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COMPUTATIONAL INTELLIGENCE IN LEARNING ANALYTICS: A MINI REVIEW

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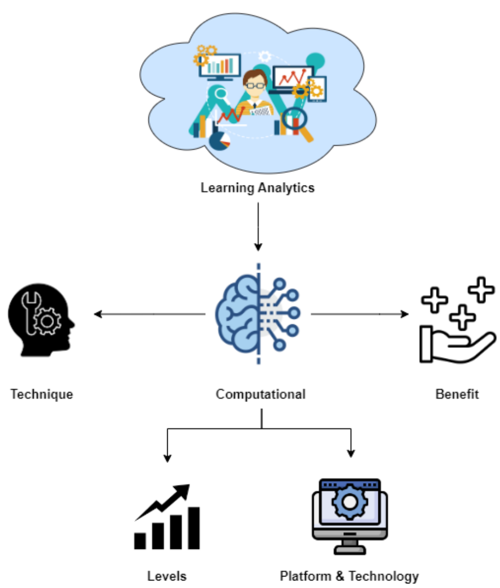
Graphical abstract



Abstract

The field of Learning Analytics (LA) has witnessed remarkable growth, with a growing emphasis on the utilization of data-driven insights to enhance educational practices. Learning Analytics, encompassing the acquisition, analysis, and interpretation of student data, holds immense promise in transforming education. This review paper synthesizes the key advancements in Learning Analytics, focusing on its definition, benefits, and various levels of learning analytics. A comprehensive literature review has been conducted to delve into existing platforms, LA levels, and technologies. It critically evaluates the significance of predictive Learning Analytics in identifying trends and patterns in educational data. Moreover, the review delves into the integration of Artificial Intelligence (AI) in LA, highlighting its multifaceted utility, from personalized recommendations to intelligent tutoring systems. Several case studies are examined to underscore the real-world applications of AI models in Learning Analytics. This paper offers insights into the advantages of AI-driven LA, such as early intervention and adaptive learning. Challenges and ethical considerations in AI-powered LA are also discussed. Furthermore, it shines a spotlight on the field of machine learning within Learning Analytics, emphasizing its role in automating data analysis and prediction, thus streamlining educational processes. This comprehensive review provides a foundational understanding of the evolving landscape of Learning Analytics, AI, and Machine Learning in education.

Keywords: Learning Analytics, Artificial Intelligence, AI Model, Predictive Learning Analytics, Machine Learning, Education

1.0 INTRODUCTION

The field of learning analytics is gaining more attention from educators and researchers. Learning analytics includes acquiring, measuring, analyzing, and reporting data about learners [1] as well as their digital behaviors to ensure optimal learning [2]. Academics have increasingly displayed a burgeoning curiosity in the field of learning analytics, particularly with the availability of advanced analytics techniques like machine learning, which can improve its potential [3,4]. The goal is to utilize data from students and learning settings to support and enhance learning at all levels. Owing to the advancement of technology, learning analytics has made it easier to make informed decisions about academic performance and track progress and behavior in virtual learning environments, ultimately leading to an improved quality of education.

The growth of learning analytics was boosted by the increased availability of unconventional data such as discussion, feedback, from multiple sources such as open forums and social media platforms, which could aid in measuring learning performance and effectiveness beyond traditional e-learning systems. However, the diversity of data structures used in learning analytics poses a challenge for educators and data scientists. Educational data comes in various forms, including structured data like test scores and grades, and unstructured data like student notes and social media posts. Additionally, sources like student information systems, course registration systems, learning management systems, student feedback surveys, and social media platforms also act as the important source of data for learning analytics. The large volume and variety of educational data can make it difficult to manage, store, and analyze effectively using advanced analytics techniques to generate useful insights.

This review paper serves as a comprehensive guide to learning analytics, encompassing AI integration, data storage, and the development of intelligent solutions. It not only synthesizes existing knowledge but also advances the field by proposing intelligent storage and analytics solutions to meet the evolving demands of education in the digital age.

2.0 LEVELS OF LEARNING ANALYTICS

Referring to the latest research work [5], LA is classified into four main levels which are descriptive, diagnostic, predictive and perspective levels as shown in Figure 1.

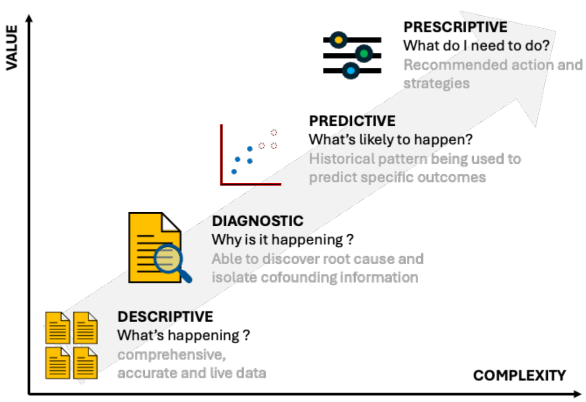


Figure 1 Four levels of LA

2.1 Descriptive Level

At the descriptive level of learning analytics, data is collected and analyzed to provide a clear comprehension of the present condition of learning procedures and results. This level is focused on answering questions such as "what happened?" and "who did what?". This level involves gathering data on student performance, behavior, and engagement with course material to enhance our grasp of the dynamics of student engagement within the learning environment. The data is then used to discover patterns and trends that can inform instructional design, resource allocation, and student support services [6].
According to the study [7], descriptive analytics is one of the most used levels of LA in educational settings. The authors note that descriptive analytics is particularly useful for providing insights into student performance, identifying patterns of usage for educational resources, and evaluating the effectiveness of teaching strategies.

For example, a descriptive analysis of student engagement data might reveal that students who participate in online discussion forums have higher course completion rates than those who do not [6]. This information could then be used to encourage more students to participate in discussion forums by highlighting the benefits of doing so.

2.2 Diagnostic Level

Diagnostic level is the use of data and analytics to identify the reasons behind specific learning outcomes, and to diagnose and understand the factors that lead to those outcomes. In other words, the diagnostic level aims to answer the question of "why" a certain learning outcome occurred. This level of learning analytics focuses on analyzing data to identify specific areas where a student may need additional support, feedback, or resources to improve their learning outcomes. For example, using diagnostic analytics, an instructor can identify students who are struggling with a particular topic or concept. Subsequently, offering tailored feedback or supplementary materials to assist these students in surmounting their challenges.

The study [8] explored the use of diagnostic analytics in an online learning environment to predict students' performance and provide personalized recommendations. The study used machine learning techniques to analyze student engagement data, course content data, and assessment data to identify factors that were associated with students' academic performance. Based on this analysis, the system provided personalized feedback and recommendations to each student, such as providing additional resources or recommending that the student review certain course content.
Another study [9] also focused on diagnostic analytics in an online learning environment, but with a focus on discovering students who were at risk of dropping out of the course. The study used clustering methods to group students based on their engagement data, and then used logistic regression to identify the factors that were related with students dropping out. Based on this analysis, the system provided personalized interventions to students who were identified as being at risk of dropping out, such as providing additional support or resources. Overall, diagnostic level of learning analytics can assist instructors and institutions discover the root causes of poor learning outcomes and provide targeted interventions to support students' learning and success.

2.3 Predictive Level

Predictive learning analytics involves utilizing data, statistical algorithms, and machine learning methodologies to discern patterns within educational data and forecast future learning achievements. It includes the analysis of data related to student behavior, performance, and interactions in order to provide insights into their progress and to enable interventions to improve their learning outcomes.
According to [10], predictive learning analytics enables the ability to pinpoint learners who might be at risk and suggest countermeasures for subsequent assistance. Customization of the learning experiences could be possible with the adaptation of content and activities by matching each student’s unique preferences.

Moreover, integration and incorporation of data from various origins, including learning management systems, social media platforms, and wearable devices can further improve the effectiveness of predictive learning analytics [11]. By leveraging these diverse data sources, proponents suggest that educators can attain a broader insight into students' behaviors and requirements, enabling them to craft more precise interventions that bolster the learning process.

Overall, the predictive level of learning analytics has shown promising results in improving learning outcomes and enhancing the effectiveness of education. Nonetheless, apprehensions regarding the privacy and ethical consequences of accumulating and applying extensive quantities of student data must be thoughtfully confronted to guarantee that the advantages of predictive learning analytics are harnessed in an ethical and conscientious manner.

2.4 Prescriptive Level

Perspective level learning analytics refers to utilizing data and analytics to acquire valuable insights into the effectiveness of teaching and learning practices at a broader organizational or systemic level. This involves analyzing data across multiple courses, departments, or institutions to discern and recognize trends and patterns. in student performance and engagement, and to develop evidence-based strategies for improving teaching and learning outcomes. Perspective level is similar to prescriptive level as defined in some research papers.

Perspective level learning analytics can be used to assist strategic decision-making in educational institutions, by providing insights into factors such as student retention, graduation rates, and workforce readiness [12]. The authors argue that by leveraging the power of data analytics, educational leaders can make more informed decisions about resource allocation, program development, and institutional policy.

Furthermore, the importance of integrating multiple perspectives into the analysis of learning analytics data have emphasized [13]. They argue that in order to fully understand the complex interactions between learners, instructors, and the broader educational ecosystem, it is necessary to analyze data from multiple sources and at multiple levels. By adopting a holistic and multidisciplinary approach to learning analytics, the authors argue, educational institutions can attain a more holistic comprehension of the elements influencing student achievement.

Overall, the prescriptive level of learning analytics holds the potential to bring revolution changes in the field of education by facilitating data-driven decision-making on an institutional level and systemic levels. However, as with predictive learning analytics, there are also concerns about privacy and ethical implications of data collection and use, which must be carefully addressed in order to ensure that the advantages of learning analytics are realized in an ethical and responsible manner.

3.0 PLATFORMS IN LEARNING ANALYTICS

This section covers different platforms and frameworks used in existing works for education use. These platforms help manage student studies to increase their success, improve teaching and learning process. With the availability of different platforms, the learning analytics process becomes more efficient and effective which helps students and educators gain valuable insights into learning patterns, tailor educational experiences to individual needs, identify areas for improvement, and ultimately enhance the overall quality of education. A summary about these platforms and their potential challenges is included in Table 1.

3.1 Open University Analyse (OUA)

The Open University UK has developed a system called OUA, which is a predictive learning analytics (PLA) tool that uses advanced statistical and machine learning techniques to pinpoint students who might be at risk of failing to submit their forthcoming teacher-marked assessment (TMA). OUA also predicts whether a student will complete a course based on their performance. Its primary purpose is to alert teachers about students who may require intervention to prevent dropout and improve retention rates. The system uses three machine learning methods: k-Nearest Neighbors (k-NN), Naïve Bayes classifier (NB) and Classification and Regression Tree (CART). The ultimate goal of OUA is to increase student success in their studies [14].

3.2 ILOs Calculation System

An online platform called the ILOs calculation system was proposed and developed, which aims to evaluate academic program objectives and student outcomes [15]. This system allows authorized personnel to input comprehensive information about academic programs, as well as faculty members who must provide a comprehensive course curriculum. The ILOs calculation system uses Moodle, to assess academic program objectives and student outcomes, and to improve teaching and learning processes. The system consists of three primary elements: the ILOs system, which produces statistical reports and constructs course syllabi; the Interoperability web service, which integrates with the ILOs calculation system and works alongside the Learning Management System (LMS); and the Moodle plugin component. This holistic system is designed to streamline the assessment of ILOs, covering activities that span from university mission elements to course outcomes.

3.3 Social Networks Adapting Pedagogical Practice (SNAPP)

SNAPP is a tool that is based on technology specifically crafted to generate visual depictions of social network diagrams, illustrating user interactions and behavior within discussion forums. This tool is capable of gathering data from various sources, encompassing both commercial systems like Blackboard and open-source platforms like Moodle. By analyzing metrics such as log-in frequency, dwell time, and download counts, educators can effectively pinpoint students who might be at risk of academic underperformance owing to reduced engagement levels. The tool generates reports based on this data, allowing educators to improve pedagogical practices and support struggling learners [16]. The SNAPP tool was developed and implemented by the University of Wollongong [17].

3.4 Connect for Success (C4S)

C4S is proposed and implemented in Edith Cowan University. It is a comprehensive and automated system that employs registration information and predefined cues like demographic details, behavioral patterns, and student questionnaires. Additionally, it utilizes cues from alternative data outlets like Blackboard, RightNow, academic referrals, and mid-semester grades to pinpoint students requiring additional assistance for academic success. The primary goal of this proactive alert mechanism is to enhance student success, consequently boosting retention and graduation rates. The C4S automatically highlights learners at risk and guides them toward the relevant support services available within the university. The platform consists of daily summaries, and comprehensive reports are dispatched to essential support services and facilities within the university [18].

3.5 Automated Wellness Engine (AWE)

AWE is a tool that helps to improve learner engagement and retention at UNE. This early alert system is based on the Emoticons identification activity, which is available on the UNE student portal (myUNE), and other data from different university systems such as LMS, SRM, SMS, e-reserve, unit discontinuation poll, and the Vibe. Through the analysis of students' interactions with the educational institution, their engagement with instructors, utilization of resources, and adherence to deadlines, the AWE system detects learners who might be susceptible to academic challenges or disengagement from their coursework. The AWE produces wellness reports that offer insights into the causes of withdrawal and assess the overall well-being and satisfaction of students across different schools and courses. Additionally, this tool fosters peer-to-peer student networking, facilitates the sharing of information, and establishes daily connections between support staff and students [19].

3.6 Personalised Adaptive Study Success (PASS)

PASS serves as an early alert tool that focuses on enhancing learner engagement and retention in online learning environments by integrating data from various sources, including distinctive traits, social web interactions, curriculum-related information, and physical data. The tool utilizes a comprehensive framework comprising a learning analytics engine, personalization and adaptation engine, and reporting engine to analyze diverse sets of data, enabling the identification of students at a higher risk of struggling or disengagement. PASS draws data from customer relationship management systems, the learning management system, and curriculum profiles to create three profiles: the student profile, learning profile, and curriculum profile. Through the examination of these profiles, the tool provides personalized suggestions for content and tasks accessible to students via the online learning platform's dashboard. PASS helps to identify at-risk students and provides dynamic recommendations for alternative study paths when they require help. The indicators for identifying at-risk students include visual cues, performance metrics, self-assessment data, predictive course mastery, and social interaction patterns [17].

3.7 Predictive Analytics Reporting (PAR) Framework

The PAR Framework is a collaboration between multiple institutions that aims to support student success by identifying the factors that contribute to progress and completion while preventing student loss. PAR employs various techniques such as predictive analytics, data mining, descriptive statistics, inferential techniques, and modeling techniques like clustering, decision trees, neural networks, and dimensionality reduction. Using PAR, researchers found that concurrent enrollment in multiple courses was highly correlated with an increased risk of disenrollment for students at risk, but age, gender, and ethnicity did not seem to be related to the risk profile of the student. Institution-specific factors predicted student success for students who were not at risk of disenrollment [20].

3.8 Student Information System

El-Den [21] has proposed a student information system which is a user-friendly platform that consists of many features that can help to manage the whole university management such as admission, recruitment, enrollment, registration, financial assistance, counselor, payment, librarian, and educational services, it is a web-based platform that is adaptable, user-friendly and allow fast access and documenting student significant data such as academic records from each student's file. This platform allows the university to stay updated all the time by keeping track of all the students information and provides excellent facilities for pupils and administrators also provide real time insight using the pupil data. It also encourages student involvement and collaboration as the system is simple for their use and supports multiple languages such as Arabic and English. The system is also in accordance with university regulations and policies.

3.9 Early Warning System

Another platform called Early Warning System is also developed by American Institutes for Research which is a platform that is based on student data to identify students who might have the risk of drop out of school and prevent them from dropping out [22]. Educational districts and states nationwide employ early warning systems to detect students who may be falling behind in middle and high school. These systems are instrumental in both devising and assessing interventions aimed at keeping these students on the path to graduation. This system identifies students who show risky behaviour or academic performance that will put them at risk of dropping out from school by using the student data such as behaviour data, attendance, assessment result and discipline incidents. Its tailor initiatives and supports to assist students in attaining readiness and success also provide insight on how districts are enhancing student results. The early warning system also uses technology. Machine learning models are utilized to identify features that might be established for early warning systems in predicting student academic performance [23]. Different classification algorithms such as Classification Tree, Random Forest, Neural Network, Support Vector Machine, Naive Bayes and k Nearest Neighbours are utilized and compared to discover the most suitable classification model that suits the dataset and provide the best prediction. The result shows that k Nearest Neighbours produced the highest classification accuracy of 76%.

3.10 SEQTA

As a premier support system for education, SEQTA combines Wellbeing, Acquiring knowledge, and Attendance management into a single solution. Improving learning outcomes through greater engagement with students, educators, and parents. It is also a powerful platform to do data analytics that can help in providing insight on improving the services of institutes and performance of students in an institute such as the academic achievement, attendance progress of students [24]. It will automatically create and securely distribute the reports to selected audiences. Thus, institutes can spend less time on gathering the data and make significant changes based on the insights produced. It can be programmed to synchronize with the Student Information System (SIS) to retrieve data such as class data, enrolments data, timetable and etc to do analysis and reporting such as academic achievement, academic progress and attendance analytics. The price of SEQTA is determined by the number of students and features used each month.

3.11 OnTask

OnTask is another platform that was developed to use information identified by teachers as significant to assist them monitor students' development and provide more common, effective and personalized advice [25]. This platform collects and evaluates data about students' tasks throughout the school term, allowing teachers to create customized feedback with recommendations about their learning methods. Thus, students can rapidly modify their learning by providing frequent suggestions about specific tasks in the course. It supports NoSQL databases which allows more flexible data storage and data from any e-learning platform. Also, different sources such as assessments, video, digital textbooks, forums, and so on can be integrated by using this tool. The platform also provided dashboards which show the student progress, create customized messages or email comments to clusters of students who are not reaching the performance measures and provide student a customized alert of the steps they must take to catch up such as suggesting on reading additional materials, guiding students to university assistance services and advising on the study methods for a course.

3.12 Learning Management System

Learning management system or virtual learning platform is another platform that allows connections between students and numerous academic innovations and incorporates lectures with self-directed learning activities [26]. Every interaction that is made by students with the system will be recorded and stored for further analysis. Examples of the platform are Moodle and Blackboard. The platform provides useful data as it stores every interaction made by students. However, it needed an ILO calculation system to further process the data to transform it into useful information which can assist in tracking the achievement of the academic progress of students and make improvement of the teaching methods [15].

Table 1 Summary of the learning analytics platforms.

Platforms	Highlights	Potential Challenges
Open University Analyse (OUA) [14]	Implementation of machine learning for predictive functionalities. For example, early identification of students at risk of failing.	Limited to the student demographic data and data available from the virtual learning environment, which might not holistically represent student behavior.
ILOs Calculation System [15]	System for evaluation of academic program objectives and student outcomes based on comprehensive information of curriculum and data from Moodle.	Relies on the comprehensive curriculum input from the faculty members.
Social Networks Adapting Pedagogical Practice (SNAPP) [16, 17]	Implementation of social network analysis to allow academic staff to identify patterns of student behavior using data from various LMS.	Limited to the data available in the LMS and focus more on interaction of students.
Connect for Success (C4S) [18]	Automated system with alert mechanism that utilizes registration information, demographics, behavioural patterns, and student questionnaires with alternative data from Blackboard, RightNow, etc.	Limited to the data from internal systems and LMS used and did not include social network analysis.
Automated Wellness Engine (AWE) [19]	An early alert system that uses variety of data from university systems and LMS to detect students who might be at-risk or disengage from their coursework.	Limited to the data from internal systems and LMS used and did not include social network analysis.
Personalized Adaptive Study Success (PASS) [17]	An early alert tool that utilizes diverse data and able to identify at-risk students, provide dynamic recommendations and come with multiple indicators of student performance and interaction pattern.	Limited to the data from internal systems and LMS used.
Predictive Analytics Reporting (PAR) [20]	Implementation of predictive analytics based on student data such as demographics and learning progress to support student success and prevent student loss.	Relies on the quality of the data to ensure reliability of the predictive outcome.
Student Information System [21]	A comprehensive system that covers multiple aspects including admission, recruitment etc that able to	Limited to the data from internal systems and LMS used

	integrates and keep tracks of student data and progress.	
Early Warning System [22, 23]	Implementation of machine learning to identify students who might at risk of drop out from school based on students' data.	Limited to the data available in the system where the performance of the ML models could be highly dependent on the data.
SEQTA [24]	Automated system that integrates school data analytics, curriculum, student learning, student engagement, student attendance and etc in generating insights.	Limited to the data available in the system and could be costly depending on the number of students and features.
OnTask [25]	System that allows teachers to provide personalized, timely support actions to large student cohorts based on the data about students' tasks throughout the school terms. Supports data from different e-learning platform or LMS.	Limited to the data available in the system and LMS.
Learning Management System [26]	Centralized platform for learning contents, tracking of student activities, reporting and delivery of educational courses.	Functionalities and data available might be varies depending on the LMS used.

4.0 ADVANCED ANALYTICS IN LEARNING ANALYTICS

In this section, predictive analytics, adaptive learning, and personalized learning, AI models which are all advanced educational technologies that aim to enrich the educational journey for students is discussed in terms of its uses in Learning Analytics, its current techniques used and its benefits.

4.1 Predictive Learning Analytics (PLA)

PLA is a type of learning analytics that utilizes techniques such as data mining, machine learning, and predictive modeling to anticipate future outcomes in education. PLA relies on historical data to predict future student behavior and performance, and integrates data from diverse sources including student demographics, prior academic performance, and learning behaviors. The predictive models generated from these data sources can discover students at risk of failure and anticipate future outcomes such as graduation rates or course completion [27]. By leveraging these predictive models to provide personalized support and early interventions, PLA has the capability to improve student success and retention rates [28].

According to Brooks [29], creating a predictive model involves several steps, including identifying the problem, collecting data, defining the anticipated result, choosing predictor variables that exhibit significant correlations with the specified outcome, and constructing the model employing one or more algorithms. There are various algorithms available for building predictive models, such as Decision Tree, Support Vector Machine, Neural Networks, Bayesian Classifier, K-Nearest Neighbor, and Logistic and Linear Regression [30]. The choice of an algorithm depends on elements like the nature of the problem, the characteristics of the expected results, and the variables used in the predictive procedure.

PLA is utilized to identify students who may be at risk of dropping out or failing a course by analyzing various factors such as attendance, grades, and engagement with course materials to discover students who may need extra assistance [31]. This can be challenging for instructors to do manually, but with PLA, they can closely monitor trainee progress and compare specific metrics against typical course performance indicators [32]. By identifying at-risk students early, instructors can provide targeted interventions, such as tutoring or academic counseling, to help those students succeed. This is especially important because some trainees progress through the course material at varying paces, with some lagging behind and having trouble in understanding advanced concepts.

Another potential application of PLA is in personalizing learning experiences for individual students. By analyzing data on a student's learning behaviors, preferences, and outcomes, PLA can provide recommendations for personalized learning activities that are tailored to the student's needs and interests [33]. PLA can serve as a potent instrument for enhancing the design of educational courses. For example, the Curtin Challenge platform has a good system in place for monitoring student engagement and performance. Through the platform's administration dashboards, information such as drop-off rates, student ratings of different course components, and weekly participation metrics is available. If there is a consistent drop-in activity, it could indicate a problem with the course material or difficulty level. By keeping an eye on these metrics, designers can improve the course for future students [34].

In e-learning, predictive analytics finds significant applications in workplace training and higher education. Learning Management System (LMS) platforms equipped with reporting tools play a pivotal role in gathering valuable data, which is then analyzed using predictive analytics algorithms. This analysis helps in assessing various aspects, such as whether learners are enrolled in suitable courses, maintaining consistent performance, applying the acquired training effectively in real-world scenarios, and more. As a result, the advantages derived from predictive analytics are substantial, benefiting both higher education institutions and workplaces alike [34].

In conclusion, emerged as a valuable asset in the realm of education, offering valuable insights into student behavior and performance. Through the utilization of data gathered from diverse sources, including learning management systems and student feedback, educators can identify patterns and trends that can inform instructional design and personalized learning strategies. Predictive analytics can also assist with early identification of struggling students, enabling timely interventions and support. However, predictive learning analytics is not a silver bullet solution and must be used in conjunction with other teaching and learning approaches. Besides that, as with any use of student data, there are ethical considerations associated with PLA. It is crucial to guarantee that the collection and utilization of student data adhere to responsible and ethical practices to avoid issues such as reinforcing biases or violating students' privacy [35]. With careful consideration and appropriate use, predictive learning analytics can contribute to improved learning outcomes and better support for students.

4.1.1 Uses And Benefits Of Ai In Predictive Analytics

Diverse AI prediction models encompass early warning systems, recommender systems, as well as tutoring and learner models, have significantly enhanced online higher education [36]. In recent research, offering comments to both teachers and students has emerged as a crucial aspect of these AI prediction models [37]. For instance, an adaptive predictive model was employed to develop an early warning system that offers timely feedback and intervention for students at risk of underperforming [38]. Additionally, a dropout prediction model was optimized for at-risk students in MOOCs by incorporating personalized interventions tailored to individual situations and preferences [39].

Moreover, PLA serves not only as a means of providing timely individual interventions but also as a powerful tool for improving course design. By offering insights into how specific course elements influence learning outcomes, PLA contributes to enhancing the overall course structure and effectiveness [32].

From the perspective of workplace, PLA can identify employee training needs. An effective learning approach cannot serve as a universally applicable solution for all situations. Recognizing the uniqueness of everyone's learning style is crucial for organizations. Without allowing employees to learn in a way that aligns with their preferences, the training outcomes may not reach their full potential. Fortunately, in today's data-driven era, understanding employee preferences is relatively easy. By analyzing how specific employees respond to different training programs, predictive analytics can identify the type of training in which a particular employee is likely to excel. For instance, if an employee struggles with video lectures but excels in interactive exercises, which indicates a preference for hands-on learning. Consequently, enrolling them in courses heavily relying on videos would not be the most effective choice [33].

4.2 Adaptive Learning

Adaptive learning, often referred to as adaptive teaching, is an educational approach that harnesses computer algorithms and artificial intelligence (AI) to facilitate interactions with learners and provide tailored educational materials and activities designed to cater to the individualized requirements of each student [40]. This approach allows teachers to adapt the curriculum based on learners' needs, resulting in faster, easier, and more efficient learning for students [41].

Currently, adaptive learning platforms are incorporating an array of AI-powered tools to deliver personalized learning experiences to students. These advanced tools can analyze diverse amounts of data, identifying learning patterns and offering valuable insights on how students can enhance their learning efficiency. AI-enabled learning tools empower students with increased control over their educational journey, allowing them to decide the subjects they study and the learning methods they adopt. Consequently, students thrive in the ever-changing digital landscape, benefiting from enhanced access to information and improved abilities to interact with the educational content [42].

4.2.1 Uses And Benefits Of Ai In Adaptive Learning

Adaptive learning platforms are leveraging an increasing number of AI-driven tools to deliver tailor-made learning experiences to students. These advanced tools can process vast datasets, recognizing learning patterns, and offering valuable guidance on enhancing students' learning effectiveness. With AI-powered learning tools enhancing the capacity to generate, access, and interact with information, students now enjoy full autonomy over their learning preferences. As a result, they are flourishing in the dynamic digital landscape, where rapid advancements are the norm [42].

The importance of adaptive learning is increasing within the domain of learning analytics. This entails employing data analytics to monitor students' progress and deliver immediate feedback to both educators and learners. By harnessing big data and analytics in education, the learning experience becomes more effective, providing students with a well-structured and supportive environment for their educational journey. Besides that, microlearning is a method that dissects intricate subjects into smaller, easily digestible chunks of information. Adaptive learning platforms are adopting microlearning approaches to enhance students' learning efficiency and promote long-term information retention [42].

In terms of advantages, adaptive learning allows e-learning platforms to customize learning experiences for individual students, leading to better learning results and increased student engagement. These platforms also provide personalized feedback to students, catering to their specific learning needs and preferences. As a result, students can identify areas for improvement and receive guidance on how to enhance their performance [42].

Furthermore, adaptive learning saves training resources to minimize the budget. Studies carried out by National Mentoring Day [43] have demonstrated that personalized guidance enhances learning speed. However, providing individual guides for every employee in large corporations is financially impractical. To address this, adaptive learning is utilized to maximize training resources. This advanced software employs data analysis to offer each employee relevant materials and tasks tailored to their unique learning needs. Essentially, adaptive learning functions as a personalized digital companion, delivering a customized and effective learning experience.

Moreover, Adaptive learning enhances learner engagement, fostering the development of a continuous learning culture. In contrast to traditional courses where all participants are required to adhere to a standardized curriculum, adaptive learning considers individual experiences. Consequently, team members are less likely to view a substantial portion of the course as irrelevant. In contrast, AI-powered adaptive learning ensures that each employee becomes actively engaged in the learning process. By eliminating tedious assignments that can be readily plagiarized from online sources, adaptive learning offers a personalized and unique learning path for each member, fostering skill enhancement in a customized manner [41].

Adaptive learning employs comprehensive analytics to monitor the effectiveness of training and the performance of learners. Training managers have access to metrics that provide insights into the individual progress of each employee. This valuable addition allows them to monitor success rates, identify strengths and weaknesses, and enhance the overall learning experience [41].

4.2.2 Application Of Adaptive Learning

4.2.2.1 Duolingo

Duolingo is a popular language-learning platform and mobile app that offers free language courses to users worldwide. The platform uses gamification elements to make language learning fun and engaging. Users can earn points, unlock new levels, and compete with friends as they progress through the language lessons. Duolingo offers a variety of exercises, including vocabulary building, listening comprehension, speaking practice, and translation tasks.

One of the significant features of Duolingo is the adaptive learning approach. The platform uses AI algorithms to personalize the learning experience for each user based on their performance and proficiency level. This adaptive feature ensures that learners receive content and exercises that are suited to their individual needs and progress. The software monitors multiple data points, including the frequency of word exposure, errors made in specific topics, and the user's proficiency in various topics and phrases. Through the use of AI, Duolingo predicts the likelihood of a learner recalling a word in a given context. Moreover, the technology computes the optimal amount of practice required for effective material memorization. By combining these features, the software provides a personalized and efficient learning experience to the users [41].

4.2.2.2 Prodigy Math

Prodigy Math is an educational MMORPG (Massively Multiplayer Online Role-Playing Game) with a fantasy theme, launched in 2011 by Prodigy Education. In this game, players assume the role of a wizard embarking on quests to gather gems, all while engaging in battles against the Puppet Master [44]. Prodigy Math is an educational platform that leverages adaptive learning to help students improve their math skills. The platform is designed for students in elementary and middle schools and provides a gamified approach to learning math concepts. Prodigy Math uses an adaptive algorithm to personalize the learning experience for each student. With Prodigy Math, students engage in a virtual world where they encounter math problems and challenges. The platform tracks students' progress, performance, and responses to various questions. Based on this data, the adaptive algorithm dynamically adjusts the difficulty and complexity of the math problems presented to each student.

As students' progress through the platform and answer questions correctly, they earn rewards and access new content. Conversely, if they encounter difficulties with certain concepts, the platform provides additional practice and guidance to reinforce their understanding. By utilizing adaptive learning, Prodigy Math ensures that each student receives a tailored learning experience that suits their individual learning pace and needs. This approach enables students to build a strong foundation in math and develop their skills in a way that is engaging, motivating, and effective.

4.2.2.3 Embibe

Embibe is an innovative learning platform that infuses technology to create an enjoyable educational experience. Utilizing 3D videos and AI-powered tools, Embibe assists students in their preparation for a wide array of entrance tests, competitive exams, school exams, and Government exams [45]. Embibe is primarily targeted towards students preparing for competitive exams and standardized tests in India. Embibe uses advanced AI and data analytics to analyze students' performance, strengths, and weaknesses and offers tailored study plans and recommendations.

The platform offers a wide range of educational content, including practice questions, mock tests, study material, and video lectures, covering various subjects and topics relevant to competitive exams. As students interact with the platform and attempt practice questions and tests, Embibe's adaptive algorithm continuously tracks their progress and identifies areas that require improvement.

Based on this analysis, Embibe offers personalized study plans and recommendations to address individual learning gaps. Embibe provides targeted practice sessions and suggests specific topics and concepts that students should focus on. Additionally, the platform's adaptive capabilities modify the question difficulty level in response to the student's performance, ensuring that they are consistently challenged while not overwhelmed. Embibe's adaptive learning approach aims to enhance students' learning outcomes by providing them with the right resources, practice, and support tailored to their unique learning needs. By utilizing AI-driven technology, Embibe strives to empower students to achieve their academic goals and succeed in competitive exams.

4.3 Personalized Learning

Learning is often described as a lasting and enduring transformation in an individual's knowledge and abilities [46]. Personalized learning is a multifaceted approach that stems from self-organization [47,48] or the amalgamation of learning and tailored instruction, taking into account the special needs and objectives of each individual. Personalized learning is an educational method that customizes the learning process to cater to the unique needs, interests, and abilities of each individual student. This method ensures that each student receives instruction tailored to their specific learning characteristics [49]. Personalized learning takes adaptive learning a step further, focusing on addressing students' individual strengths, weaknesses, interests, and learning styles. AI is a key enabler of personalized learning, as it can analyze vast amounts of data to create unique learning experiences.

Personalized learning is a proven approach used by organizations to enhance learning outcomes. By harnessing data concerning a learner's prior experiences and aligning it with new concepts, personalized learning cultivates a deeper comprehension of fresh content, heightened engagement, and enhanced retention of knowledge. In essence, personalized learning optimizes the educational process, rendering it more efficient and effective [50].

As technology advances and learners' expectations grow, personalized content has become ubiquitous. From personalized feeds on social media to customized playlists and movie recommendations, personalized experiences are now an integral part of our daily lives. Likewise, learners expect training programs to adapt and provide personalized content that caters precisely to their needs. In the workplace, individuals anticipate learning platforms to offer new and relevant content, personalized to their unique requirements.

4.3.1 Uses And Benefits Of Ai In Personalized Learning

By integrating AI, the utilization of an AI assistant allows instructors to focus on addressing the specific learning requirements of each individual, as the AI takes charge of By integrating AI, the utilization of an AI assistant allows instructors to focus on addressing the specific learning requirements of each individual, as the AI takes charge of curating and recommending learning materials. The AI assistant possesses comprehensive knowledge about the learner's data, including their skills and the learning path they are pursuing. It then delivers tailored suggestions to guide the learner on the most suitable content to engage with next.

Leveraging natural language processing (NLP) enhances the efficiency and accuracy of information searches for learners. With the capabilities of NLP, students can swiftly access precise information, be it in text or video format, and obtain accurate answers to any inquiries they might have. This technology empowers learners to find the exact information they need quickly and effectively [50].

Personalized learning ensures that every student receives the information they require and addresses any knowledge gaps that may exist [51]. For instance, if a teacher observes that certain students excel in a particular literacy area in Spanish but face challenges in English, these students can receive personalized literacy lessons without needing a special-education designation. This approach enables all students to maintain a consistent level of learning, with everyone receiving targeted support based on their unique strengths and weaknesses.

Furthermore, personalized learning enables one-to-one tutoring experiences by tailoring the educational approach to fulfill the unique needs of each student. In a traditional classroom setting, teachers often must teach a large group of students with varying learning abilities and styles, which can be challenging to address effectively. However, with personalized learning, the learning process is customized for each student, considering their strengths, weaknesses, interests, and preferred learning methods. This approach allows educators to provide more targeted and individualized support to students, creating a more personalized and engaging learning experience. Mentoring is a popular approach to personalized learning, wherein a more experienced employee takes on the role of an advisor for a less experienced colleague. The mentor's wealth of knowledge acquired through past experiences enables them to comprehend the challenges and obstacles faced by the mentee, guiding their learning journey towards better understanding. While this model is highly effective, the drawback lies in the limited scalability [50].

4.4 Artificial Intelligence In Learning Analytics

There are several AI models widely used to enhance educational processes and improve learning outcomes.

4.4.1 Natural Language Processing (NLP)

NLP plays a crucial role in learning analytics, transforming the way educational data is analyzed, processed, and utilized to enrich the educational journey for students and educators alike. NLP is a subfield of artificial intelligence (AI) that concentrates on the interaction between computers and human language, empowering machines to comprehend, interpret, and generate human language text.

Under NLP, automatic summarization involves condensing large volumes of unstructured text, like dissertations and academic papers, into concise versions containing the most relevant information. This process can be done through extraction-based summarization, where a summary is generated by selecting key components directly from the source text. Alternatively, abstraction-based summarization involves using deep learning algorithms to generate new phrases or sections that convey the essence of the original content in a paraphrased manner. Through the utilization of automated summarization at either the research or documentation level, researchers can effectively extract relevant information from data sources and seamlessly integrate these findings into their research papers or databases [52].

Customizable machine translation systems based on NLP cater to specialized educational needs. These systems are tailored for distinct linguistic domains or can be trained to understand the specific jargon and language used in fields like law, finance, or medicine. For English Language Learners (ELLs), natural language platforms equipped with machine translation capabilities prove highly advantageous as they enable students learning English as a second language to practice beyond the confines of the classroom. Furthermore, NLP systems with benchmarking features can assess the proficiency levels of English language learners over time and monitor their progress. Additionally, these learners can receive feedback from online language instructors on any grammatical, syntactic, or sentence-building errors they may encounter [52].

NLP has demonstrated its effectiveness in educational contexts by providing in-depth analysis of grammar and word usage, along with comprehensive scoring for essays. Additionally, NLP systems provide formative feedback and actionable insights on specific parts of written work, encouraging students to expand their writing skills beyond grammar and mechanical aspects. For example, NLP analysis can assess the presence of crucial elements like themes, arguments, and supporting data in a student's essay and offer suggestions on structuring the piece. NLP tools can offer feedback ranging from basic vocabulary suggestions to more advanced recommendations that influence the overall structure and coherence of a document or narrative. This is especially valuable when employed in conjunction with Automatic Writing Evaluation (AWE) systems.

Semantic analysis in NLP is focused on comprehending the meaning conveyed by language. It encompasses the examination of sentence structure, word interactions, and related concepts using computer systems. This analytical process unveils the overarching meaning and subject of a passage or document, as well as the significance of individual words within it. In sentiment analysis, NLP systems utilize machine learning models to classify texts based on the expressed degree of agreement or disagreement. NLP classifies passages into positive, negative, or neutral categories, and also identifies shades of opinion in between. Educational institutions' administrators and faculty can leverage NLP semantic and sentiment analysis to study student behavior in response to current teaching methods and academic or social changes. This analysis helps assess the effectiveness of curricula and teaching strategies and identifies students facing challenges or issues of various kinds.

NLP applications in education offer valuable support to students with reading difficulties. NLP algorithms can immediately discover students with reading comprehension challenges and offer instant, automated feedback for enhancement, a task that would be impractical for teachers in a classroom setting. Moreover, the capability of NLP to pair students with suitable reading materials, encompassing those that are both challenging and rewarding, further underscores its importance in the field of education. Additionally, NLP technology has shown superior accuracy in grading student reading scores compared to traditional methods, like the Flesch-Kincaid Grade Level exam, influencing the growing use of NLP API solutions in the education sector [52].

A sequence-to-sequence model for speech recognition shares a structural resemblance with a question-answering model. This entails the transformation of a student's spoken questions or responses into written text. Additionally, chatbots, functioning as robotic instructors with conversational AI, play a role in providing answers to student queries. The process continues by generating responses or evaluating student answers using a question-answering approach. The outcomes are then read back to the student using text-to-speech synthesis. To offer a more engaging experience, the synthetic voice can be enriched with intangible characteristics like enthusiasm, tolerance, lovingness, friendliness, and even accents to provide reassurance to the student.

4.4.2 Generative Pre-trained Transformer (GPT) Models

GPT is a state-of-the-art language model developed by OpenAI. GPT falls under the category of machine learning models that utilize deep learning techniques to generate natural language text. The latest version, GPT-3, is trained on an extensive data source containing text from various sources like books, articles, and websites. Utilizing this training data, it has the capability to generate new text that closely resembles the patterns observed in its training corpus [53].

GPT models possess remarkable capabilities in various educational applications. One of these applications is automated essay scoring, where GPT can be harnessed to automatically evaluate and score essays written by students. This feature enables educators to provide prompt feedback and assessment, facilitating timely improvements and monitoring of learning progress. Another significant use case is dialogue generation for tutoring systems. GPT models can simulate human-like interactions, making them invaluable for constructing virtual tutoring systems that can engage with students in interactive conversations, address their queries, and offer personalized guidance throughout the learning process.

Furthermore, GPT models excel in content generation for personalized learning experiences. They can create educational content, such as exercises, quizzes, and explanations, specifically tailored to serve an individual students' unique learning styles and needs. This personalized approach enhances students' overall learning experience and promotes a more profound comprehension of the subject matter.

Moreover, GPT models can effectively support language learning initiatives. By utilizing them to create language learning tools, such as language translation systems, grammar exercises, and vocabulary expansion exercises, students can enhance their linguistic proficiency in a more interactive and engaging manner. Lastly, GPT models can power question answering systems in educational settings. By deploying them as the backbone of question-answering systems, educators can provide timely responses to student queries, deliver insightful explanations, and offer additional learning resources to support students' academic journey and foster a more effective learning environment.

4.4.3 Deep Reinforcement Learning (DRL)

DRL is a promptly advancing area that merges Reinforcement Learning and Deep Learning. DRL in education is a subject of growing interest [54]. DRL is currently one of the most popular branches of machine learning due to its ability to address complex decision-making challenges that were once beyond the capabilities of machines. DRL enables machines to tackle real-world problems with a level of intelligence reminiscent of human-like reasoning and problem-solving [55].

Conventional educational settings frequently employ uniform instructional methods, irrespective of the unique learning requirements and capabilities of individual students. However, students have diverse learning styles, preferences, and prior knowledge. Adaptive learning aims to tailor the learning experience to each individual learner, optimizing their understanding and knowledge retention.

DRL achieves adaptive learning by allowing an AI system, often referred to as an "agent," to interact with a dynamic learning environment and learn from the feedback it receives. The agent operates by making decisions influenced by its present state, and the environment responds with feedback in the shape of rewards or punishments. The agent's objective is to enhance its cumulative reward over time by acquiring the ability to choose actions that result in favorable results while abstaining from actions that yield unfavorable consequences.

In the context of education, the learning environment can be represented as a virtual learning platform where the agent interacts with students. The agent can adapt the instructional approach based on individual student responses, performance, and learning outcomes. For example, in a tutoring scenario, the AI agent might interact with a student, presenting questions or learning tasks, and observing the student's responses. If the student struggles with a particular concept, the agent can modify the level of difficulty or give additional explanations or hints. On the other hand, if the student demonstrates proficiency, the agent can offer more challenging tasks to foster further learning.

DRL enables the agent to continuously learn and update its approach based on the feedback received from multiple students. This creates a dynamic and personalized learning experience for each student, maximizing their understanding and knowledge acquisition. Furthermore, DRL allows the AI system to explore different instructional strategies and adapt its behavior over time. The agent can experiment with different approaches and prioritize those that lead to better learning outcomes. This flexibility enables the AI system to continuously improve its instructional methods, ensuring that it adapts to the changing needs and progress of each student.

Overall, DRL applied in adaptive learning scenarios holds the promise of transforming education, as it can offer students personalized and highly effective learning journeys. By harnessing the capabilities of deep learning and reinforcement learning, DRL enables AI systems to become effective adaptive tutors, guiding students through their unique learning journeys and maximizing their learning potential.

4.4.4 Case Studies Showcasing The Use Of AI In Learning Analytics

4.4.4.1 Intelligent Tutoring Systems (ITS)

Intelligent Tutoring Systems (ITS) which is available in the market stand as the most widespread implementation of AI within the realm of education, often benefiting from substantial financial support. Their primary objective centers on delivering computer-based instructional modules that guide students step-by-step through structured subjects like mathematics. With an adaptive approach, an ITS tailors the content, activities, and quizzes to suit the individual needs of each student. As the student interacts with the system, it collects an abundance of data points, such as click patterns, typed responses, correct answers, and identified misconceptions.

This data is then analyzed to identify the coming set of information, activities, and quizzes to be presented to the student, creating a personalized learning pathway. This iterative process continues throughout the learning journey. Some ITS also offer teacher dashboards that allow educators to monitor their students' progress and accomplishments.

An illustration of a commercial ITS is Spark, developed by the French company Domoscio. Spark employs personalized learning routes and gives educators with a dashboard equipped with learning analytics tools [56]. An alternative noteworthy system is Gooru Navigator, which aims to be a comprehensive learning platform similar to Google Maps [57]. Gooru extensively employs data-driven AI technologies, such as analyzing open educational resources and aligning them with the unique profiles and competency needs of learners. Currently, Gooru hosts approximately four million AI-curated learning resources. Additionally, a few ITS incorporate an open learner model, enabling students to view and comprehend their achievements [58].

4.4.4.2 AI-assisted Applications

In leading app stores, there is a rapidly expanding array of commercially available AI-assisted educational apps. These apps encompass various fields, such as language translation tools like SayHi [59], which have gained significant advancements and raised concerns that they might diminish the significance of learning foreign languages in academy. Similarly, impressive AI-assisted mathematics apps like Photomath [60] have also sparked concerns about their potential to undermine mathematics learning. These worries echo the apprehensions that arose when calculators were introduced in schools about fifty years ago. The underlying fear is that if these AI tools can automatically perform tasks like long division, language translation, or equation solving, students may not feel the need to learn these skills, ultimately hindering their overall learning [61].

Significantly, the Chinese Ministry of Education has addressed this matter by implementing a ban on AI-assisted assignment applications that offer automatic online solutions to inquiries captured and submitted by students [62]. This decision was driven by the concern that relying too heavily on technology for assistance could potentially undermine the learning process.

4.4.4.3 AI-assisted Simulations (Game-based learning, Virtual Reality (VR), Augmented Reality (AR))

While not typically classified as AI technologies, commercially available VR and AR simulations, along with digital games-based learning, have increasingly integrated image recognition, AI machine learning, and NLP. This integration has led to their growing adoption in educational environments. For instance, AI-assisted VR has demonstrated its value in providing tutoring for neurosurgical residents, covering a diverse range of neurosurgical approaches [63]. Similarly, AR has been employed to empower students to interact with and manage 3D-models of organic molecules, enriching their understanding of chemistry [64]. Google has notably created an extensive library of VR and AR Expeditions specifically designed for educational use. Furthermore, Digital Games-Based Learning (DGBL) is increasingly incorporating AI technologies, allowing game experiences to be customized according to the unique needs of each individual student [65].

4.4.4.4 AI to Support Learners with Disabilities

Numerous AI-driven systems in education and learning, designed with a focus on students (often referred to as AIED), particularly Intelligent Tutoring Systems (ITS), have undergone further development to provide support for students with learning disabilities [66]. Additionally, various AI techniques have been employed for diagnosing learning disabilities like ADHD [67], dyslexia [68], and dysgraphia [69].

Furthermore, considerable studies have been carried out on the integration of robots in education, with a particular focus on supporting children on the autism spectrum [70]. On the other hand, certain widely used AI tools, like text-to-speech applications and automatic image captioning, have been adapted for the purpose of assisting students who face learning challenges. Additionally, a limited number of AI-assisted apps have been specifically designed for targeted assistance, like automatic sign language interpretation for children with hearing difficulties, such as Huawei's StorySign [71].

4.4.4.5 Automatic Essay Writing (AEW)

Essays is a crucial aspect of educational evaluation worldwide, but the issue of plagiarism, where students submit others' work as their own, has been prevalent for a long time. The internet has made it easier to access custom-made essays through online commercial essay mills. The emergence of advanced AI language models, like GPT-3 from OpenAI, has the potential to intensify this situation (GPT-3, 2020). Currently, there are a few commercial organizations providing Automatic Essay Writing (AEW) tools that can produce single paragraphs or whole essays in response to essay prompts.

While the writing produced by AEW tools can sometimes lack depth and coherence [72], distinguishing between text generated by an algorithm and one written by a human student can be challenging. The impact of AEW tools on student learning remains uncertain.

4.4.4.6 Chatbots

AI-assisted chatbots have become a subject of research and are readily available in commercial applications, increasingly finding utility in educational settings for diverse purposes [73,74]. These chatbots are designed to offer ongoing support and guidance to students in various areas, including facilities, accommodation, examinations, IT, academic services, and health. For instance, a student could use a chatbot to inquire about various topics, such as their morning lessons, the location of tomorrow's exam, or the grade they received in their latest homework.

An outstanding illustration of an educational chatbot is Ada. Ada has been created by a UK community college and leverages IBM's Watson Conversation platform [75]. During an enormous computer science class, this TA bot responded to student queries as if it were a human TA, automatically addressing questions it had answers to in its database and redirecting others to human Tas. This approach holds significant potential, particularly in massive-scale online educational institutions where human staff may struggle to handle the volume of student inquiries. However, ethical concerns arise when the virtual TA did not disclose its AI nature to the students and occasionally employed tactics, such as delayed responses, to mislead students into thinking they were communicating with a human.

4.4.4.7 AI Teaching and Assessment Assistant

As mentioned earlier, many AIED technologies aim to optimize time for educators, but in doing so, they may end up taking over teaching tasks, possibly diminishing the role of teachers to a functional capacity [76,77]. An alternative approach involves using AI to assist educators in their tutoring by enhancing their proficiency and abilities through an AI teaching assistant. The specific functions and roles of such an AI teaching assistant are yet to be identified, as this continues to be a hypothetical use case, and currently, there is no known relevant research or commercial products in this area.

However, a recently introduced commercial tool, Graide [78], presents an intriguing approach. Instead of delivering automated assessments like autograders, Graide aids the teacher in their assessment procedures. For instance, it offers pre-existing phrases that the teacher has authored and employed in the past, which can be reused for evaluating the current assignment. In essence, it is the educators who conduct the exam, not the AI. This method enables the AI to provide support and enhance the teacher's assessment process rather than completely replacing their role.

4.4.5 Benefits Of Using Ai In Learning Analytics

The integration of AI brings numerous advantages to Learning Analytics, including personalized learning, data-driven decision-making, and timely student interventions.

4.4.5.1 Increased Personalized Learning

AI in education offers personalized learning as a significant advantage, and further advancements are anticipated in this area. AI-driven learning platforms will persistently analyze student data, including behavior, performance, and learning preferences, to deliver customized content and teaching approaches. This personalized approach will enhance students' learning efficiency and effectiveness, leading to improved overall learning outcomes [79].

4.4.5.2 Feature Instructional Design

AI empowers educators to utilize advanced analytics, enabling them to gain valuable insights into learner advancement and achievements. This data-driven approach facilitates the identification of effective teaching strategies, optimization of curriculum design, and adaptation of instructional methods to cater to diverse learning styles, resulting in more engaging and effective learning experiences [80].

4.4.5.3 Automation Of Routine Tasks

AI has the capability to automate routine administrative tasks like grading assessments, generating reports, and organizing learning materials. By reducing the administrative burden on educators, AI liberates their time and energy, enabling them to concentrate on high-value activities such as mentoring, offering personalized support, and nurturing critical thinking skills [80].

4.4.5.4 Seamless Integration with LMS

The growing implementation of LMS in educational institutions has led to a rising demand for AI-powered tools that seamlessly integrate with these systems. AI-driven chatbots, virtual assistants, and other tools can offer real-time support to students and teachers, contributing to enhanced engagement and satisfaction with the learning process [79].

4.4.5.5 Early Intervention

Learning analytics integrated with AI enables early detection of struggling students and alert educators to provide timely interventions and support. Early intervention refers to the ability of AI systems to detect signs of academic struggles or challenges faced by students at an early stage. By analyzing vast amounts of data related to student performance, behavior, and engagement, AI algorithms can identify patterns that indicate potential learning difficulties. This could include lower-than-expected quiz scores, reduced participation in class activities, or a decrease in overall academic performance. The early intervention is a proactive approach that helps prevent learning gaps and improves student success rates.

4.4.5.6 Features Improvement

The continuous improvement process facilitated by AI-based learning analytics allows educators to be agile and responsive in their teaching practices. They can modify their approach regarding the evolving needs and progress of their students, ensuring that the learning experience remains relevant, engaging, and effective. By leveraging real-time data and feedback, educators can generate a dynamic and personalized learning environment that maximizes student learning outcomes and fosters a culture of continuous growth and improvement.

5.0 DISCUSSION

LA has emerged as a critical tool in education, enabling educators and administrators to gather and analyze data about students' academic performance and behavior. While it holds enormous promise, there are also significant challenges associated with Learning Analytics, particularly when it comes to citation.

5.1 Challenges Of Learning Analytics

One of the primary challenges of LA with citation is the sheer volume of data involved are difficult to manage and analyze. To accurately cite this data, researchers must ensure they are using appropriate citation styles and that their citations accurately reflect the data's source. Learning Analytics faces technical challenges related to data assimilation and presentation. Data inaccuracies can distort findings and lead to misinterpretations of the broader population, especially in the context of online learning. For example, an instructor might generate a fictitious learner for the purpose of testing the submission system or identifying curriculum deficiencies. This extraneous data does not reflect actual student information but rather comprises instructor-generated misinformation. When collecting and analyzing data for learning analysis, such data can introduce a substantial margin of error into the final results. Although such erroneous data can be easily identified when conducting manual data analysis, it becomes more challenging to detect when working with data from learning analysis [81]. LA involves the interpretation of complex data sets.

Since data can come from numerous different sources such as learning management systems, online courseware, and other educational technologies, the use of student data for LA raises ethical and privacy concerns. Institutions need to ensure that they have appropriate policies and procedures in place to secure the privacy of student data. There is a need to address ethical considerations, such as consent, data ownership, and data security [44]. Institutions must develop policies and procedures to safeguard student data privacy. These policies should address the collection, storage, use, and sharing of data. Institutions must ensure that they are transparent about their data collection practices and provide students with clear information about what data is being collected, how it is being used, and who has access to the data. Data quality is also another concern of LA. LA relies on the quality of data collected from various sources. Institutions need to ensure that the data is accurate, reliable, and consistent. Inaccurate data can lead to incorrect conclusions and poor decision-making [82].

Learning Analytics has the capability to reinforce biases or create new ones if the data used is biased against certain demographic groups. Institutions need to be aware of the potential for bias and ensure that LA is used in a fair and unbiased manner [83]. For example, if data is collected only from students who have access to certain technology, such as personal laptops or high-speed internet, it may not be representative of the entire student population. Additionally, institutions must guarantee that the algorithms employed for analysis and interpret the data are transparent and that they do not perpetuate biases. For example, an algorithm that prioritizes grades or standardized test scores may favor certain demographic groups over others.

Furthermore, the accuracy and validity of data are another challenge of LA. The accuracy and validity of LA data are crucial for making informed decisions about student learning outcomes. Institutions must ensure that the data used for LA is accurate and valid and that any errors or inaccuracies are identified and corrected promptly [27]. Besides, LA raises various legal and ethical concerns, such as data privacy, ownership, and consent. Institutions must make certain that they adhere to legal and ethical frameworks during the processes of collecting, analyzing, and utilizing LA data [84].

In conclusion, while LA holds great potential to improve educational outcomes, it also faces several challenges. Addressing these challenges requires a concerted effort from institutions, policymakers, and researchers. By addressing these challenges, institutions can leverage LA to improve student success and achieve their educational goals.

5.2 Challenges Of Using Ai In Learning Analytics

5.2.1 Ethical Considerations

It is imperative to exercise meticulous consideration of the ethical ramifications associated with AI in education. Placing a priority on addressing issues concerning data privacy, transparency, algorithmic bias, and ensuring equitable access is of utmost importance. Upholding principles of fairness, respecting privacy, and avoiding the perpetuation of existing educational inequalities are essential aspects to ensure responsible use of AI systems [80].

Moreover, ethical guidelines and policies should be established to regulate the utilization of AI in educational environments, promoting responsible and accountable AI practices. Transparent communication with students, parents, and educators about the use of AI technologies is essential to build trust and foster a positive learning environment.

In recent times, there has been a growing emphasis on ethical considerations within the AI field, leading to the development of over 80 sets of ethical AI principles [85-87]. A considerable portion of these principles follows a rights-based approach with a focal point on human rights. Nonetheless, despite the substantial impact of AI in education on educators, parents, students, and other stakeholders, there is a relatively modest body of published research that specifically delves into the ethical aspects of AI in education. Noteworthy exceptions include the works by [88-92].

5.2.2 Technology Integrations and Implementation

Integrating AI technologies into existing educational systems can be complex and challenging. Educators and institutions need to invest in infrastructure, provide training, and develop digital literacy skills among staff to effectively utilize AI tools. Additionally, ensuring seamless integration with existing educational practices and systems is crucial to avoid disruption and maximize the benefits of AI [80].

To elaborate further, implementing AI technologies in educational settings requires a robust technical infrastructure capable of handling the data processing and computational demands of AI algorithms. This might involve upgrading hardware, investing in cloud computing resources, and establishing secure data storage and management protocols.

Seamlessly integrating AI with existing educational practices is essential to minimize disruption and resistance to change among students, teachers, and other stakeholders. This involves carefully aligning AI technologies with the curriculum, instructional methods, and assessment practices already in place. By integrating AI into familiar workflows, educators can enhance their teaching without overwhelming themselves or their students with novel approaches.

Overcoming the complexities and obstacles of integrating AI in education requires a strategic and systematic approach. Institutions need to recognize the long-term benefits of investing in AI technologies and the capacity to profoundly transform the learning experience for students. By embracing this transformation and actively addressing the challenges, educators and institutions can lay the foundation for a more effective and inclusive educational landscape powered by AI.

5.2.3 Bias and Fairness

Bias and fairness pose critical considerations when applying AI algorithms in education. AI carries substantial potential to revolutionize industries and bring about positive impacts on people's lives. However, bias remains one of the significant challenges in development and deployment of AI systems. Bias means systematic inaccuracies in decision-making processes that lead to unjust outcomes. Bias may occur due to various sources, including biased data collection, algorithmic design, and human interpretation. Machine learning models, a subset of AI systems, can unintentionally adopt and perpetuate biased patterns present in their training data, resulting in outcomes that are unfair or discriminatory [93].

In the context of education, algorithmic bias can have significant consequences. For example, if historical data used to train an AI system shows that certain groups of students have historically performed poorly in standardized tests, the AI may unfairly predict lower performance for students from those groups in the future, leading to unequal learning opportunities. This perpetuates existing inequalities in education and can hinder students' academic growth and potential.

Moreover, biases can also manifest in the content and resources recommended by AI-powered learning platforms. For instance, if an AI recommends reading materials or educational content that predominantly represents one cultural perspective, it may marginalize other cultural perspectives, limiting students' exposure to diverse viewpoints and experiences.

Addressing bias in AI algorithms is essential to ensure fair and equitable learning experiences for all students. Addressing this issue requires careful consideration of the data used to train the AI, as well as ongoing monitoring and evaluation of the algorithm's performance. Researchers and developers must actively work to identify and mitigate biases by refining the data selection process, employing techniques to reduce bias, and implementing fairness-aware AI models.

To uphold fairness and equity in AI-driven education, educators and policymakers must remain vigilant in detecting and correcting biases within AI algorithms. Regular audits and assessments should be conducted to ensure that AI systems are not perpetuating discrimination or hindering the progress of certain student groups. By actively working to mitigate bias, the education community can harness the potential of AI, responsibly and inclusive, providing all students with equal opportunities to thrive in their educational journey.

5.2.4 Human-Computer Interaction and Social Interaction

AI's potential to improve personalized learning is noteworthy, but achieving an effective educational experience requires a delicate balance between technology-driven instruction and human interaction. While AI can provide tailored content and adaptive learning pathways, it should not overshadow the significance of social and emotional aspects of learning. Collaborative activities, effective communication, and empathy foster meaningful connections between students and educators, contributing to students' holistic development [80].

AI's strengths lie in analyzing vast amounts of data, identifying learning patterns, and delivering personalized content and feedback to students. This data-driven approach optimizes learning experiences, tailors' instruction to individual learning styles, and efficiently addresses specific learning needs.

However, AI's role in personalized learning should not overshadow the crucial significance of human interaction in education. Social and emotional learning is an essential aspect of a comprehensive education, fostering vital skills like teamwork, empathy, and communication. Engaging in collaborative projects, discussions, and face-to-face interactions with teachers, peers, and mentors' nurtures critical thinking, problem-solving, and emotional intelligence in students.

By combining AI's capabilities with meaningful human interactions, educators create a harmonious learning environment that maximizes the benefits of both approaches. AI can provide valuable insights and support to teachers, enabling them to tailor instruction and support based on student data. Meanwhile, human interactions foster a sense of belonging, emotional well-being, and personal growth, essential components of a holistic and enriching educational experience.

In summary, AI's data-driven approach complements personalized learning by optimizing content delivery and addressing individual needs. However, it is vital to maintain a balanced educational approach that values human interactions, as they play a fundamental role in nurturing students' social and emotional skills, critical for their overall development and success in life.

6.0 CONCLUSION

Advancement and availability of various platforms in the field of education has led to the rapid growth of data related to learners. Availability of these platforms has accelerated the implementation of different levels of learning analytics that helps educators gain more insights and holistic understanding about learning progress and performance. Wide adoption of these platforms has produced various types of data. Coupled with these different sources and types of data have sparked many studies and efforts on investigating the implementation of artificial intelligence and machine learning in more advanced predictive analytics. However, there remains some limitations when come to computational intelligence in learning analytics in the aspects of ethics which requires close governance of use of AI to ensure privacy of data and accountable practices. While in the aspect of implementation, integrating AI technologies requires robust technical infrastructure and enculturation of the analytics in the institution to ensure its effectiveness. Next is the issue of potential bias from the AI predictive outcome, which requires close monitoring of the predictive performance and outcome to ensure minimal bias so it able to be generalized to different persona of students.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper

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