Enhancing Personalized Learning and Sustainable Education using AI: A systematic review

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Abstract

The integration of artificial intelligence (AI) into education represents a paradigm shift, transforming traditional teaching and learning practices. AI technologies, such as adaptive learning systems, automated assessments, and intelligent tutoring, offer unprecedented opportunities for enhancing educational outcomes. However, despite its promise, the education sector faces challenges, including inefficiencies, skill gaps, and the persistent issue of low literacy rates, which require innovative solutions. Indeed, AI tools is used in education to enhance critical thinking and problem-solving skills among students, to automate routine tasks, enabling educators to focus on pedagogy, to identify areas for improvement through advanced analytics, to feature engineering refines datasets and to enhance the performance of predictive models. Previous research highlights the effectiveness of machine learning algorithms in educational contexts. However, challenges like data biases, algorithmic fairness, and ethical considerations must be addressed to maximize AI's potential in education. This paper provides a comprehensive overview of the use of artificial intelligence (AI) in education, exploring its transformative potential to enhance teaching and learning processes. It delves into various applications of AI, such teaching and learning, Learning for the Sustainability of Education Management System, and Feature Engineering in Education which cater to individual student needs and learning styles. Furthermore, it addresses the challenges and ethical considerations associated with AI integration in education, including data privacy, algorithmic bias, and the digital divide. By analyzing current trends, potential benefits, and obstacles, this paper aims to provide educators, policymakers, and researchers with a holistic understanding of how AI is shaping the future of education and how it can be effectively leveraged to achieve equitable and high-quality learning outcomes.

Keywords: Artificial Intelligence, school curriculum, teaching and learning, Learning for the Sustainability of Education Management System, Feature Engineering in Education, Predictive Analytics

Introduction

In a world where ultra-personalization is becoming the rule and where mutualization is becoming the exception, one field seems even more exciting than the others, it is artificial intelligence in education. Indeed, digital education and artificial intelligence will profoundly change the way we teach. The enthusiasm that we are seeing today for their potential has nothing to do with a fashion effect. "With the rise of the Internet and mobile applications, innovations in educational digital technology have multiplied: virtual classes, exam preparation, MOOC (Massive Open Online Course) [1-3]. A technology that entered American universities about fifteen years ago and which is now among the most promising. The teachers know it well, to be effective, a teaching must be as personalized as possible.

But faced with a class of 30 students with different levels, they have neither the time nor the means to meet everyone's expectations. Hence the interest of resorting to platforms that offer each young person courses, exercises or assessments to be done online according to their pace and preferences [4]. If each adaptive learning platform has its own methodology, most often it all starts with a quiz-type positioning test. The student answers questions categorized according to their level of difficulty. Depending on his success rate, the algorithm submits a course adapted to his mastery of the subject, his speed of understanding. "If the student does not pass an exercise, the machine offers him others until the skill is acquired.

In education, AI makes it possible to automatically correct certain types of work, thus offering the possibility to teachers to invest this time in other pedagogical tasks. It is certain that the applications - especially available in English – that automatically correct dissertations are not yet developed, and that human intervention is still necessary, but the progress of automatic correction tools is surprising. It facilitates the continuous assessment of learners. The learning experiences created while using AI will make it possible to follow the learner through his entire learning journey, and to know with relative precision his degree of competence at a specific moment. AI can allow teachers to adjust certain parts of their lessons. This is what the Coursera10 platform has set up, a MOOC11 platform, which informs the teacher as soon as a large number of learners submit a wrong answer to a question or an assignment.

On the other hand, AI makes it possible to implement intelligent tutor systems in distance learning platforms. There are more and more distance learning platforms where smart tutors are used. In a context where this form of learning, increasingly mobile, occupies an important place in our society, this is a major advantage, both for learners and for trainers. It can transform the way we interact with information. For example, without always knowing it, Google adapts the results of a search according to our geolocation or our previous searches. Amazon does the same by offering purchases related to what has been purchased previously. Apple's Siri voice recognition system adapts to our needs and requests, etc. AI increases the possibilities of feedback for learners, as is the case with the UTIFEN platform where learners receive personalized text messages from the platform, related to their learning journey. With AI, feedback can not only be personalized, it can be faster, more frequent, etc. With AI we can facilitate the adaptation of learning content, as is the case with the digital books of the Pearson and McGraw-Hill publishing houses. AI makes it possible to increase the interactions between the learner and the learning content, in particular with chatbots, these communication interfaces between a human and a software. These chatbots, like speakers connected to the home (HomePod, Amazon Echo, Google Home), understand the user's language and are thus able to respond to them. In addition, AI can transform the teacher's work by leading him, for example, to play a role of facilitator instead of transmitter of content. But we must not be fooled: the role of teachers remains central to the school, and the use of AI only supports it in its complex task. AI can also facilitate homework help, personalized, related to the academic challenges faced by students. This would therefore be an important and necessary avenue to take for Hello prof12, a platform dedicated for more than 20 years to homework help. AI can facilitate the use of immersive technologies in education, such as virtual learning environments or virtual worlds. For example, the educational use of the Assassin's Creed game allows young people to learn history while living it (virtually), even by being the hero of historical events. Immersive technologies thus allow learners to live richer and more interactive experiences, which aims to directly promote their learning. This field can allow schools to prevent school dropout, especially on the basis of data already collected from students. AI then allows schools to be informed more quickly about students at risk and the latter would thus be able to provide them with the appropriate help, promptly, and this, before it is too late. AI can propel the popularity of distance learning even more, thus allowing learners to learn from anywhere, anytime, but also as part of tailor-made training. This is kind of what Duolingo brilliantly offers for language learning. With AI, several tasks that are considered important in education will be automated by intelligent systems; thus, humanoid robots will increasingly be present in classrooms, not to replace teachers as some Hollywood films might suggest, but rather to help the teacher in his task14, which is sometimes complex and time-consuming.

1. Applications of artificial intelligence in education

The education sector has long been a great field of promise for the uses of artificial intelligence. The full range of AI building blocks can be used in education: whether to process language, images, structured data or even simplified automated reasoning [5-7]. The anticipated applications often touch on the personalization of distance learning via intelligent conversational agents capable of following and accompanying students step by step in their progress. the potential applications of AI in training are quite numerous. Student support via a conversational agent, which presupposes a well-formalized educational environment in the agent. The latter should also have access to the student's personal history, know everything about him from his schooling and about his strengths and weaknesses. On elementary tasks, this kind of tool would lighten the task of teachers, allowing them to better play the role of mentor. These tools would also make it possible to accompany students outside of classes and in distance learning tools (MOOCs) to personalize teaching, the assimilation of skills and the success of tests. However, various recent studies have shown that students learning only via MOOCs performed worse than students taking face-to-face classes [8-10]. It analyzes the level and the way of learning of the students to offer them the appropriate content and at the right time, in order to promote memorization. It is used for continuing education and in higher education. Accompanying a class, allowing teachers to identify the strengths and weaknesses of a group of students, the well-assimilated or not parts of a course and their level of attention. Techniques using cameras and other sensors already make it possible to capture the general attention of an audience and to segment groups of individuals by behavior. This also makes it possible to adjust the course content because the attention also depends on the teacher's practices. This is part of the scope of American companies such as Content Technologies, which however does not target only the education sector, economic model obliges and Carnegie Learning which is focused on mathematics education in secondary and higher education. Based on the test results, machine learning-based solutions allow automatic classification of students into homogeneous groups.

2. Generative AI tools for enhancing teaching and learning

Generative artificial intelligence (GenAI) represents a transformative technology that uses deep learning models to create content, such as text, images, and speech, in response to user prompts. Recent advancements, including tools like ChatGPT, Sora, and Voice Engine, have expanded the potential applications of GenAI in education. Despite its promise, teachers face challenges in adopting these technologies due to limited professional development and a lack of supportive environments.

Authors of Ref. [11] investigate the acceptance of GenAI tools among primary and secondary school teachers in Hong Kong, employing an extended version of the Technology Acceptance Model (TAM) that incorporates self-efficacy (SE) and subjective norm (SN). Data from 367 teachers reveal that fostering SE, perceived usefulness (PU), and attitude toward use (ATT) is crucial for increasing behavioral intention (BI) to adopt GenAI tools. Policy recommendations and teacher development programs are proposed to enhance AI literacy and the meaningful integration of GenAI into K–12 education. In [11] a total of 367 primary and secondary school teachers from Hong Kong participated in the study. Demographic data reveal a diverse sample in terms of gender, age, education level, and school type. A structured questionnaire measured six constructs: SE, PU, PEU, ATT, SN, and BI. Items were rated on a 5-point Likert scale, with reliability and validity confirmed through exploratory and confirmatory factor analyses. Quantitative methods, including structural equation modeling (SEM), were employed to test the proposed model and hypotheses. Descriptive statistics, correlation analyses, and mediation tests further validated the relationships among constructs.

In [12], authors discuss the integration of digital technologies, including Artificial Intelligence, into teaching varies significantly across developing countries in the Global South due to diverse, context-specific factors such as teacher preparedness. Using the Theory of Planned Behavior (TPB) as a theoretical framework, this study investigates the behavioral intentions of pre-service science teachers in South Africa and Thailand toward integrating AI into their teaching practices. The research aims to inform teacher training, support mechanisms, and resource allocation policies. In [32] a non-experimental comparative descriptive survey was conducted involving 97 final-year Bachelor of Education (BEd) students from South Africa and 95 from Thailand. Data were collected through a structured online questionnaire designed to measure TPB constructs—attitudes, subjective norms, and perceived behavioral control—and were analyzed using descriptive and inferential statistical methods to compare trends between the two samples. The findings [32] revealed that both South African and Thai pre-service teachers demonstrated positive attitudes and intentions toward integrating AI into their teaching. However, Thai participants reported significantly higher perceived control and normative beliefs, suggesting stronger confidence in their ability to use AI and greater perceived social support for its adoption compared to their South African counterparts.

Authors of [13] investigate factors influencing teachers' motivation and engagement in leveraging GenAI for teaching and learning. Specifically, we examined contextual factors—such as in-school support for GenAI use, time pressure, and disruptive student behavior—as predictors of motivation (GenAI self-efficacy and GenAI valuing) and subsequent engagement (GenAI integration in teaching-related tasks and student learning activities) over one school term. Data were collected from 368 Australian primary and secondary school teachers. Results showed that in-school support for GenAI significantly predicted higher levels of GenAI self-efficacy and valuing. Interestingly, time pressure was also positively associated with greater GenAI valuing, whereas disruptive student behavior had no significant relationship with GenAI motivation or engagement variables. Furthermore, GenAI self-efficacy was a strong predictor of both types of GenAI integration, while GenAI valuing was specifically associated with integration in teaching-related work.

The work presented in [14] aimed to analyze students' behavioral intentions and actual academic use of communicational AI (CAI) as an educational tool. An integrated framework combining the Unified Theory of Acceptance and Use of Technology (UTAUT2) and self-determination theory was employed to identify key influencing variables. Data were collected through an online survey of 533 respondents and analyzed using Structural Equation Modeling. The findings revealed that perceived relatedness had the most significant impact on students' behavioral intentions to use CAI, followed by perceived autonomy. The results indicate that students primarily engage with CAI to achieve specific academic objectives and enhance productivity, rather than for alternative purposes in educational contexts. Among the UTAUT2 constructs, only facilitating conditions, habit, and performance expectancy demonstrated significant direct effects on behavioral intention, as well as indirect effects on actual academic use. Ref.

[34] provides valuable implications for the design of educational tools and strategies to support AI integration in academic environments. Additionally, the methodology and framework offer a foundation for future research into educational technology adoption. These findings underscore the importance of fostering relatedness, autonomy, and facilitating conditions to enhance students' engagement with CAI. As the teaching-learning landscape continues to evolve, these insights are crucial for understanding and shaping students' interactions with emerging technologies.

The work presented in [15] investigate the factors that influence learners' behavioral intentions to use AI. The proposed model was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) on data gathered from a self-reported survey of 886 learners, ranging from junior high school to college level, in Cebu, Philippines.The results indicated that 5 out of 9 hypothesized paths were significant. Specifically, social influence and perceived knowledge of using AI were found to be significant predictors of learners' attitudes toward using AI. Furthermore, three factors had a significant effect on behavioral intention: performance expectancy, perceived knowledge of using AI, and attitude toward using AI.

Table 1. Comparative summary of AI techniques and approaches in personalized learning.

Ref.	Limitations	Finding
[11]	The study employed a cross-sectional survey design, which captures data at a single point in time. This limits the ability to assess changes in teachers' attitudes and behaviors over time, especially in response to evolving GenAI tools and technologies. Longitudinal studies are needed to understand how teachers' acceptance and use of GenAI tools might change as they gain more experience and familiarity with these technologies. While the sample of 367 teachers provides a substantial dataset, the study does not detail the demographic characteristics of the respondents in depth (e.g., age, teaching experience, subject area, or grade level). Variations in these factors could influence the results, and more granular demographic data could provide insights into how different groups of teachers perceive and use GenAI tools. The study uses an extended Technology Acceptance Model (TAM) with six constructs, but other potential factors influencing GenAI acceptance, such as institutional support, access to technology, or external barriers, were not included. Exploring a broader range of variables could provide a more comprehensive understanding of the factors that affect teachers' adoption of GenAI tools.	These results underscore the importance of tailored teacher training programs and the development of supportive educational policies to enhance AI readiness, particularly in resource-constrained settings. By addressing disparities in teacher preparedness and fostering enabling environments, this study highlights the potential to bridge gaps in AI integration in the Global South's educational systems.
[12]	The study involved a relatively small sample of 97 South African and 95 Thai final-year BEd students. Given the limited sample size, the findings may not be fully representative of the broader population of pre-service teachers in these countries, particularly in rural or less accessible areas. The study focuses on two countries with different educational, cultural, and technological contexts. While comparisons between South Africa and Thailand offer useful insights, the results may not be generalizable to other countries in the Global South, where different social, economic, and infrastructural factors may influence the adoption of AI in teaching.	The findings highlight key factors that can facilitate the effective adoption of GenAI in educational settings. Insights from this study provide actionable knowledge for designing support systems and professional development programs for teachers, not only in Australia but also in other educational contexts globally, to optimize the potential of GenAI in education.

	The research adopted a non-experimental comparative descriptive survey method, which limits the ability to draw causal inferences about the relationship between the constructs of the Theory of Planned Behavior (TPB) and the actual integration of AI. The lack of experimental manipulation means that the study cannot conclusively determine cause-and-effect relationships. Data were collected through a structured online questionnaire, relying on self-reported responses from participants. Self-report data can be subject to biases such as social desirability or misinterpretation of questions, which may affect the accuracy of the findings.	
[13]	While the sample of 368 Australian teachers provides a robust dataset, the study does not offer detailed demographic information, such as teachers' years of experience, subject specialization, or school type (public vs. private). These factors could influence teachers' attitudes toward and engagement with genAI tools, and further demographic analysis could provide deeper insights into how these variables interact. The study focused on motivation (self-efficacy and valuing) and engagement (genAI integration), which are important predictors of behavior but do not necessarily correlate with actual usage. Further research should explore the actual adoption and application of genAI tools in the classroom to complement findings about teachers' intentions and motivation. The study found that disruptive student behavior was not linked to motivation or engagement with genAI tools, but this may reflect a limitation in the measurement or scope of the variable. The influence of classroom dynamics on teachers' ability to engage with technology might be more complex and warrants further exploration in future studies.	These findings underscore the importance of fostering relatedness, autonomy, and facilitating conditions to enhance students' engagement with CAI. As the teaching-learning landscape continues to evolve, these insights are crucial for understanding and shaping students' interactions with emerging technologies.
[14]	The study analyzed students' behavioral intentions and academic use of CAI in a broad context, but it did not explore specific subject areas or educational settings in depth. Different disciplines or levels of education may have different patterns of CAI usage, and contextual factors like teaching methodologies or subject relevance might influence the findings. The study uses an integrated framework based on the UTAUT2 and self-determination theory, but not all UTAUT2 constructs were found to be significant. It would be beneficial to examine additional factors that may influence students' use of CAI, such as peer influence, teacher support, or technology accessibility. The study uses a quantitative approach based on Structural Equation Modeling, but qualitative data could provide deeper insights into students' attitudes and perceptions about CAI. Interviews or open-ended survey responses might shed light on the nuanced ways in which students perceive and engage with CAI tools, beyond what is captured in the quantitative analysis.	These findings suggest that learners' intentions to use AI are shaped by external social influences and their own knowledge of AI tools, which contribute to their positive attitudes. Additionally, learners are more likely to engage with AI because they believe it will enhance their performance and productivity, coupled with their belief in the value of AI and their familiarity with the technology.
[15]	While the study identified several key predictors of learners' attitudes and behavioral intentions toward AI, it did not explore other potentially influential factors such as institutional support, access to resources, or societal factors (e.g., government policies or cultural attitudes toward AI).	These findings suggest that learners' intentions to use AI are influenced by their social environment and their knowledge of AI tools, which

	Future research could examine these external factors to provide a more comprehensive understanding of the factors that influence AI adoption. The study focused on learners' behavioral intentions and attitudes toward using AI, which are important predictors of future behavior. However, intentions do not always translate into actual usage. The study did not investigate whether learners who intended to use AI tools actually followed through with their intentions, and thus the findings may not fully capture the actual adoption and integration of AI tools in learners' educational activities. The study relied solely on quantitative methods, which limits the depth of understanding regarding learners' motivations and experiences with AI. Qualitative data, such as interviews or focus groups, could provide richer insights into learners' perceptions, challenges, and specific use cases for AI in education, adding depth to the findings.	shape their attitudes toward the technology. Additionally, learners are more likely to use AI because they believe it will enhance their performance, they are knowledgeable about how to use AI, and they hold a positive attitude toward incorporating AI into their work.

2.1. Implications

2.1.1. Teacher Development

Training programs should prioritize improving social-emotional (SE) learning and professional development by equipping teachers with the skills and knowledge needed to effectively use generative AI (GenAI) tools. This involves not only familiarizing educators with the technical aspects of GenAI but also demonstrating how these tools can be integrated into their teaching practices to foster creativity, critical thinking, and personalized learning experiences. Additionally, training should emphasize ethical considerations, data privacy, and strategies for maintaining a balanced approach to technology use, ensuring that AI supports, rather than detracts from, the human connection essential to education. By doing so, educators will be better prepared to leverage GenAI tools to enhance student engagement, streamline administrative tasks, and adapt their methods to diverse learning needs.

2.1.2. Policy Support and Literacy

Educational policies must create environments conducive to the integration of generative AI (GenAI) by providing the necessary resources, infrastructure, and professional development opportunities for educators. This includes ensuring access to reliable technology, such as devices and high-speed internet, and developing comprehensive training programs that enable teachers to effectively incorporate GenAI tools into their classrooms. Policies should also establish clear guidelines on the ethical use of AI, data security, and student privacy to build trust and accountability. Moreover, fostering collaboration between policymakers, educators, and technology developers can ensure that GenAI applications align with educational goals, support diverse learning needs, and promote equity across all educational institutions. By addressing these elements, policies can empower schools to harness the potential of GenAI to enhance teaching and learning outcomes.

Teachers need a robust understanding of AI principles, capabilities, and limitations to maximize the potential of generative AI (GenAI) in classrooms effectively. This includes foundational knowledge of how AI systems function, the data they rely on, and the processes behind content generation. Equally important is an awareness of AI's limitations, such as biases in data, ethical considerations, and the risk of over-reliance on technology. By developing this understanding, educators can critically evaluate AI tools, select the most appropriate ones for their teaching objectives, and use them to enhance creativity, problem-solving, and personalized learning. Training programs should emphasize practical applications, demonstrating how AI can streamline administrative tasks, provide actionable insights into student performance, and enrich educational content while highlighting the importance of maintaining a human-centered approach to teaching.

3. implementation of AI in feature engineering

Feature engineering, a crucial phase of machine learning, provides a means to extract meaningful patterns and insights from raw data. This study addresses the gap in research on AI-driven feature engineering in the education sector, aiming to refine predictive models and improve decision-making processes. By employing advanced methodologies—ALasso, ANN, and SVR—the study identifies influential factors shaping educational performance, paving the way for targeted interventions and strategic improvements.

Authors of Ref. [16] investigate the use of artificial intelligence (AI) in feature engineering to enhance the efficiency and effectiveness of educational systems. By leveraging advanced machine learning models, including Adaptive Lasso (ALasso), Artificial Neural Networks (ANN), and Support Vector Regression (SVR), the research identifies critical features impacting educational outcomes. Comparative analyses using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) establish SVR as the most effective model, showcasing its superior predictive capabilities. The findings of [36] highlight the transformative potential of AI in optimizing learning processes, supporting individualized education, and informing data-driven policymaking. Despite its growing importance, research on AI implementation in the banking sector remains limited, authors of Ref. [37] aims to assess the intention to continue adopting AI technology in Indonesia's banking sector. Using an extended technology acceptance model (TAM) framework, the study incorporates factors such as AI awareness, subjective norms, perceived risk, and perceived trust. Data were collected through a survey of 388 bank customers who have interacted with AI-driven services. The work presented in [17] offers significant contributions to the banking industry in developing countries by emphasizing the importance of implementing AI technology with robust security measures to foster customer trust and widespread adoption. Similarly, Ahuja and Sharma [18] investigated the application of machine learning in addressing educational challenges and enhancing tutor performance. Their study employed five key feature selection approaches to process the provided data and applied 12 classification algorithms to evaluate the outcomes. The findings highlighted the significant role of machine learning tools in improving the efficiency of educational administration. A crucial step in this context is feature engineering, which is widely employed to extract meaningful information from raw data. In the literature, studies such as that of OuahiMariame [19] have explored the use of feature engineering and neural networks to analyze and predict student performance based on educational datasets, demonstrating its potential in educational analytics.

Table 2. Taxonomy of AI methodologies and implication of AI in education.

Ref.	Methodology	Findings	Implication
[16]	- This study employs a data-driven approach to investigate the application of artificial intelligence (AI) in feature engineering within the education sector, focusing on its potential to enhance individualized learning	This study highlights the potential of artificial intelligence (AI) methodologies to enhance feature engineering in the education sector, improving individualized learning and academic outcomes. The key findings are as follows: - The correlation matrix analysis revealed strong associations	- The findings highlight the effectiveness of AI-driven feature engineering in identifying and leveraging significant factors in educational data. - The results advocate for the adoption of advanced AI methods in various educational contexts to

	and academic outcomes. - A correlation matrix was constructed to analyze the relationships among features in the dataset. - Three s machine learning techniques were utilized to address the limitations of conventional models: Adaptive Lasso (ALasso), Artificial Neural Networks (ANN), Support Vector Regression (SVR) - The effectiveness of the models was assessed using two performance metrics Root Mean Squared Error (RMSE and Mean Absolute Error (MAE)	between specific features, such as Gender (X5), Education (X1), Hours of Work (X4), and Marital Status (X6). - These correlations rendered conventional models less effective, necessitating the use of advanced machine learning approaches. - The Adaptive Lasso (ALasso) model identified influential features that significantly impact outcomes, such as salaries. These features include Gender, Education, Hours of Work, and Marital Status, underscoring the importance of targeted feature selection in modeling. Among the three machine learning techniques employed—Adaptive Lasso (ALasso), Artificial Neural Networks (ANN), and Support Vector Regression (SVR)—the SVR model demonstrated the best performance. - SVR achieved the lowest Root Mean Squared Error (RMSE) of 0.595 and Mean Absolute Error (MAE) of 0.423, outperforming the other methods in accuracy and prediction efficiency.	improve model performance and inform evidence-based policymaking.
[17]	- The research extends the traditional TAM ramework by incorporating four additional constructs: Awareness of Artificial Intelligence, Subjective Norms, Perceived Risk, Perceived Trust - A total of 19 hypotheses were proposed to examine the relationships among TAM constructs and the extended variables. - The study employed a survey-based approach to gather data. - A structured questionnaire was designed to measure the constructs within the extended TAM framework.	- All 19 proposed hypotheses were accepted, validating the extended Technology Acceptance Model (TAM) framework. - The study confirms that factors such as awareness of AI, subjective norms, perceived risk, and perceived trust significantly influence customers' behavioral intentions. - Customers with greater awareness of AI technologies are more likely to adopt and continue using AI-enabled banking services. - Social influences, such as recommendations from peers or family, positively impact customers' intention to use AI in banking. - While customers are concerned about potential risks (e.g., privacy breaches or errors), these concerns are mitigated by strong	The findings emphasize the necessity of implementing AI technologies with a high level of security to address customer concerns and build trust. - Banks must prioritize implementing AI technologies with robust security measures to alleviate customer concerns and build trust. - Banks can use AI to develop personalized and efficient customer services, further boosting perceived usefulness and ease of use. - Developing strong regulations and policies to ensure the ethical use of AI in banking is crucial. - Developers should design AI systems that are intuitive and user-friendly, reducing

	- The collected data were analyzed using statistical tools to test the proposed hypotheses.	trust in the banking system and the secure implementation of AI technologies. -Trust in AI systems and the banking institution was identified as a critical factor driving continued AI adoption.	perceived complexity and increasing ease of use.
[18]	- Five techniques were applied to identify the most significant features: Random Forest, Principal Component Analysis (PCA), Recursive Feature Elimination (RFE), Univariate Feature Selection, Genetic Algorithm - The performance of these models was evaluated using: Accuracy, Recall, Precision, F-score - o confirm that the results were statistically significant and not due to random variations, the ANOVA one-way test was applied to compare the performance of different classification models.	The combination of Agglomerative Clustering and K-means algorithms successfully labeled the unlabelled dataset into three categories, enabling the application of supervised learning methods. Out of the twelve machine learning models applied, the Support Vector Machine (SVM), in combination with PCA feature selection, achieved the best performance metrics: - Accuracy: 99.66% - Recall: 99.66% - Precision: 99.67% - F-score: 99.67% - The ANOVA one-way test confirmed that the differences in performance across the tested models were statistically significant, validating the robustness of the results.	Educational institutions can use this model to provide objective and data-driven feedback to instructors. This approach can assist in identifying areas where instructors excel or need improvement, leading to targeted professional development. By relying on data-driven insights, administrators can avoid biases and subjectivity in the evaluation process, ensuring that all instructors are evaluated based on consistent and reliable criteria.
[19]	Four feature selection algorithms were applied in this research: Sequential Forward Selection (SFS), Sequential Floating Forward Selection (SFFS), Linear Discriminant Analysis (LDA), Recursive Feature Elimination (RFE), Principal Component Analysis (PCA) - Various classification algorithms were tested for predicting students' academic performance: Naïve Bayes (NB), Support Vector Machine (SVM), Random Forest (RF) and Artificial Neural Networks (ANN)	- Among the various classification algorithms tested, **Artificial Neural Networks (ANN)** performed the best in predicting students' academic performance. - **ANN** outperformed other classifiers such as **Naïve Bayes (NB)**, **Support Vector Machine (SVM)**, and **Random Forest (RF)** on the specific dataset used in the study. - The application of **Feature Selection (FS) algorithms** significantly improved the performance of classifiers. - The study suggests that **neural networks** are a powerful tool for predicting student outcomes, and the **appropriate use of feature selection** can enhance the accuracy and effectiveness of educational data mining models.	By using **Artificial Neural Networks (ANN)** combined with **feature selection algorithms**, educational institutions can more accurately predict student performance. This enables early intervention for students who may need additional support, potentially improving overall academic outcomes. - By predicting academic performance more accurately, educational systems can tailor learning experiences to individual student needs. Personalized learning paths can be created to address gaps in knowledge or provide additional challenges to high-performing students, ultimately enhancing the educational experience.

By leveraging advanced machine learning (ML) models, these works show that AI offers a new perspective on identifying and addressing factors that influence learning outcomes. Indeed, feature engineering is critical in machine learning, as the quality of input features significantly impacts the performance of predictive models. For instance, AI will automate and enhances this process in the education sector by firstly by identifying relevant variables, such as attendance, socioeconomic background, or engagement metrics, that influence learning outcomes, then by discovering hidden patterns and relationships in educational data that may not be apparent through traditional statistical methods and finally by reducing dimensionality by selecting or creating features that better explain variance in student performance.

These papers show that one of the most valuable contributions of AI lies in its ability to generate actionable recommendations. These insights can guide policymakers, educators, and administrators toward more effective strategies. AI-driven feature engineering aligns well with the global push for sustainable development goals (SDGs) in education, particularly ensuring inclusive and equitable quality education and promote lifelong learning opportunities for all. In spite of its potential, the integration of AI into feature engineering for education is not without challenges. One of the most challenge thing in AI is ensuring the confidentiality and security of sensitive educational data. **Besides, p**roviding the necessary computational resources and training educators to use AI tools effectively is also the second point that researches on AI should focus.

4. AI based Digital Learning for the Sustainability of Education Management System

Immanuel Kant (1724–1804) was not only a renowned philosopher but also a significant figure in educational reform, known for advocating the principle "have the courage to be wise" (*Sapere aude*). He emphasized the importance of individual effort, independent thinking, and self-reliance, urging people to take responsibility for their own understanding rather than relying on others to make decisions for them. Kant championed the freedom to use one's reasoning publicly in all matters, which he saw as essential for achieving educational success and functioning as a moral citizen within society. For Kant, the freedom and courage to reason formed the cornerstone of morality [20].

In 1981, Terrell Howard Bell, the U.S. Secretary of Education (1981–1985), responded to concerns from military and business leaders about graduates lacking critical thinking skills by appointing a commission to investigate excellence in education. This effort led to the 1983 publication of *A Nation at Risk* by the National Commission on Excellence in Education. The report warned of a “rising tide of mediocrity” threatening the nation and emphasized the urgent need for educational reform. One significant outcome was the integration of critical thinking into university curricula to address deficiencies among incoming college students [21, 22].

In modern times, management education draws inspiration from Kant's ideas, emphasizing students' roles as moral citizens in a global society [23]. The focus has expanded beyond profit to include environmental sustainability, human and societal goals, and the development of workplace ecosystems that align with these values.

5. Ethical and Bias Considerations in AI for education

As artificial intelligence (AI) gains prominence in healthcare, particularly in education, ethical implications and potential biases within these systems require careful scrutiny [24-29]. AI and machine learning (ML) have demonstrated remarkable capabilities in tasks such as image recognition, natural language processing, and predictive analytics. However, alongside these advancements, significant ethical considerations and biases arise. Privacy and security concerns around patient data, algorithmic transparency, and the equitable distribution of AI benefits are critical issues that demand attention. Biases in AI systems can exacerbate existing healthcare disparities, affecting vulnerable populations disproportionately. These biases, whether introduced through data or algorithmic design, undermine trust in AI technologies and highlight the need for rigorous validation and ethical oversight. Moreover, biases in AI models—arising from training data, algorithm design, or user interactions—can lead to inequitable and potentially harmful outcomes. These biases stem from factors like data representativeness, clinical variability, and evolving practices. This review discusses the sources and manifestations of bias in AI systems, alongside the ethical principles of autonomy, beneficence, nonmaleficence, justice, and accountability that guide their development and implementation. Strategies for mitigating bias, including adherence to FAIR (Findability, Accessibility, Interoperability, and Reusability) principles and compliance with AI-specific guidelines, are explored to ensure transparency, fairness, and equitable healthcare outcomes. By addressing these issues, stakeholders can promote responsible AI innovation that aligns with ethical standards.

AI adoption in education presents several ethical challenges, particularly regarding autonomy, beneficence, nonmaleficence, justice, and accountability. Justice requires equitable distribution of AI's benefits and burdens. This involves addressing systemic inequities that influence AI model performance, such as geographic disparities in healthcare access and socioeconomic factors. AI developers and policymakers must collaborate to ensure that underserved populations are not further marginalized by AI-driven healthcare systems. AI systems in education rely on vast amounts of student data to function effectively. Safeguarding this data from breaches and misuse is critical. Educational institutions must ensure compliance with data protection laws, such as GDPR or FERPA, while implementing robust security measures to protect sensitive information. The integration of AI tools can exacerbate existing inequalities if not carefully managed. Students in underprivileged areas may lack access to the necessary technology or internet connectivity, creating a digital divide. Ensuring equitable access to AI-powered education tools is essential for inclusivity. AI systems can inherit biases present in the data they are trained on. In education, this could lead to unfair treatment of certain groups based on race, gender, or socioeconomic background. Addressing algorithmic bias requires diverse datasets, transparent development processes, and ongoing monitoring. The ethical implications of AI in education must be carefully considered. Issues such as the potential over-reliance on AI for decision-making, lack of human oversight, and questions around the role of AI in shaping educational content require thoughtful regulation and debate. In addition, Adopting AI in classrooms requires significant changes in how teachers and students interact with technology. Teachers may need training to effectively use AI tools, while students must develop digital literacy skills to navigate these systems. Resistance to change or a lack of training resources can hinder adoption.

Thus, determining the impact of AI on educational outcomes can be complex. Establishing reliable metrics and long-term studies to evaluate AI's contributions is necessary to guide its implementation and optimization.

Conclusion

Over the last few years, artificial intelligence was reserved for the field of science fiction. Nowadays, AI is intruding into our daily lives. Although there is still a lot of room for growth and development, there has never been a better time to look at how AI can contribute to the learning process. Many AI applications are already being used in education, but the current state of AI presents some challenges. For example, when it comes to grading students' work, teachers assign grades in the form of letters based on the human factor, which cannot be replaced by an algorithm. However, the consistent patterns found in the evaluation criteria can be used to automate the scoring process. Learning and teaching are not supposed to be limited to books and classrooms; rather, they should take the form of an interactive experience. Nowadays, there have been many technologies that allow students and teachers to interact in real time through video streaming and virtual reality headsets. This makes it possible to improve the existing school curriculum and motivate students. This paper examines current trends, potential benefits, and challenges to offer educators, policymakers, and researchers a comprehensive perspective on how AI is transforming the future of education and how it can be strategically utilized to promote equitable and high-quality learning outcomes.

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