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A Critical Evaluation of the Use of Artificial Intelligence in Learning

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Abstract

The growing prominence of Artificial Intelligence (AI) presents an opportunity to revolutionise learning by tailoring instruction according to individual student needs. Proponents of AI predict its potential to enhance student engagement, address learning gaps, and optimise academic performance. AI can identify strengths and weaknesses and recommend remedial paths and activities to cater to diverse learning styles, paces, and needs through the analysis of student data. Nevertheless, relying on AI in teaching and learning requires a critical examination of the possible benefits and drawbacks of making learning increasingly dependent on AI systems and solutions. Thus, this study critically evaluates the role of AI in personalised learning, highlighting its benefits and challenges in the context of higher education. While AI enhances engagement and learning outcomes, ethical and practical concerns, including algorithmic bias, are also discussed.

Keywords: artificial intelligence, large language models (LLMs), personalised learning, education.

1. Introduction

The recent launch of Artificial Intelligence (AI) in public use has spread its dominance to almost every field, including education, thereby reshaping traditional teaching and learning practices (Yasmin & Mazhar, 2023). Artificial intelligence, defined by Coeckelbergh (2020) as machine-simulated intelligence, can optimise the current system to address various learning challenges and make learning more efficient and effective. However, incorporating AI into educational practices requires careful evaluation of the potential advantages and disadvantages of making the learning process entirely reliant on AI-based solutions. In this respect, this study's argument is based on the premise that while AI-powered personalised learning offers transformative potential by enhancing student engagement, addressing learning gaps, and developing critical thinking, it also raises significant concerns regarding the challenges it poses. Thus, this paper discusses both the promises and pitfalls of AI in education and proposes strategies to optimise its use by addressing ethical challenges and maintaining a human-centred approach to ensure equitable and effective learning experiences. Finally, this paper investigates the long-term consequences of using AI in education, how it will continue to shape the educational system, and how it may eventually lead to the obsolescence of the traditional teacher-student model.

2. The Promise of Personalised Learning (PL)

The impact of Artificial Intelligence is set to revolutionise teaching and learning, as well as the management of the educational sector. Future educational systems will likely leverage Artificial Intelligence to enhance student recognition and personalise learning (Yasmin & Mazhar, 2023). Thus, the adoption of Large Language Models (LLMs), such as ChatGPT, has been received, in most cases, as a natural evolution of technology integration within modern classrooms (Almarzouqi et al., 2024), thus enhancing learning efficiency (Lazkani, 2024). Consequently, this use of LLMs in education has significantly amplified the discourse surrounding personalised learning (PL), which is the main objective of implementing AI in education (Khadragy, 2024). This integration reflects the growing recognition of the potential of technology to enhance the learning experience. However, the successful implementation of such pedagogy requires further investigation and development (Popenici, 2023).

As Shemshack and Spector (2020) explain, the concept of personalised learning has a long history, predating the advent of modern technology. For centuries, apprenticeships and mentoring relationships have provided individualised instruction tailored to specific skills and knowledge. The latter part of the twentieth century saw the development of educational technologies that facilitated PL. Intelligent tutoring systems (ITSs) exemplify this trend by tailoring instruction to individual student progress and feedback. However, the twenty-first century presents a new opportunity to revolutionise personalised learning through big data and learning analytics. These technological advancements can be leveraged to develop highly customised learning environments that address the specific requirements and preferences of individual learners. Chatterjee et al. (2020) suggested that this approach can establish a more captivating and productive learning environment for all students.

In this sense, implementing personalised learning approaches requires the collection and analysis of data on each student's learning process. However, manually managing whole-class instruction while simultaneously gathering data to support individual students places a significant burden on teachers. In this context, Artificial Intelligence has the potential to alleviate this pressure by automating some aspects of relevant data collection and analysis, which could allow teachers to dedicate more time to effective class instruction and provide targeted support for individual students' needs (Yu & Lu, 2021).

Considering the pitfalls of traditional educational systems, the incorporation of AI into personalised learning has many potential benefits for educational advancement. With the constant shift of education from traditional, lecture-based instruction to more enquiry-based, problem-solving methodologies, AI-powered personalised learning aims to be the next generation teaching pedagogy. Computational infrastructure is becoming more readily available to schools at a lower cost. Similarly, the rise of one-on-one device programmes and blended learning has made it easier to integrate technology into learning processes.

3. Potential Benefits of AI for Personalised Learning

The potential benefits of implementing AI technologies in personalised learning systems promise improvements in student engagement, address learning gaps, and enhance critical thinking skills. Together, these aspects constitute the foundation of an environment for personalised learning.

3.1. Improved Student Engagement and Motivation

People are naturally more motivated and better able to understand difficult concepts when they are interested in the subject. When students are given control over what they study, instructors can help them find and focus on topics that interest and excite them. However, such a learning model would be difficult and impractical to apply on a wide scale in traditional education systems. Alternatively, a personalised learning environment with an intelligent tutoring system is essentially a technological emulation of one-on-one instruction, where the student has total control over the pace and the material covered. Therefore, the integration of AI presents a transformative opportunity for personalised learning, as this system can identify areas of difficulty for targeted support while offering increased challenges in subjects in which the student excels.

Furthermore, AI can provide continuous and individualised feedback on learning progress. This is particularly beneficial for students with negative self-perceptions of their ability. In this case, receiving feedback based on progress rather than comparisons with others encourages students to attribute success to effort and personal capability. Ultimately, establishing a “learning-how-to-learn” culture equips students with essential lifelong learning skills, as they are more likely to maintain interest and motivation in their studies when educational experiences are tailored to their individual preferences and abilities (Lazkani, 2024). Incorporating AI tools into teaching and learning makes the latter more learner-centric and empowers students to take ownership of their learning journeys, which is an immense promise that personalised learning holds for the future of education.

3.2. Addressing Learning Gaps and Encouraging Critical Thinking

An adaptive learning environment can identify a learner’s strengths and weaknesses in terms of both knowledge and motivational factors and provide learning activities that adapt to the performance of the learner. The aim is to keep the learner immersed in a learning activity that is neither too hard nor too easy, resulting in an increase in knowledge, considering that different students have different learning styles and aptitudes. For example, ChatGPT’s interactive nature enables students to independently revisit content in what is known as ‘self-paced learning’, which is one of the features of personalised learning (A. Salloum et al., 2024). This example justifies why proponents of AI-powered learning tools highlight the potential of these tools to surpass human educators in terms of information-processing speed and knowledge delivery (Bhise et al., 2023). In this respect, AI-driven educational platforms can provide teachers with detailed student information, including learning preferences, individual capabilities, continuous progress tracking, and data-driven insights to personalise instruction (Gupta et al., 2023).

While learning is highly personal, traditional methods of instruction leave much to be desired in recognising and responding to individual student needs, which is where AI seems to be highly useful. A well-designed and user-centric AI system can dynamically track students’ learning pace, performance, and knowledge gaps. These data can then be leveraged to personalise study plans, content recommendations, and learning styles for each student, thereby optimising learning efficiency. Furthermore, AI tools can continuously learn and adapt based on students’ results, past performance data, and group dynamics. This iterative process creates an ever-expanding knowledge base and a more potent learning environment for the students. Additionally, AI-powered insights can inform educators about areas requiring increased focus, allowing them to optimise teaching strategies and achieve desired learning outcomes, which may positively reflect on the development of students' critical thinking skills.

One example of an effective way to develop critical thinking is enquiry-based learning; however, it is difficult, if not impossible, to implement it on a wide scale because of the intensive nature of teacher-student interaction. To solve this issue, intelligent tutoring systems can significantly enhance enquiry-based learning by providing tailored guidance for each student. These systems ensure consistent support and optimise learning outcomes across the board by delivering personalised enquiry prompts based on each student's progress. This level of effectiveness in providing personalised guidance with enquiry is not feasible with human tutors; however, AI has the potential to overcome the limitations of traditional teaching methods.

Although the benefits of AI in personalised learning are substantial, it is equally important to address the potential challenges to ensure balanced and equitable implementation.

4. Potential drawbacks of AI-powered Personalised Learning

While AI-powered personalised learning offers a promising future for educational advancement, it is crucial to acknowledge and address several potential drawbacks inherent to this approach. These drawbacks pertain to several issues at the top of which there is algorithmic bias and a shift in the role of humans in AI-powered personalised learning, as well as other drawbacks that are worth discussing.

4.1. Algorithmic Bias and Unfairness in AI Systems

Algorithmic bias occurs when an AI system makes unfair or inaccurate decisions because of the design or training of the system. This bias occurs when the data from which AI learns reflect human prejudices, stereotypes, or inequalities. Bias can stem from biased training data, flawed algorithm design, or system deployment. Because AI systems rely on patterns found in data, they can unintentionally learn and repeat the same biases that exist in society.

In the general context of AI technology and its implementation in various computer systems, data collection, access to data, and the passage of data between various systems and sources can produce biased instances. Large language models and other AI models offer vast repositories of information. However, the inherent limitations of these models, including the possibility of errors and the presence of outdated information, necessitate rigorous human validation and oversight of the generated content. This is essential to guarantee that the information delivered to the learners is relevant and accurate (A. Salloum et al., 2024).

In this respect, Chorás et al. (2020) identified several potential factors contributing to bias within training datasets that can result in unfair AI outcomes. These are as follows:

- *Skewed Samples:* Training data misrepresent real-world populations, particularly in areas where there is a constant change in trends over time.
- *Tainted Examples:* Existing biases in historical datasets can be replicated by AI models trained on such data. These biases, often stemming from human prejudices in the past, can perpetuate discriminatory patterns if left unchecked during data collection and cleaning processes.
- *Limited Features:* The reliability of data labels for certain minority groups can be compromised owing to factors such as unreliable collection methods or less informative data points.
- *Sample Size Disparity:* When data sample size for a particular group is insufficient, it hinders the AI model's ability to learn effectively and make accurate predictions. This disparity can result in unreliable or unfair results.
- *Proxy Bias:* Even if AI models are not explicitly trained on sensitive attributes like race or gender, correlations between these attributes and other characteristics used in the training data can introduce bias into the predicted outputs. This "proxy bias" can lead to discriminatory results, even though the AI model does not directly consider these sensitive attributes.

In the context of AI in education, data bias involves other issues that affect the quality of decisions based on AI output. A particularly promising application of Artificial Intelligence lies in the early prediction of student performance. This feature enables the identification of students at risk of academic withdrawal, facilitating the prompt provision of the support they need (Kulkarni et al., 2023). However, one key concern is the possibility of bias and algorithmic injustice in AI models. This could result in AI having a bias towards students who study more or complete their courses, providing a less effective tool for those who underachieve.

Uninformed decisions regarding AI implementation, particularly in such contexts, can have serious repercussions (Bhise et al., 2023).

However, the potential for technology to replicate or intensify existing educational inequality is concerning. AI models, such as ChatGPT, can unintentionally incorporate biases found in the massive amounts of online data used for training (Almarzouqi et al., 2024). In other words, AI algorithms are trained on datasets that can inadvertently contain biases reflecting societal prejudices. As AI systems are often trained on historical datasets, they are vulnerable to inheriting and exacerbating such biases. If left unchecked, these biases could be perpetuated, potentially disadvantaging certain student groups. For instance, owing to inherent biases, an AI system could consistently downplay the academic potential of students from specific backgrounds.

As an example of algorithmic bias, the United Kingdom's implementation of an algorithm to predict A-level grades sparked significant public controversy in 2020. This dispute arose from allegations that the algorithm unfairly penalised students from underprivileged communities while benefiting those from affluent schools. This incident highlights the potential for algorithmic bias to intensify existing educational inequalities within the education system (Idowu, 2024). This could have detrimental consequences, such as limiting the educational opportunities and career paths of these students (S. A. Salloum, 2024). Therefore, having in-place mechanisms capable of addressing these biases is primordial, yet more complex, but in a way, the only option that should exist (Popenici, 2023).

Similarly, large Language Models such as ChatGPT, possess a versatile toolkit for data analysis, encompassing descriptive, comparative, predictive, and correlational analyses, as well as the interpretation of data visualisations. Although these capabilities can streamline many data analysis processes, they are currently limited in their capacity to handle complex datasets and perform sophisticated analytical tasks. Deep data interpretation and intricate statistical analysis often require human expertise and judgment, as these processes require a critical understanding of the subject matter and evaluation of the results. More importantly, the reliability of LLM-processed tasks can vary, with potential inaccuracies arising during the interpretation of complex diagrams or advanced statistical analyses (Talha Junaid et al., 2024). This algorithmic bias can result in personalised learning systems that unfairly favour or disfavour certain groups of students, potentially widening educational inequalities.

4.2. Shift in the Human Role in Education

Technological innovation is often viewed as a mechanism that effectively and efficiently reduces human effort by performing certain tasks, which is the reasons behind the provision of AI-based personalised learning. Teachers' jobs have now shifted from being information givers and mentors to facilitators and supervisors. Hence, the teacher's job is reduced to deciding on the student's learning plan and easing problems during the learning process by providing human wisdom, rather than knowledge. Consequently, AI software is currently replacing lectures and tutoring. It should be noted that in the presence of teaching and tutoring software, there is a possibility that teaching jobs are now shared between software and actual teachers because the allocation of software might be more cost-effective than that of actual teachers. This is a dangerous step because AI is still far from achieving general human intelligence.

There are still several limitations to AI systems that stand in the way of the total integration of these systems in education. For instance, current AI cannot emulate certain human traits that are vital to communication and learning, such as empathy and the capability to instantly change teaching methods. In AI tutoring, learning is considered effective if the student can correctly grasp the concept or answer multiple-choice questions without any errors. This is a flaw because errors are part of learning, and AI tutors cannot provide explorations and test students on problems that are outside their learning plans. Consequently, students who fail to understand will be frustrated because the AI tutor cannot convey explanations effectively and they will not be allowed to ask off-topic questions. An AI tutor will not be able to detect or change its method to help students employ different learning styles.

By the same token, although Artificial Intelligence can redefine education by offering efficient and effective personalised learning experiences, it is difficult for this technology to teach human creativity, complex critical thinking, emotional intelligence, or high-level interdisciplinary syntheses of knowledge, the skills that will be required in the future. Moreover, overreliance on AI-driven tools could lead to a decline in critical thinking and problem-solving skills, which are crucial competencies for academic and professional success (A. Salloum et al., 2024). Therefore, it is crucial to harmonise AI-assisted learning with conventional teaching methods that cultivate independent thought and critical analysis. This balanced approach empowers students to independently assess information, construct logical arguments, and effectively address complex challenges.

Automated learning technologies will also struggle to provide constant and personalised feedback that is most beneficial to students. Technical mastery in learning to solve specific types of problems can occur later in the learning process. Students who have learned to learn effectively, persistently, and with as full an understanding as possible, are most likely to succeed in the world beyond education. This ongoing exchange encourages progress on both fronts, creating a dynamic environment that continuously pushes the boundaries of knowledge and learning (Roumate, 2023).

AI tutors also cannot recognise emotions, such as feelings of stress and confusion, or the methods to deal with them. The AI tutor may still decide, for example, that stress and confusion are derailments of the learning plan. Moreover, the AI learning environment is less personal because students prefer interacting with each other and with teachers. Therefore, interactions in an AI environment cannot be considered effective. Furthermore, AI tutors cannot emulate joint problem-solving among students or between students and teachers. This entire case would result in learning to become less human and more akin to the mere trivial task of skill training and drills.

4.3. Other Potential Drawbacks

In implementing a personalised learning system, there are still many issues and challenges that might inhibit the achievement of the desired learning goals. One issue is the lack of learning resources to support the implementation of a personalised learning system. Such a system requires learning resources that can be assembled to meet the needs of each learner individually. This requires massive learning resources and a reliable system to arrange them. However, many learners still do not have access to a rich variety of learning resources, and many countries do not have reliable systems or computer technology.

AI's ability to teach a variety of subjects and age ranges can allow radical restructuring of traditional schooling schedules, classroom layouts, and assessment methods that the present system cannot achieve owing to the reliance on human teacher input. However, there is also a danger that this will simply be an "updated" version of what has come before, which uses technology as an aesthetic upgrade rather than a tool for genuine change. Moreover, although a personalised learning system has many advantages, many educators may not be convinced by this learning system and argue that it is too risky and has not proven to be a better learning method than the traditional approach.

Another danger in the AI-driven learning process is the loss of the social aspects of learning, such as collaboration, discussion, and critical thinking, through isolation from peers and mentors. Learners who prefer interaction and collaboration may be left behind those who prefer to work independently, thus demoralising groups of students who simply learn differently. It remains unclear how AI can provide a truly personalised learning experience for all learning types without human interaction. Considering that AI-driven learning will continue to make major gains in the educational environment, we need to consider how to effectively provide personalised learning for various learning styles.

This is particularly true for higher education distance learners, who may need the most support in self-paced learning with limited access to professors and other academic staff. Considering students' individual needs, this is a considerable drawback given that personalised learning is not an end in itself; it is a method to empower students at all levels to learn more effectively. The goal is to produce independent learners who can think critically, work cooperatively, and be self-directed learners. Since learning is a social process, there are real concerns that personalised learning may not serve students well in developing the skills necessary to become independent, lifelong learners. One potential solution is to use AI to personalise learning in a group or community setting, stimulating interactions between peers and mentors with learning resources as a supplement to face-to-face interaction.

Intelligent tutoring systems, adaptive learning platforms, and virtual assistants are AI tools that can significantly improve the learning outcomes. However, excessive reliance on AI can affect the development of critical thinking skills, as learners may become overly accustomed to receiving immediate solutions without engaging in in-depth problem-solving processes. This could potentially impede students' development of vital skills, such as academic and professional skills, independent learning, and problem-solving (Almarzouqi et al., 2024). This raises concerns that too much focus on using artificial intelligence in education will most likely result in a "decline of human intelligence" (Popenici, 2023, p. 177). Moreover, Overreliance on AI-powered learning tools may limit student interactions, potentially hindering socio-emotional development and teamwork abilities that are crucial for real-world collaboration (Almarzouqi et al., 2024).

Furthermore, excessive reliance on technology in the classroom can lead to the dehumanisation of learning. An overdependence on AI tutors could create a sterile learning environment that lacks the human connections and emotional support provided by teachers. Social interaction and collaboration are essential for learning and development. Students learn not only from content but also by interacting with their peers and teachers. An overly technological approach to education can hinder these crucial aspects of social and emotional development. This shift in focus can render passive students, for example, those accustomed to traditional modes of teaching, disempowered, confused, and disoriented.

Instructors may also feel disempowered through a shift of control to AI systems and a reduction of their marking and assessment role to a mere ‘monitoring’ role. The transfer of the instructor’s role to monitoring through the widespread integration of AI into education could potentially reshape teaching. Human elements remain irreplaceable in nurturing social-emotional learning and critical thinking skills and providing personalised guidance beyond the scope of pre-programmed responses. Teachers are instrumental in cultivating a nurturing learning atmosphere and inspiring a genuine passion for knowledge that transcends simple memorisation.

Data privacy is another significant concern in AI-powered learning environments. There are significant privacy concerns regarding the methods of collecting and using student data in AI tools for education purposes. Data collection practices should be transparent and secure to ensure that students’ privacy is protected from unauthorised access. Additionally, the potential for misuse of student data necessitates the development of robust ethical frameworks to govern data collection and use.

Accessibility and equity have emerged as critical concerns. Access to technology and reliable Internet connectivity is unevenly distributed among students in the country. This digital divide could intensify educational inequalities if AI-powered learning becomes the dominant paradigm in education. Fair and equal access to technology and high-speed Internet are essential for providing personalised learning opportunities to all students. Without such access, AI-powered learning could further marginalise certain groups of students. Moreover, the cost and sustainability of implementing and maintaining AI-powered learning platforms require careful consideration by educational institutions. The latter must conduct thorough cost-benefit analyses before implementing AI-powered systems on a large scale, as cost is another challenge they must face. The cost of preparing learning resources and implementing the system is one of the reasons why many countries and educators refuse to adopt personalised learning systems and defend the traditional learning approach.

It is well established that access to technology outside school is associated with higher family income and parental education. With general education moving increasingly online and the use of big data to target applications for specific groups of students, education technology can re-segregate education, directing the most effective teaching and learning tools to more privileged students. Moreover, the automation and outsourcing of tasks enabled by technology may result in teacher displacement in the field of special education. All students have the right to equitable education that enables them to succeed in achieving their learning objectives. However, students with disabilities are at the greatest risk of being left behind. Therefore, ethical considerations regarding equitable access and encouraging independent learning must be prioritised during AI integration into higher education (Vacarelu, 2023).

5. Optimising AI for Personalised Learning: Recommendations

When considering the potential of AI applications for personalised learning, it may be useful to distinguish between what is possible and what is not. We might usefully think of AI as what is available and will soon be on offer as a tutor, something that can get to know the pupil or student quite well and offer learning experiences and a level of support tailored closely to the learner's needs. To do so, mitigating algorithmic biases and ensuring a minimum level of human presence are indispensable strategies for ensuring the constant optimisation of AI for personalised learning.

5.1. Strategies for Addressing Algorithmic Biases

Algorithmic bias is a significant challenge in AI development, as it can lead to unfair and discriminatory outcomes in AI systems. Ntoutsi et al. (2020) categorize bias mitigation approaches into three main groups. First, there are 'pre-processing methods', techniques that focus on cleaning and balancing the training data itself, aiming to create datasets that are more representative and less prone to bias. The logic is that a fairer dataset leads to a less-discriminatory model. Second, there are 'in-processing methods' that directly modify machine-learning algorithms during training to incorporate fairness considerations. This may involve techniques such as regularisation, adding fairness constraints, or training on specific labels that reflect fairness goals. Finally, post-processing methods address bias after the model is trained by modifying its internal workings or adjusting its predictions. This could involve altering the model outputs or certain internal parameters to achieve fairer outcomes.

As bias in AI systems is a major concern, and various strategies can be employed to address it, Ferrara (2024b) explored these strategies in terms of collecting and pre-processing data, ensuring that the algorithms are fair, evaluation and monitoring, and adversarial robustness. The foundation for mitigating bias in data collection and pre-processing lies in the datasets used to train AI models. Various strategies can be employed to mitigate these imbalances and enhance the representativeness of the dataset. 'Oversampling' amplifies underrepresented groups by generating additional data points, whereas 'undersampling' reduces the frequency of overrepresented instances. 'Synthetic data generation' offers another approach by creating artificial data points for minority classes, thereby improving the overall dataset composition. Finally, stratified sampling ensured the proportional representation of different groups within the dataset by drawing samples from each category according to their relative size in the population.

In terms of algorithmic fairness, specific algorithms can be employed to address biases within the model itself. Machine learning algorithms designed with fairness in mind integrate bias mitigation strategies into their training processes. This approach aims to reduce discriminatory outcomes in diverse populations. Additionally, 'post-processing' may be applied to fine-tune the output of the trained AI models to ensure that the results are accurate.

In addition, continuous evaluation and monitoring are essential to ensure fairness in AI systems. A multifaceted approach is required to assess and mitigate the bias in AI systems. Fairness-aware metrics explicitly measure outcome disparities across groups. AI auditing tools systematically examine model behaviour to identify potential biases. Moreover, understanding how AI models make decisions (i.e., model interpretability) aids in detecting unfairness. Continuous monitoring of system performance and gathering user feedback are crucial for identifying and rectifying emerging biases.

Another crucial consideration is robustness bias, which refers to the potential for variations in data or algorithmic design to disproportionately impact different groups. Techniques for improving AI model robustness include training models to resist manipulation using deliberately crafted data points intended to deceive the model. Various defense mechanisms can be implemented to enhance the resilience of models against adversarial attacks. These include augmenting the training data with adversarial examples and combining multiple models (i.e. ensemble methods). In addition, certifying model robustness under adversarial conditions and developing methods for detecting malicious inputs are crucial for mitigating this threat.

Ferrara (2024a) mentions several other ways to reduce bias in AI systems. These methods aim to address the sources of bias and ensure the equity and fairness of AI systems. Ferrara suggested the following mitigation strategies:

- *Improving data quality*: This approach to mitigating bias relies on improving the quality of the datasets used to train machine learning models. This could involve collecting more diverse and representative datasets to reduce the data bias. Incorporating more diverse data into training datasets, also known as 'dataset augmentation', is a strategy to reduce bias and increase representativeness.
- *Designing bias-aware algorithms*: Another strategy is to design algorithms that are explicitly aware of various forms of algorithmic bias to reduce their effects on the output of the AI system. Bias-aware algorithms take into account the potential biases in the data and the algorithm design itself and strive to produce fair and unbiased results.
- *User feedback mechanisms*: These mechanisms identify and correct biases in AI systems by receiving user assistance. Biases can be identified and addressed more effectively by relying on the feedback of active users to evaluate and improve the AI systems.
- *Interdisciplinary collaboration*: Ferrara emphasised the importance of interdisciplinary collaboration in addressing bias in AI. Addressing this challenge necessitates a collaborative effort involving experts specialising in diverse areas, such as ethics, law, and computer science, to devise effective solutions that prioritise ethical implications.

Similar to Ferrara (2024b, 2024a), González-Sendino et al. (2024) maintain that the foundation for mitigating bias lies in the training data used in AI models. According to González-Sendino et al., one way to address this issue is to ensure diversity in training data. This involves collecting data that reflect the demographics of the population with which the AI system will interact to reduce bias towards specific groups by exposing the model to a broader range of characteristics. Moreover, educators can use "fairness sampling" techniques to address data representation imbalances. This technique involves 'oversampling' to increase the representativeness of underrepresented groups, and 'undersampling' to reduce the dominance of overrepresented groups, which helps create a more balanced dataset for training. However, it is important to note that while these approaches can help mitigate bias, there is ongoing research and debate regarding the best methods and their limitations. Additionally, legal issues related to bias mitigation, such as data protection and anti-discrimination laws, should be considered when implementing these approaches.

The promise of AI-based personalisation to provide effective and efficient learning guidance to all learners on all topics is tied to the quality of the models constructed and the methods used to apply them. Thus, a critical issue for AI in the education research community is how to ensure diversity and appropriateness in the models that are learned and applied. This issue presents a substantial opportunity for AI to contribute to better educational practices, but also presents many pitfalls and unsolved problems.

5.2. Ensuring a Human-Centred Approach

One of the main concerns for AI advocates in personalised learning is maintaining a human-centred and student-focused approach. Students and teachers should not have to model their learning and teaching styles to meet the technological requirements. The technology should be intuitive and adaptable enough to meet the needs of students and instructors. This means that education must maintain its focus; otherwise, it will lose its essence and efficacy. With the increasing role AI plays in education, it is easy to get caught up in the "fancy" capabilities of AI and lose sight of the actual goals of education itself. AI may be integrated into the education sector, with an emphasis on augmenting rather than replacing human efforts. Teaching requires an understanding of the human learning process, knowledge of the subject matter, and the ability to adapt instruction to the needs of the learner.

Similarly, the emergence of Large Language Models (LLMs) has caused significant anxiety in academic and higher education communities (Talha Junaid et al., 2024). However, these models also hold immense potential to revolutionise teaching and learning practices. One key benefit is the potential of LLMs to alleviate faculty workload by automating tasks such as generating personalised learning materials and providing basic student support. Moreover, LLMs, such as ChatGPT, are capable of performing a wide range of tasks, including generating text, writing code, providing educational support across multiple subjects, and creating realistic characters for virtual environments (A. Salloum et al., 2024). Hence, LLMs can free up valuable time for educators by assuming the burden of repetitive or routine tasks, such as grading, thereby allowing them to focus on more demanding activities and tasks, such as curriculum development and individualised instruction. The current threat is that AI systems will compete for the same roles and ultimately replace educators. Therefore, emphasis must be placed on developing AI tutors as complements to human instructors rather than as substitutes.

In addition to the teaching process, LLMs offer promising applications in post-teaching analysis and evaluation. AI-powered solutions can be used to automate the analysis of student learning data, providing educators with valuable insights into student’s strengths and weaknesses. This information can be used to personalise learning experiences and optimise outcomes. However, as Shwedeh et al. (2024) argued, taking full advantage of the ability of AI tools to create sustainable education requires substantial resources to be allocated to developing AI technology, equipping educators with AI skills, and restructuring educational programs.

6. Conclusion

This study reviews the possible benefits and drawbacks of using AI systems for personalised learning. The intent is to help stakeholders understand the conditions under which AI-driven personalised learning solutions may be effective, the problems they can address, and the issues that need to be resolved for future applications.

Personalised learning with AI brings both benefits and drawbacks to higher education, but the future will likely focus on viewing AI as a tool to harness the benefits while mitigating the drawbacks. One of the largest potential benefits of AI is the cost savings related to its more efficient use of resources. If used properly, exacting levels of personalised instruction could be achieved through automation, freeing up educators’ time for more students, many of whom previously could not access this level of instruction. AI can also account for a wider range of learning styles than human educators and predict and prescribe the most effective learning modality for each student. Automated education can be considered a solution to the problem of limited access to high-quality instruction in a few areas. Using AI, students can gain access to education equal to that of elite private sectors. Finally, AI has the potential to increase retention and graduation rates by identifying at-risk students early and guiding them along a corrective path. Students leaving the system because of their inability to understand, disinterest, or external factors could be retained at higher rates than they currently do.

Disclosure Statement

No potential conflict of interest was reported by the author(s).

Notes on Contributors

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