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Applications of Artificial Intelligence in Education: A Review of Learning Analytics and Open Educational Data Sources

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Abstract
Artificial Intelligence (AI) is quickly transforming the educational world, enabling personal, scalable and data-driven learning systems. The third element of AI technologies, learning analytics, and open educational sources of data, has opened new opportunities to enhance the effectiveness of teaching and student performance. Learning analytics deems relevance in deriving meaningful significance out of large volumes of educational information in support of activities such as predicting student performance, tracking engagement and early intervention. Meanwhile, open educational data sources, such as MOOCs, open educational resources, and institutional repositories, offer the required basis to train and optimize AI-driven models. Combining these aspects enables the development of adaptive learning systems, intelligent tutoring systems, and recommendation engines to tailor educational experiences to the needs of individual learners. Despite these attempts, there are still challenges such as data privacy, algorithmic bias, interoperability, and unequal access to technology that hinder the full potential of AI in education. These are key points that must be tackled to achieve ethical, transparent and inclusive implementation. Overall, the merging of AI, learning analytics, and open data is a major move towards more efficient, fair, and student-centered systems of education.

Keywords:
- Artificial Intelligence in Education
- Learning Analytics
- Open Educational Data
- Educational Data Mining
- Personalized Learning

1. INTRODUCTION

AI (Artificial Intelligence) has emerged to be one of those technologies in the modern world of education which have significantly altered the manner in which teaching, learning, and assessing take place in the educational setups. AI can be described as the computational technology which can perform functions usually associated with human intelligence in solving problems, recognizing patterns and decision making (Russell & Norvig, 2022). The use of AI in the education sector has taken off recently with the inclusion of several AI-based tools, such as intelligent tutoring systems, grading systems, and personalized learning systems, in the education industry, aimed at enhancing the process of teaching and improving students' performance (Holmes et al., 2019). Innovations such as these have contributed towards the transformation of education away from traditional teacher-centered approaches towards more student-centered methods. The rapid development of digital technologies has only increased the rate at which AI can be applied in education. LMSs and MOOCs have contributed towards the generation of large volumes of data, which are commonly known as educational big data (Daniel, 2017). The student's interaction patterns, performances, and other related metrics can be analyzed through the available information to determine the processes associated with the students. As a result of increased availability of such information, there have been significant changes within the teacher-student relationships with the focus shifting from intuition towards decision-making through data utilization and improved teaching techniques (Siemens & Baker, 2012). Education systems are therefore becoming digitally enhanced ecosystems with the data taking the centre stage in determining pedagogical practices. Learning analytics has become an important discipline that uses data to learn and optimize learning and the context under which it takes place within this context. Learning analytics refers to the process of gauging, recording, analyzing and reporting information regarding learners and their settings (Long & Siemens, 2014). Using analytic skills on education data, the institutions can be used to determine at-risk students, forecast academic achievement, and create specific interventions to enhance learning outcomes (Ferguson, 2012). Moreover, learning analytics enables ongoing feedback processes, which allows learners and educators to make decisions in real-time. Such an ability is especially valuable in online and blended learning courses, where more conventional methods of tracking student progress might be constrained. The other notable trend that has led to AI-based education is the emergence of open educational resources. The Open Educational Resources (OER), MOOCs, and publicly available education datasets offer easy-to-use and reusable information that can be used in research, model building, and teaching enhancement (Wiley et al., 2014). Such open data resources help in the collaboration, transparency, and innovation in the educational field as they enable researchers and practitioners to experiment with large-scale data without facing any major access control. Furthermore, open educational data is essential in the training of AI models, which allows the creation of scalable and generalizable solutions to a wide range of learning scenarios (Atenas & Havemann, 2015). Thus, AI and open data can democratize education and create equal access to high-quality education opportunities. With these developments, there are still a number of challenges and gaps in research on effective application of AI in education. The major problem is that the investigations in the area of AI, learning analytics, open data, etc. are often disjointed and seldom combined (Zawacki-Richter et al., 2019). Also, there are problems with data privacy, ethical use of student data, and algorithmic bias, which can be among the major obstacles to universal adoption (Selwyn, 2019). The existence of thorough reviews that will investigate the interaction between AI technologies, learning analytics, and open educational data sources in a single field is also lacking. These gaps need to be filled to develop holistic and sustainable AI-based educational systems. Taking these factors into account, the provided review will be used to explore the applications of AI in education in more detail, with a particular focus on the learning analytics and open educational data sources. The purpose of the review is triple: to determine the conceptual assumptions and significant technologies that aid AI in education; to evaluate the significance of learning analytics in facilitating the quality of education and to elaborate on the role of open educational sources in the production and use of AI-based solutions. While synthesizing the existing studies in the relevant areas, the research focuses on presenting an insight into current trends and issues, as well as future possibilities of artificial intelligence-based education.

2. CONCEPTUAL FOUNDATIONS OF AI IN EDUCATION

Artificial Intelligence (AI) in education is the use of computational algorithms and intelligent systems to improve education, learning, and administration. It entails a broad spectrum of technologies that aim at imitating the cognitive processes of humans like reasoning, learning, and problem-solving in the educational environments (Luckin, 2018). AI in education goes beyond automation with a goal to develop adaptive, personalized and scalable learning environments that can react to the needs of individual learners. With the growing digitalization of educational systems, AI can be viewed as a backbone to the transformation of the conventional pedagogical systems into more information-driven and person-centered ones (Chen et al., 2020). AI in education is rooted in the number of key technologies, with Machine Learning (ML) being the most prominent one. Machine learning is an approach that brings algorithms to the systems that help them learn by observing data and enhance their performance without the need to be programmed (Alpaydin, 2020). ML has also found extensive application in education in predictive analytics and student performance modeling, as well as in recommendation systems. As an illustration, using historical student data, ML algorithms can forecast their success in school or those who are at the risk of dropping out, thus providing an opportunity to implement timely measures (KOTSIANTIS et al., 2004). These functions will help in improving the decision-making process in learning institutions. Natural Language Processing (NLP) is another important element that is concerned with giving machines the ability to comprehend, decode and produce human language. In education, NLP is used in many applications such as automated essay scoring, chatbots as tutors, and language learning systems (Jurafsky & Martin, 2023). By using NLP, AI systems will be able to give students real-time feedback on their writing, can be used in interactive learning and can support multilingual education. Moreover, NLP-driven conversational agents are also becoming more common in simulating interactions with a human, thus enhancing engagement and accessibility of learners (Winkler & Soellner, 2018). Deep Learning is a branch of machine learning that further increases the potential of AI systems through the use of artificial neural networks to produce complex and high-dimensional data. The deep learning models are especially efficient in solving problems like image identification, speech recognition, and pattern identification (LeCun et al., 2015). These models find application in education in the fields of emotion detection, adaptive assessment and intelligent content generation. As an example, facial expressions or voice patterns can be analyzed using deep learning algorithms to determine student involvement and emotional conditions and are useful in personalized learning (D'Mello & Graesser, 2012). Implementation of deep learning in learning technologies, in turn, facilitates more complex and context-sensitive learning systems. Based on these technologies, Intelligent Tutoring Systems (ITS) are one of the most well-known applications of AI in the educational field. ITS are computer-based systems that are aimed at presenting personalized instructions and feedback to learners without involving human beings (VanLEHN, 2011). These systems replicate one-on-one tutoring through the adaptation of content, pacing, and strategies of instruction, in regards to the performance of the individual learners. It has been demonstrated that ITS can considerably enhance the learning results because it provides personalized instructions and real-time feedback (Ma et al., 2014). Additionally, ITS can be implemented with a variety of subjects and levels of learning, thus they can be an effective tool in both formal and informal learning. Intimately connected with ITS are adaptive learning systems, which dynamically adapt learning pathways in response to student information and interactions. In contrast to the old systems that are static, the adaptive systems constantly measure the progress of the learners and adjust the instructional content by meeting the needs of the learners (Brusilovsky & Millán, 2007). These systems use the power of AI algorithms to suggest resources, modify the difficulty level, and customize the assessment. As a result, adaptive learning supports a personalized and self-paced learning process, which leads to increased engagement and retention. The rising prevalence of adaptive technology in online learning environments and the LMS systems is clear evidence of their significance in contemporary educational processes. It should also be noted that the theoretical foundations for the use of AI in education are based on existing theoretical foundations, such as constructivism and connectivism. Constructivism believes that knowledge is actively constructed by the learner as he/she engages with his/her surrounding environment and experiences (Piaget & Inhelder, 2008). The AI-powered tools, including simulation-based learning and interactive tutor systems, are compatible with the principles of constructivism since they allow learning that is based on experience and inquiry. Through these tools, learners are able to experiment with concepts, hypotheses, and also get feedback, thus making it easy to understand the concept further. In contrast, the focus of connectivism is on the importance of networks and digital associations in learning. It postulates that knowledge is spread through networks of individuals and technology and learning is the capacity to move and use the networks (Siemens, 2005). AI technologies, especially those that are combined with online platforms and open data sources, facilitate connectivist learning because they allow accessing extensive information networks and promote a collaborative learning environment. As an illustration, based on recommendations and social learning, learners can find and share appropriate content and interact with their peers, thus, increasing knowledge sharing and co-creation.

The combination of these technologies and theoretical views creates a holistic approach to comprehending AI in education. This framework highlights the interaction between AI tools, educational systems, and learning outcomes, providing a structured approach to analyzing the impact of AI on teaching and learning processes. Figure 1 depicts the interplay of AI technology and educational systems, as well as learning outcomes.

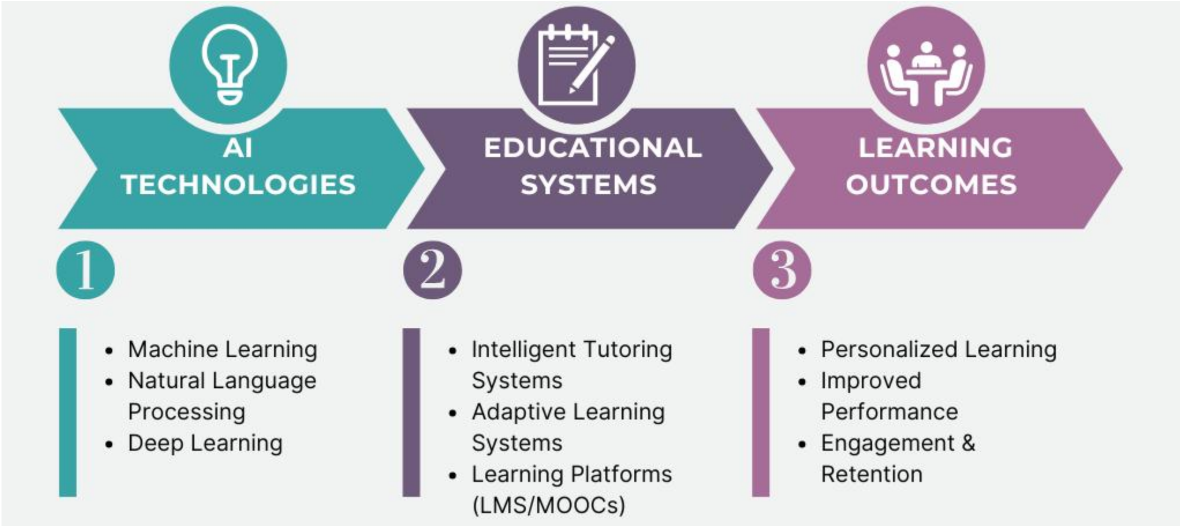

Figure 1: Conceptual Framework of AI in Education

3. LEARNING ANALYTICS: CONCEPTS, TOOLS, AND APPLICATIONS

Analytics in Learning Learning analytics is a relatively new field in the technology of education, which addresses the systematic utilization of data to improve the learning experience and outcomes. The broad definition of it is the process of gathering, quantifying, analyzing, and reporting information on learners and their situations to get to know and maximize learning (Chatti et al., 2012). The development of learning analytics is directly connected with the growth of online learning, especially the Learning Management Systems (LMS), MOOCs and online educational systems, which produce enormous data on interaction between learners (Greller & Drachsler, 2012). Learning analytics has progressed over time to more complex tools and applications that can perform predictive and prescriptive decision-making, which has become the focal point in data-driven education. There are three broadly outlined types of learning analytics: descriptive, predictive, and prescriptive analytics. Descriptive analytics is a type of analytics that concentrates on summarizing historical data to make information about what has already taken place in the learning process. As an example, student attendance, grades, and participation level dashboards can assist educators in tracking student progress and recognizing trends (Dyckhoff et al., 2012). Predictive analytics, in its turn, is based on statistical models and machine learning methods to predict future results, e.g., the performance of students or their likelihood of dropping out. Predictive models help to identify students in need of further assistance by examining trends in past data (Tempelaar et al., 2015). Prescriptive analytics takes it a step further to prescribe certain actions or interventions, based on predictive insights. Such analytics is especially useful in informing the decision-making process, as it allows teachers to use specific strategies to enhance the learning outcomes (Ifenthaler et al., 2019).

A variety of computational methods are vital to the success of learning analytics. One of the most popular methods is data mining, which presupposes the extraction of meaningful patterns and relationships based on extensive educational data (Romero & Ventura, 2010). Data mining techniques are able to reveal hidden information about the behaviour and learning patterns of students through the use of clustering, classification and association rule mining. Another significant method for the prediction of future outcomes is the use of predictive modeling. The algorithms which could be used in this case include linear regression, decision trees, and neural networks (Baker et al., 2016). They can be of great assistance especially when dealing with situations that involve the identification of at-risk students and the implementation of early intervention measures. Moreover, visualization dashboards play an essential role in learning analytics because they make the process of understanding complicated information simpler. Dashboards facilitate the real-time graphic representation of the key performance indicators, such as student engagement levels, student progress, and student achievement levels (Verbert et al., 2013). Dashboards enable educators and learners to interact with data visually through graphs and charts among other visual elements, thereby facilitating informed decision-making and nurturing self-directed learning. In addition, analytics systems and visualization tools will help in visibility and user-friendliness and bring data insights nearer to action.

Learning analytics can be implemented in educational environments in many different ways, which has a significant impact on the teaching and learning process. Student performance prediction is among the most eminent uses. Learning analytics systems can recognize trends related to success or failure by examining historical academic data, and this will allow institutions to make predictions regarding student performance at a high level of accuracy (Arnold & Pistilli, 2012). This predictive capacity is used in proactive interventions in which teachers can address learning difficulties before they get out of control. The other field is that of developing early warning systems. These are based on real-time information gathering aimed at detecting any danger signs in academia, reduced engagement, and take corrective action (Macfadyen & Dawson, 2010). Online learning systems are particularly the settings where early warning systems can be used because it is required to keep an eye on students at all times to ensure their retention and success. Such systems contribute to improved performance of students and reduced dropout rates due to provision of accurate and timely feedback and assistance. Another important use of learning analytics is to facilitate engagement monitoring. Analytics systems can evaluate the amount of student engagement in learning activities by monitoring their attendance and engagement rates, length of time spent on tasks, and involvement in discussions (Henrie et al., 2015). This data can help teachers to recognize uninterested students and take measures to boost their motivation and engagement. Also, the data on engagement could be helpful in assessing the efficiency of instructional design and learning materials and the educational practices can be constantly improved. In general, learning analytics is an effective instrument to improve the quality and effectiveness of learning. Combining the latest analytical methods with the data on education, it allows institutions to understand learning processes better, help in personalized education and enhance decision-making. To demonstrate the systematic nature of learning analytics processes, Figure 2 illustrates the flow of all the processes (data collection-decision making) and emphasizes the systematic approach that is necessary to achieve successful implementation. Table 1 provides a comparative overview of the descriptive, predictive, and prescriptive learning analytics, their methods, and uses.

Table 1: Comparison of Learning Analytics Types and Applications

Type	Description	Techniques Used	Educational Applications
Descriptive	Summarizes historical learning data to understand past performance	Data aggregation, basic statistics	Progress tracking, performance reports
Predictive	Uses data to forecast future student outcomes	Machine learning, regression, classification	Student performance prediction, dropout risk
Prescriptive	Recommends actions based on predictive insights	Optimization models, AI-based systems	Intervention strategies, personalized learning

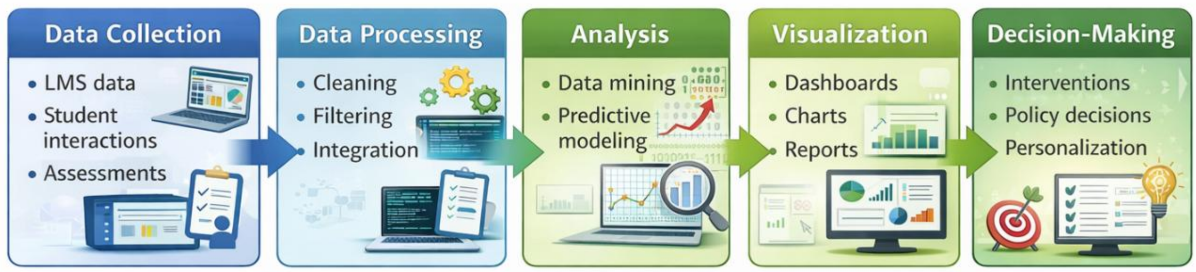

Figure 2: Learning Analytics Process Flow

4. OPEN EDUCATIONAL DATA SOURCES AND THEIR ROLE

Open Educational Data (OED) is freely available, openly licensed data that relates to education processes, educational resources, and education systems that can be used, reused, and redistributed by researchers, educators, and institutions. OED is a further development of the wider Open Education movement that focuses on transparency, access, and collaboration in education practices (OECD, 2015). In comparison to the traditional proprietary datasets, open educational data offers the chance to conduct analysis and innovations on a scale, especially the creation of the AI-based educational tools. OED also promotes evidence-based research and creation of scalable and varied learning solutions by allowing free access to a variety of datasets (Eynon, 2013). Massive Open Online Courses (MOOCs) are considered to be one of the most important sources of open educational data. Coursera, edX and Udacity, among others, produce large amounts of data that covers demographics of learners, history of interaction, evaluation scores and activity measurements. These data sets can be used to study learner behavior on a scale and predict student success (Kizilcec et al., 2013). MOOCs offer an excellent opportunity to experiment and researchers can investigate various groups of learners and apply AI-related interventions in practice. Moreover, due to the openness of most MOOC data, cross-institutional cooperation and comparative research are possible. Another source of educational data is Open Educational Resources (OER) platforms. OER consists of teaching resources, textbooks, videos, and courseware which are openly licensed to be reused and adapted (Hilton, 2021). These platforms are not just able to offer access to learning content but also generate metadata and usage data which can be analyzed to comprehend the patterns of learning and resource efficiency. As an example, monitoring the interactions of learners with the content of OER may be utilized to determine which resources are most helpful in enhancing the learning outcomes. These can be applied to better the content design and guide AI-based recommendation systems. Institutional repositories also have a vital role to play in open educational data ecosystem. Research institutions and universities have repositories where academic publications, datasets, course materials and student records are stored. Such repositories usually contain structured and semi-structured data, which can be used to benefit educational research and analytics (Lynch, 2017). Institutional repositories amalgamate the information of various sources and offer a holistic perspective on the learning activities, which allows conducting more holistic analysis and decision-making. Also, open data policies are being implemented in numerous institutions in order to foster transparency and cooperation that further increases access to educational data. The three Vs of big data, volume, variety and velocity characterize open educational data. Volume is defined as the immense amount of data that the digital learning environments produce, which may involve millions of interactions between learners. Variety refers to the variety of data, including structured data like grades and attendance data as well as unstructured data like posts in a discussion forum and multimedia material. Velocity measures the rate at which data is produced and processed, especially in real-time learning situations (Williamson, 2017). These attributes render OED very useful in AI applications since they offer richness and complexity to be able to train powerful and generalizable models. Access to open educational data is a crucial factor in developing and training AI models in education. Machine learning algorithms need extensive datasets (high in both size and variety) to learn trends and make proper predictions. Such datasets are offered by OED, allowing prediction of student achievements, recommended content that is tailored to a student, and adaptive assessment (Piety et al., 2014). Besides, the presence of the data allows the researchers to verify the findings, which enhances the trustworthiness and dependability of the AI-based solutions. AI systems can be developed using OED to address a wide range of educational challenges, such as improving learning outcomes and optimizing resource allocation. Despite the potential it has, the implementation of open educational data is associated with several challenges. A significant issue is the quality of data, which can include inconsistencies, missing data, and errors in open datasets, which can influence the quality of the analytical models (Borgman, 2017). Preprocessing and validation are processes that can be resource-intensive and time-consuming to ensure the quality of the data. Another issue of concern is interoperability where data in various sources can be in incompatible formats or may use different standards. This non-standardization can make data integration difficult and constrain the power of AI applications (Pawlowski & Zimmermann, 2007). Accessibility is also another significant problem of using open educational data. Although the information is technically open, the use of the data may be hampered by technical skills, poor infrastructure, and insufficient awareness (van Deursen & van Dijk, 2014). Furthermore, the issue of data privacy and its ethical use must be taken into keen consideration in an attempt to ensure that open data initiatives do not erode the rights and interests of learners. Achieving a delicate balance between openness and confidentiality is one of the means through which the required trust can be obtained and assurance ensured that the information from education will be used for the right purposes.

Table 2 below presents an organized overview of the various sources of open educational data and their applicability in the domain of artificial intelligence.

Table 2: Types of Open Educational Data Sources

Source Type	Examples	Data Type	Use in AI Applications
MOOCs	Coursera, edX, Udacity	Interaction logs, assessments, and clickstream data	Student performance prediction, dropout analysis
OER Platforms	OpenStax, MERLOT, OER Commons	Learning materials, usage metadata	Content recommendation, learning pattern analysis
Institutional Repositories	University digital libraries	Research data, course materials, and student records	Academic analytics, curriculum improvement
Government/Open Data Portals	Data.gov, UNESCO datasets	Educational statistics, demographic data	Policy analysis, large-scale educational modeling

5. INTEGRATION OF AI, LEARNING ANALYTICS, AND OPEN DATA

In combination with learning analytics and open educational data, Artificial Intelligence (AI) provides a revolutionary approach to education systems in the modern world. It is interesting how these three fields are interconnected, forming a data-driven system that enhances the learning process and contributes towards scalable solutions for education. AI makes it possible to process and analyze mass educational data using learning analytics, and open data provides a free-of-charge foundation as far as training and validating intelligent systems are concerned (Bakharia et al., 2016). The field of learning analytics is a type of AI application that is based on the use of complex algorithms to analyze the patterns in data related to learners and deliver information to be used. Both structured and unstructured data about the behavior, performance, and engagement of students can be provided by learning analytics, and can be analyzed by AI systems to generate predictive and adaptive models (Papamitsiou & Economides, 2014). To illustrate this, machine learning algorithms can use the past performance data to determine trends and forecast future outcomes so that the institutions can take timely interventions. In addition, AI increases efficiency and scalability of analytics by processing the data automatically and increasing the accuracy of predictions, thus making analytics more efficient and scalable. OED is very important in training AI models because it offers a variety of data sets that are extensive. To learn the patterns and generalize in various contexts, AI systems need a large amount of training data to learn. MOOCs and institutional repositories are open data sources that provide rich datasets that may be used to create powerful AI models (Reich, 2015). These data sets can help researchers to test their various algorithms and test their models in diverse learning environments. Moreover, open data enhances transparency and reproducibility in research, which are crucial to the further development of AI applications in education. Developing AI, learning analytics, and open data as integrated systems are becoming more common in the educational setting. These systems integrate data collection, analysis and intelligent decision-making into one system. As an illustration, the current Learning Management Systems (LMS) integrate analytics dashboards and recommendation engines powered by AI to tailor learning (Drachsler & Kalz, 2016). Thanks to such integration, it is possible to monitor the progress of students in real time and create adaptive content that addresses the needs of each student. Consequently, the integrated systems increase the effectiveness of teaching and student interest. This integration is proven to be effective by several practical applications. Recommendation systems are common to recommend learning material, course or activity depending on the preferences and performance of the student. These systems are based on the AI algorithms and learning analytics data to give personalized recommendations and enhance learner engagement and satisfaction (Manouselis et al., 2012). The other significant use is the dropout prediction, in which the predictive models are used to process behavioral and academic data to determine students likely to drop a course. Early detection helps the institutions to offer specific assistance and minimize the dropout rates and enhance retention (Xing et al., 2016). Another technology in AI that is becoming useful in education is smart content generation. In response to existing content and the needs of the learners, AI systems can automatically produce quizzes, summaries, and learning materials. Using open educational data and analytics, such systems will be able to generate personalized content that follows individual learning patterns (Holmes et al., 2019). This not only eases the burden on the educators, but also makes sure that learners are offered pertinent and timely instructional resources. There are various benefits associated with the integration of AI, learning analytics, and open data. Personalization is among the greatest advantages as AI systems can modify learning experiences in response to individual preferences, skills, and learning levels. This leads to improved engagement, motivation, and learning outcomes (Kerr, 2016). Another important advantage is scalability since AI-based systems can accommodate high numbers of learners at a time without degrading the quality of services. This is particularly required in online and distance learning where traditional teaching methods may not be sufficient. However, the integration of these technologies also has its problems. One of the largest problems is algorithm bias, which may occur because of biased or unrepresentative training data. This bias can cause the unfair or inaccurate predictions being made, which impacts some groups of learners in a disproportionate manner (O'Neil, 2016). Data governance is another issue which is of paramount concern as the gathering, storage and use of educational data must comply with legal and ethical standards. To preserve trust and accountability in AI-driven systems, it is necessary to ensure proper data management practices (Prinsloo & Slade, 2017). The relationship between AI, learning analytics and open educational data can be visualized as a combined ecosystem as shown in Figure 3.

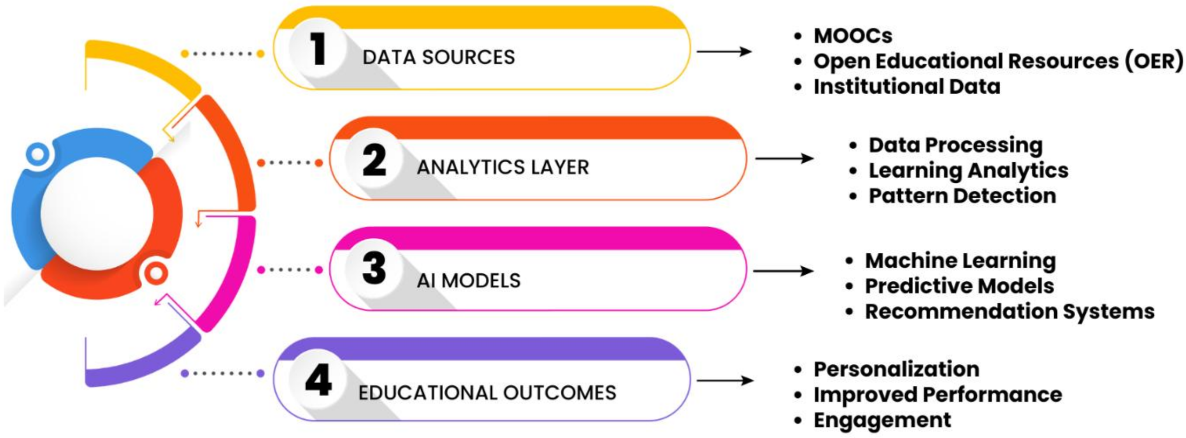

Figure 3: Integrated AI-Learning Analytics-Open Data Ecosystem

6. CHALLENGES, ETHICAL ISSUES, AND FUTURE RESEARCH DIRECTIONS

The development of the idea of Artificial Intelligence (AI) within the education industry has led to many developments in the learning process; however, it is accompanied by many challenges ranging from ethical, technological, to policy-based. With the increasing use of AI technologies in leveraging large amounts of student data, the issue of privacy and security becomes a major challenge. It is imperative that such issues be addressed for the technology to be productively applied (Dignum, 2019).

Perhaps one of the most important issues that arise regarding the use of artificial intelligence in education is that of privacy. AI captures a large amount of personal and behavior-related data, such as grades, social interactions, and sometimes even bio-metric data. These are all types of information that require careful handling as they might pose a risk of abuse (Prinsloo & Slade, 2017). The protection of privacy is impossible without proper data management policies, consent processes, and adherence to ethics. Educational organizations should ensure that information is de-identified and will not be used against the students by ensuring that it will only be accessed for legitimate reasons. Data security is directly related to privacy. With the increasing reliance on online and cloud-based services, educational data may become a target of cyberattacks. Such consequences might include identity theft and lack of trust among educational institutions in case of an unauthorized breach of student data (Hashizume et al., 2013). Consequently, a good cybersecurity strategy such as encryption, proper authentication, and auditing of the system must be put in place for integrity and confidentiality. These organizations will have to make an effort in investing in both infrastructure and skills to counter these threats. Transparency is another issue that is important to consider in relation to AI in education. This is because most of the AI algorithms are not easy to interpret, hence referred to as black boxes. This problem poses a challenge to explain decision-making processes in case the algorithm either predicts or provides recommendations on their performance (Lipton, 2018). Without any explanation, stakeholders may doubt whether the decision-making based on the application of AI technologies is free from any bias and prejudices. Increasing transparency through applying explainable AI models and efficient communication techniques is an important aspect to consider in building trust and accountability in AI applications. Along with these ethical issues, it is important to mention some technical issues that need to be overcome to implement AI successfully. In this regard, data integration can be considered the major issue because educational data are often stored in different sources. The following data types that cannot be easily integrated include LMS data, institutional data, and external data types (Nguyen et al., 2020). Such inconsistencies or lack of completeness in data can have an adverse effect on the performance of the AI systems and it is important that there is consistency in data structures. Reliability of models is yet another issue. The AI system must provide consistent and reliable results in different environments. Nevertheless, trained models might not be relevant for use across the entire population (Mehrabi et al., 2022). Evaluation, validation, and updating of models have to be conducted constantly in order for them to remain efficient and unbiased. In addition to that, the use of more than one dataset would help to diminish biases and improve the AI systems. Moreover, issues concerning governance and policy are of paramount importance when it comes to the employment of AI in education. For ensuring the proper use of these technologies, the governments and institutions have to create appropriate regulations and guidelines which would address the issue of the ownership and legal compliance of data (Cath, 2018). The lack of clear governance frameworks could lead to inconsistency or misuse, or even unwanted outcomes, from the implementation of AI. Cooperation between policymakers, educationalists, and technologists will be crucial in establishing a sound governance framework. Another problem associated with AI integration into the educational sector will be the digital divide. This is an existing problem that has hindered the appropriate use of AI in the educational setting. It is often the case that AI implementation is reliant on digital infrastructure, such as internet connectivity and advanced hardware, which underprivileged or rural learners may not be able to access (Helsper, 2021). However, the policies that will contribute to improved inclusiveness and accessibility should ensure that the digital divide issue is solved, especially in relation to infrastructure. Every learner needs access to AI to ensure that the education is achieved effectively.

To solve the issues described above and improve the significance of AI in education, some promising research directions may be considered in the future. The explainable artificial intelligence (XAI) has been getting more popular in recent years, as it offers solutions for making AI transparent. Explainable AI focuses on developing AI systems that offer understandable reasoning and decision-making processes (Gunning et al., 2019). This becomes particularly important in the domain of education because of the impact that the decisions may have on the learners. The second topic for future studies is Human-AI partnership. It is assumed that AI should not substitute humans; instead, it should serve to augment human abilities and assist in teaching activities. If AI knowledge and human knowledge are combined in cooperation systems, better results will be obtained (Luckin, 2018). For example, AI technology could help educators identify students requiring assistance and give feedback individually, yet still retain the option of making their own teaching decisions. Finally, the rise of inclusiveness and sustainability of AI technology is becoming increasingly apparent. By definition, inclusivity refers to the development of technologies that would meet the requirements of different types of students, whether disabled or belonging to another culture. Conversely, sustainability is concerned with the sustainability and ethicality of AI technology, its environmental impact, and so forth (Vinuesa et al., 2020). By prioritizing inclusivity and sustainability, the researchers and practitioners can ensure that AI will be more beneficial in the future of education. In conclusion, AI has immense potential to transform the education sector, but the ethical, technical, and policy-related challenges should be addressed to ensure its successful adoption. The development of transparency, collaboration, and equitable access to AI-driven educational technologies should be prioritized in future research.

7. CONCLUSION

The integration of artificial intelligence in the field of education, along with the emergence of learning analytics and sources of open educational data, has brought about a change in the manner educational institutions operate. This literature review sheds light on the use of artificial intelligence tools in making personalized learning more appealing, efficient decision-making, and improving the engagement of students through stimulation. Learning analytics is used as the basis for analysis of learning behavior, while open educational data serves to enhance AI models in diverse learning settings. The combination of these elements leads to the development of intelligent interactive learning environments. However, there is no need to identify problems related to the wide-scale application of artificial intelligence in education. The problems that require addressing for the implementation of AI in education to be responsible include issues of data privacy, data security, ethics, and algorithm bias. Moreover, the problem of the digital divide remains one of the obstacles in making AI-based learning accessible to all learners. The future growth must be directed to improve the transparency that can be explained by AI, promote cooperation between humans and AI, and present inclusive and sustainable educational technologies. Lastly, AI can change education but implementation must also be met with equilibrium between technology and ethical responsibility and accessibility in order to make the good impacts of AI accessible to all.

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