNOLOGIES

The integration of transformative technologies into the conventional educational system has the potential to revolutionize personalized recommendation systems. By incorporating

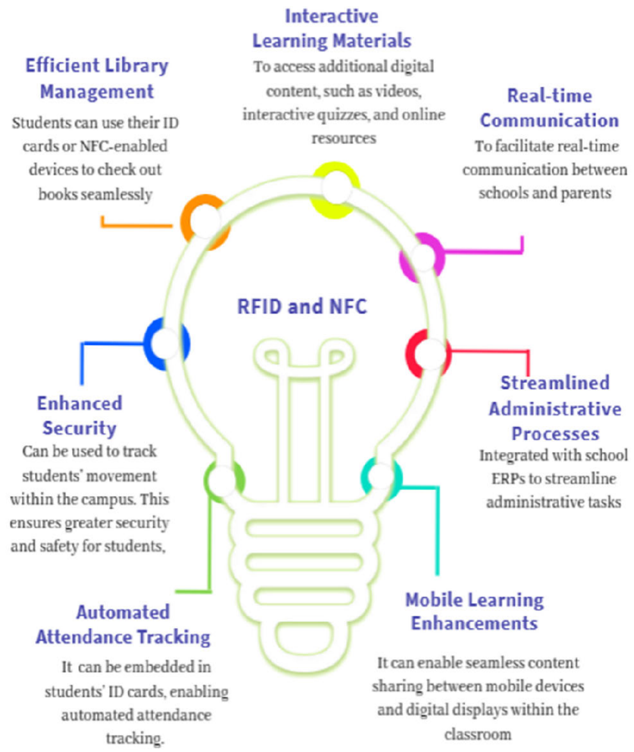

FIGURE 6. Benefits of RFID and NFC technology.

adaptive new technologies see in figure 7 such as the Neurosky EEG Biosensor, AI-driven chatbots, AI-powered Virtual Proctoring, AI-enabled cameras and sensors, Fluxy AI, Alter Ego, Twin Technology, RFID, and NFC Technology, the educational landscape can experience a paradigm shift that benefits both students and educators.

Effective Personalized Learning Experiences: The integration of these technologies enables the creation of dynamic and interactive sessions of live with one-to-one guidance or teaching for effective learning environments that adapt to the unique learning styles and paces of individual students. These technologies gather data on students' behaviors', preferences, and progress, allowing the recommendation system to tailor learning content, resources, and activities to each student's needs.

Personalized Learning Paths: The data collected from the Neurosky EEG Biosensor can be utilized to generate personalized learning paths for individual students. By identifying the cognitive strengths and weaknesses of each student, educators can tailor educational materials and activities to match their favored learning styles and optimize their academic progress.

Fully Enhanced Student Engagement: The use of AI-powered catboats and interactive technologies like Fluxy AI and Alter Ego fosters higher levels of student engagement. These tools provide real-time feedback, answer questions, and facilitate interactive learning experiences, keeping students actively involved in their education.

Individualized Support: AI-powered Virtual Proctoring and AI-enabled cameras and sensors can monitor student performance and behaviour, finding areas where learners might struggle or need additional guidance to ensure student success. This data-driven approach allows educators to provide targeted interventions and support.

Data-Driven Insights: The integration of these technologies generates vast quantities of data related to student behaviours, preferences, and progress. Advanced analytics and machine learning can process this data to provide visions of student-perfect learning patterns, enabling educators to make cognizant choices about instructional strategies and curriculum design.

Privacy and Data Security: Virtual Proctoring systems often prioritize student privacy and data security. They are designed to fulfil data safety and ensure that student information remains confidential.

Improved Learning Outcomes: Personalized learning experiences that cater to students' unique needs and preferences result in improved learning outcomes. Students are more likely to be motivated and achieve mastery when learning content arranged in line with their student's interests and abilities [82].

Efficient Teacher Guidance: AI-driven systems provide educators with real-time data on student progress, enabling them to identify struggling students early and offer targeted assistance. This leads to more efficient use of teacher time and resources.

Personalized Learning: The system tailors educational content and interactions based on individual cognitive states, preferences, and learning needs.

Continuous Improvement: AI algorithms analyze user interactions to refine recommendations and learning pathways.

This innovative personalized education recommendation system combines cutting-edge technologies to create a holistic and adaptive learning experience for students. The system leverages NeuroSky EEG, Fluxy AI, RFID and NFC, AlterEgo, AI Chatbots, Virtual Proctoring and Twin Technology to tailor educational content and interactions based on individual cognitive states, preferences and learning needs. All these components work together to create an enhanced comprehensive personalized education recommendation system that takes into account each student's unique needs, preferences and learning styles, learning paths and knowledge improvement from the basics and it works like 360 angles to students' and teachers' perspectives. Certainly! In the context of personalized recommendation systems in education, the integration of machine learning (ML) [75] methods holds significant promise for addressing future needs. ML-based approaches can offer advanced capabilities for analyzing learner behaviour, content relevance, and learning patterns to generate more accurate and personalized recommendations. These methods can include collaborative filtering, matrix factorization, deep learning, and reinforce-

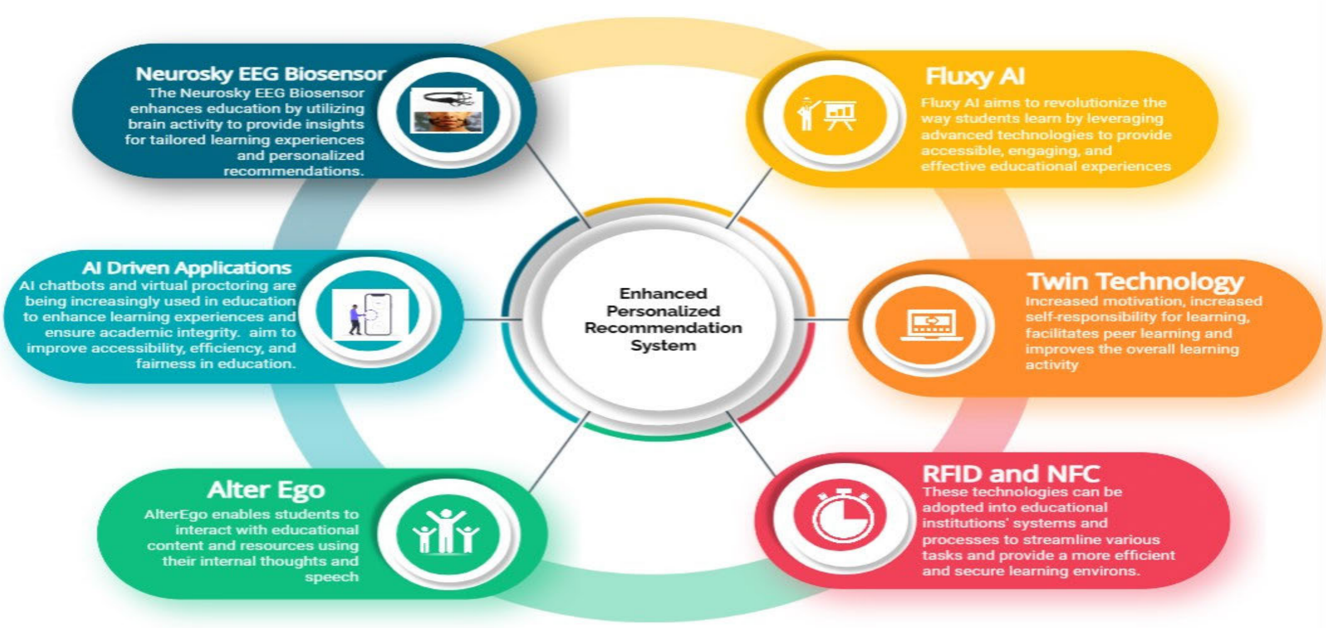

FIGURE 7. Digital technologies for enhancing personalized recommendation system.

ment learning techniques to model complex relationships and user preferences.

Additionally, the future of ML-based recommendation systems in education may involve the incorporation of natural language processing (NLP) to understand and process textual data from educational resources and learner interactions. This could enable the system to provide more context-aware recommendations and support for language-related challenges. The article ensured rigor and reliability in sampling and data analysis through methods like feedback surveys, sentiment analysis refinement, and incorporating multimedia elements into recommended resources.

Furthermore, the use of ML algorithms for adaptive learning can enable the system to dynamically adjust recommendations based on real-time user interactions and performance, creating a more responsive and personalized learning experience. The future of ML-based recommendation systems in education is poised to leverage advanced algorithms and data-driven insights to enhance personalization, adaptability, and effectiveness in supporting diverse learning needs.

When evaluating new technologies in education, considering their sustainability and scalability is crucial. Key considerations include cost-effectiveness, ease of implementation, scope of applicability, future directions, and policy and institutional support. By assessing these factors, educational institutions and policymakers can make informed decisions to adopt technologies that are effective, sustainable, and scalable in the long term, ensuring improvements in educational outcomes and ongoing adjustments to enhance their impact.

User participation and feedback mechanisms are crucial for the successful implementation of personalized recommender systems to adopt a user-centric approach by engaging users in the design process and incorporating their feedback. Implement mechanisms for user profiling and preferences, allowing users to specify their learning goals and interests. Provide diverse feedback channels for users to share their experiences and suggestions, enabling continuous iteration and improvement of the system based on user input. Ensure transparent and explainable recommendations, empower users to customize their preferences, and foster collaboration through community-building features like discussion forums and peer-to-peer interaction platforms. By following these principles, the system can better meet the needs and expectations of students and teachers, enhancing user satisfaction and engagement.

VI. CONCLUSION

The integration of adaptive new technologies into the personalized recommendation system within educational institutions offers a range of transformative results and advantages. Students benefit from personalized learning experiences, increased engagement, and improved learning outcomes, while educators gain insights to provide effective guidance and support. This approach modernizes education, preparing students and educators to excel in a technologically-evolving world. It creates Digitalized era in the education system. Considering all the pre-defined benefits and results we need to design a Personalized Education Recommendation System, Integrating with NeuroSky EEG, Fluxy AI, RFID and NFC, AlterEgo, AI Chatbots, Virtual Proctoring, and Twin Technology. In future, need to introduce this comprehensive digital personalized education recommendation system that transforms traditional learning paradigms by harnessing the power of advanced digital technologies to create adaptive, engaging, and effective learning experiences for student center learning in conventional organizations.

CONFLICTS OF INTEREST

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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DHANANJAYA. G. M. received the bachelor's and master's degrees in computer science and engineering from Visvesvaraya Technological University, Belagavi, Karnataka, India, where he is currently pursuing the Ph.D. degree in computer science and engineering. With six years of teaching experience in engineering education, he focuses his research on personalized learning environments in engineering education. His areas of expertise include data mining, data warehouse, big data, cloud computing, agile technology, advanced database management systems, information retrieval, research methodology, and personalized learning recommendation systems. He is an Active Lifetime Member of IFERP (Membership ID No: PM14396728) and a member of the non-profit International Association of Engineers (Member No.: 314882).

R. H. GOUDAR received the B.E. degree in computer science and engineering, the M.Tech. degree in computer network engineering, and the Ph.D. degree in computer science and engineering. He is currently an Associate Professor with the Department of Computer Science and Engineering, Visvesvaraya Technological University, Belagavi. He has 19 years of teaching experience with professional institutes across India. He was a Faculty Member of the International Institute of Information Technology, Pune, for four years; and the Indian National Satellite Master Control Facility, Hassan, India. He has published more than 150 papers in international journals, book chapters, and conferences of high reputation. His research interests include the semantic web, cloud computing, big data, machine learning, and deep learning and its applications. He has received various awards, such as the Outstanding Faculty Award, the Research Performance Award, the Young Research Scientist Award from VGST Karnataka, and the Eminent Engineer Award from the Honorable Chief Minister of Karnataka.

ANJANABHARGAVI A. KULKARNI received the B.E. and M.Tech. degrees in computer science and engineering from Visvesvaraya Technological University, Belagavi, Karnataka, India, in 2012 and 2018, respectively, where she is currently pursuing the Ph.D. degree in CSE with the Department of Computer Science and Engineering. She is also a Research Scholar with Visvesvaraya Technological University.

VIJAYALAXMI N. RATHOD received the B.E. degree in information science and engineering and the M.Tech. degree in computer science and engineering from Visvesvaraya Technological University, Belagavi. She is currently a Research Scholar with the Department of Computer Science and Engineering, Visvesvaraya Technological University. Her research interests include image processing and big data, cloud computing, pattern recognition, information retrieval, and machine learning.

GEETABAI S. HUKKERI received the Ph.D. degree in computer science and engineering from Visvesvaraya Technological University, Belagavi, India. She is an Assistant Professor with the Department of Computer Science and Engineering, Manipal Institute of Technology Bengaluru, India. She has published several papers in international journals and international conferences and international book chapters. She has published a book on *Understanding Big Data Technologies—A Simple Approach*. Her research interests include artificial intelligence, deep learning, machine learning, big data, computer vision, computer networks, and multimedia information retrieval. She is a member of ACM.