Educational Administration: Theory and Practice
2023, 29(4), 01-08
ISSN: 2148-2403
https://kuey.net/
Research Article

AI and Learning Disabilities: Ethical and Social Considerations in Educational Technology

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Citation:Heera Lal Rai , et al (2023), AI and Learning Disabilities: Ethical and Social Considerations in Educational Technology *Educational Administration: Theory and Practice, 29*(4), 01-08
Doi: 10.53555/kuey.v30i5.4263

ARTICLE INFO

ABSTRACT

The goal of this study is to determine how artificial intelligence (AI) has been utilized to serve students with learning disabilities Processes (SWLDP). I have evaluated research and focused on dyslexia, dyscalculia, and the remaining on learning disorders generally. According to the study, just half of the research was done on school-age children. Adaptive learning, facial expression, chat-bots, three categories of AI technologies that were utilized to serve SWLDP. Among them, adaptive learning was the most popular. We discovered that AI has been used to support SWLDP in a variety of ways by applying the SAMR-LD (substitute, augment, modify, and redefine learning disability) paradigm. The results demonstrated AI's potential to support SWLDP; however, the paucity of empirical studies also suggests important gaps and the need for additional study on AI's capacity to support SWLDP in ways that go beyond simply detecting and diagnosing learning disabilities.

Keywords: *Ethical, Social Impact, AI Driven Analysis, Students with Learning Disabilities Processes.*

INTRODUCTION

Globally, there are 79.2 million people with learning disabilities, and the number is continuing to rise (UNICEF). Children with learning disabilities have significant needs for special education because they have difficulties with speaking, listening, thinking, reading, writing, arithmetic, science, and spelling. Due to learning disabilities, over 2.3 million public school students in the United States receive special education services; in nations with less developed socioeconomic systems, this need is even more significant because of the scarcity of resources (National Centre for Education Statistics). This group of kids consistently scored lower on reading, science, math, and other courses, indicating difficulties with reading, writing, or math reasoning that limited their opportunities to excel in learning compared to their peers (Asghar et al., 2017). According to Ouherrou et al. (2019), learning difficulties affect pupils not only in a broad range of academic capabilities but also in their emotional and social capacities. Studies have revealed that compared to their peers without learning impairments, students with social and emotional learning disabilities (SWDs) report higher rates of negative emotions like loneliness and depression. As a result, helping SWLDPs meet their academic needs will also aid in their social and emotional growth. Furthermore, learning problems have an especially negative effect on pupils in STEM fields. This is because learning in these fields necessitates that students have the ability to process information in multiple ways, including absorbing, remembering, and applying what they have learned in class (Asghar et al., 2017). Teachers assist students with learning disabilities (SWLDPs) in the classroom, but because each student's learning impairment presents differently, it can be difficult to address the needs of every SWLDP in the classroom. As a result, in order to help them recognise each student's unique needs and develop ways to address them, teachers need sophisticated technologies, such Artificial Intelligence (AI) applications. Furthermore, it is crucial to support SWLDPs since their academic struggles have an emotional impact on them. By providing them with academic support, AI can lessen the chance that these students may experience loneliness or depression. For many years, AI has been utilised to support SWLDPs in diagnosis and intervention (Drigas & Ioannidou, 2013). Drigas and Ioannidou (2013) reported that artificial intelligence (AI) might be used to test or diagnose dyslexia as well as other impairments' symptoms including poor attention spans. According to Drigas & Ioannidou (2012), artificial intelligence (AI) has the ability to score essays automatically, determine the reading and writing challenges of SWLDPs, develop psychological profiles for SWLDPs, and assess their spelling issues. But the main focus of these studies (Rauschenberger et al., 2019; Rello et al., 2018; Zvoncak et al., 2019) is on learning disability screening and diagnosis. Although screening and diagnosis are important, they are not enough for teachers to support students with disabilities (SWDs) and create individualised lesson plans for them. For SWLDPs, AI learning treatments could be developed (Drigas & Ioannidou, 2012, 2013). According to the literature, some applications like intelligent tutoring systems might offer social skill development, speech therapy, and personalised feedback (Drigas & Ioannidou, 2012, 2013). As academics push for fair applications of AI to improve education for all (Zhai & Nehm, 2023), examining current AI applications for SWLDPs in greater detail, learning which applications are employed and how those technologies have been combined to serve SWLDPs in terms of learning and intervention is critical to fill the existing gaps.

Primary research was conducted with six special schools in India, illuminating practical use cases:
1. Vision Special School Rohini Sector 8
2. Vision Vinklang Punarvas Kendra Rohini Sector 9
3. Santos Memorial Research and Rehabilitation Center Narnaul, Haryana
4. Vision Special School Faridabad, Haryana
5. Navnidhi Special School Delhi
6. Children's valley special school Delhi

Insights from these schools inform recommendations for equitable, community-engaged integration of AI in special education.

STUDENTS WITH LEARNING DISABILITIES PROCESSES (SWLDP)

Hence, learning disabilities do not include any learning difficulties that may be caused by visual, hearing, emotional, or motor disabilities, nor do they include any learning difficulties that may be caused by environmental, cultural, or economic disadvantages (Learning Disabilities Association of America, Individuals with Disabilities Education Act, 2007). Learning disabilities, also known as neuro developmental disorders, are caused by genetic or neurobiological factors that alter brain functions. One important element of American legislation, the Individuals with Disabilities Education Act, defines learning disability precisely. A disorder affecting one or more of the fundamental psychological processes involved in comprehending or using language, either spoken or written, which can lead to difficulties with listening, thinking, speaking, reading, writing, spelling, or performing mathematical calculations. These disorders include dyslexia, minimal brain dysfunction, brain injury, perceptual disabilities, and developmental aphasia (Individuals with Disabilities Education Act, 2007). According to the Learning Impairments Association of America, learning impairments are processing issues that affect not only fundamental learning skills like reading, writing, and math but also more complex abilities like organisation, scientific reasoning, attention, and long- or short-term memory. The Learning Disabilities Association of America, has classified learning disabilities based on domains. These include dyslexia, which affects reading and related language-based processing skills, dysgraphia, which affects handwriting ability and fine motor skills, dyscalculia, which affects understanding numbers and learning math facts, and non-verbal learning disabilities, which affect the interpretation of nonverbal cues. Students' performance in math, reading, and writing can be strongly correlated with a learning problem. Additionally, low self-esteem, behavioural issues, or social difficulties brought on by academic struggles might have an impact on students' social and emotional well-being. Helping SWLDP manage and cope with their academic obstacles can enhance their social and emotional development in addition to helping them succeed academically. Büttner and Hasselhorn (2011) discovered that these performances related to learning disabilities cannot be explained by outside causes. Researchers have also discovered that illnesses other than learning difficulties can cause learning disabilities. The learning disabilities group does not cover conditions such as Attention Deficit Hyperactivity Disorder (ADHD), Autism Spectrum Disorder (ASD), and Attention Deficit Disorder (ADD). Students who have these impairments, meanwhile, may also have a learning problem, making them fall into both categories.

MATERIALS AND METHODS

(i) Data Analysis- The process of examining, purifying, converting, and modelling data in order to find relevant information, make inferences, and aid in decision-making is known as data analysis. It is essential to many disciplines, including science, business, finance, healthcare, and more. Programming languages like Python and R, as well as specialised software like Excel v2401, Tableau, Power BI v2.122.746.0, RapidMiner v10.3, and numerous statistical programmes, are often used tools and software for data analysis. The particular methods and strategies employed in data analysis might differ significantly based on the objectives of the research and the nature of the data being examined. Making decisions, solving problems, and getting insights across a variety of domains all depend on data analysis.

(ii) Analytics Platform- Several tools, which are briefly discussed in this paragraph, were selected in order to carry out our analysis:

- The initial dataset management and data integration processing were done using Microsoft Excel.
- Microsoft created PowerBI, an interactive data visualisation programme, with an emphasis on business intelligence. In this research instance, RapidMiner-processed data were imported into the programme and utilised to generate an interactive dashboard for result exploration and analysis. The majority of the graphics shown in this presentation were taken directly from an official PowerBI dashboard.
- Instead, data mining tasks including clustering algorithm execution were carried out using RapidMiner. Within the field of educational data mining, this technology enjoys widespread recognition. Unlike other visual tools, RapidMiner does not require knowledge of a particular coding language to be used for the construction of data mining analysis and model creation. Its accessibility and user-friendly interface are two of its main advantages; yet, it might not give as much versatility as specialised coding languages like Python or R.

(iii) Clustering Algorithms- James MacQueen developed the straightforward unsupervised machine learning method k-Means in 1967. It is well-known in the field of educational data mining. By attempting to reduce the distance between each point and the designated cluster centroid, the algorithm seeks to assign each dataset point to a cluster. K-medoids, an algorithm that is similar to k-means but has some significant modifications, was the other algorithm that was tried. In k-means, centroids can also be points that are not part of datasets, although in datasets, they are always selected from points.

(iv) The Data2Learn@Edu Project- The two pilot projects, Pilot_INVALSI and Pilot_PoliMi, which are what give life to the project's experimental component, are what the lead actor, Leading_PoliTo, depends on in Figure 1. Working closely with the schools selected to serve as testbeds and within them is how this is accomplished. To facilitate comparisons between ideas, practices, and organisations, they are situated in two dissimilar, nonhomogeneous geographic locations. This configuration can aid in the creation of a dashboard tool that is suitable for educators, administrators, and governing bodies. As a result, the viewpoint is shrinking from a large to a little one, with the issues and goals being described in a way that limits their significance to a more specific situation.

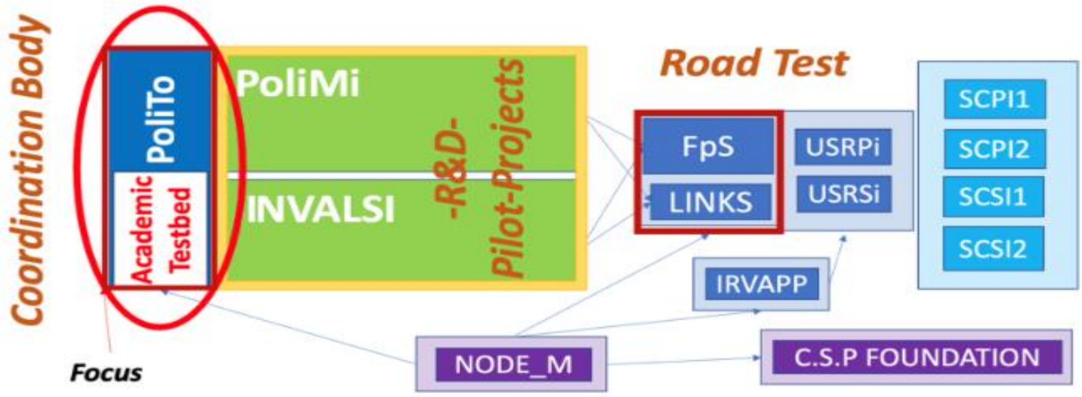

Figure 1- Data2Learn@Edu. Project partners' identification and roles

DATASET ANALYSIS OF CLUSTERING PROCESS

(i) Course performance records- The exam assessments for every student from the 2022–2023 school years are contained in these recordings. The identification of the student and the assessments completed in various exam sections and sessions are connected by these records. This contains information about the final exam scores and results (i.e., TopQ, MedQ, LowQ, and VLowQ).

(ii) Student Personal Information- The information system at Politecnico provided this data. They include data about the colleges from which students previously graduated with their bachelor's degrees, the kind of enrolment, the kind of high school, and additional information that can be useful in creating student profiles.

Table 1- Davies Bouldin index distribution

Number of Clusters	k-Means	k-Medoids
4	−1.106	−1.059
5	−1.036	−0.976
6	−1.035	−1.266
7	−0.904	−1.379

Table 2- k = 5 k-medoids cluster numerosity

Cluster	Numerosity %
Cluster_1	7%
Cluster_2	33%
Cluster_3	4%
Cluster_4	53%
Cluster_5	3%

Table 3- Students' Assessment distribution

Section	Description	Weight
A.	Project Work	75%
B.	Arduino platform	7.5%
C.	Reverse Engineering (UML)	7.5%
D.	Behavior	10%

To get the optimal K value, the cluster number K is an input required by the k-means and k-medoids algorithms. The number of clusters by which K fluctuates was used to express the metric "average within centroid distance" on a "elbow graph" for this purpose. In both methods, K was set to 5, which is the value at which the curve produced a "elbow." It is also the point at which the intra-cluster distance and, hence, the algorithm's performance do not significantly decrease with an increase in the number of clusters (k). In order to close this phase, the Davies–Bouldin index was used to compare the performance of the k-means and k-medoids algorithms in order to identify which one was best suited for the clustering process. The Davies–Bouldin index was close, as shown in Table 1 and 2 for the chosen k-value of 5, however the outcomes indicated that the k-Medoids method would outperform k-means. As a result, this strategy was selected and tried. Conversely, the k-means algorithm produced clusters with higher information quality by displaying far more intriguing figures while maintaining a suitable Davies Bouldin score. For this reason, the k-means method was ultimately selected. A three-dimensional scatter plot of the clusters is presented in Figure 3, which is helpful in understanding how the clusters are distributed across the attributes that were used to cluster the data (provided on the plot's axis). The assessment methodology used in the GISP course is shown in Table 3.

K-MEANS ALGORITHMS BEING DEPLOYED STUDENTS WITH LEARNING DISABILITIES PROCESSES

- K-means clustering is used to cluster learners in MOOC forums, segment datasets based on similarity, and identify learning behavior patterns.
- Heterogeneous value difference metric (HVDM) and naïve Bayes classifier (NBC) provide adaptive learning support by measuring similarity between learners and predicting their needs.
- Reinforcement learning (RL) is employed to optimize learning paths and learning objects using implicit feedback from learners.
- Conditional generative adversarial networks (cGANs) adapt a model of the learner's characteristics to simulate performance and improve training.
- Logistic regression, SVM, ARIMA, deep neural networks, and RNNs are combined to enhance and customize the learning environment.
- Collaborative filtering (CF) constructs personalized learning platforms.
- Deep learning (DL) analyzes students' learning situations, providing targeted resources.
- Q-learning recommends adaptive learning paths.
- Genetic algorithms map optimal individualized learning paths.
- Two-stage Bayesian functions as a recommendation system, customizing learning materials.
- Light gradient boosting machine (LGBM) identifies learning styles and predicts academic performance.

In the evolving landscape of learning, AI/ML algorithms play a pivotal role, offering a multitude of methods from K-means clustering to light gradient boosting machines. These methodologies aid in tailoring content, predicting academic performance, mapping knowledge gaps, and offering dynamic assessments. Through this intricate web of techniques, e-learning platforms are steadily revolutionizing the educational experience, making it deeply personalized, proactive, and responsive to individual learner needs.

RESULTS

The state of education today necessitates quick response and a thorough examination of new viewpoints. In accordance with the guidelines that Politecnico's Board of Directors established, a university needs to take ownership of its data analytics infrastructure and make it available for use for educational purposes. Establishing transparent governance procedures is necessary to promote the health and efficiency of the academic community. The academic publishing landscape is characterized by a deeply ingrained and rapidly evolving infrastructure, whereas the incorporation of data analytics and artificial intelligence is still in its early stages and is constantly evolving. Therefore, it is imperative to avoid giving up all authority over these operations to profit-driven businesses, which naturally put the maximization of returns for their investors first.

(i) Adaptive learning- Supporting students with learning disabilities (SWDP) presents additional challenges due to the diversity of their learning demands compared to those of students without learning disabilities. Customised learning support or material adaptation are the most effective instructional strategies to address this difficulty. A sort of AI technology called adaptive learning was used in five out of the sixteen investigations in this review. The studies targeted a wide range of ages and disabilities, including dyslexia, dysgraphia, and others, as well as those under the age of five.

(ii) Facial expression- Expression on the faceSupporting students' learning, especially the learning of SWLDs, begins with getting them involved in the classroom. Researchers have found that one indicator of students' involvement with the material is their facial expression. Out of the 16 research, three employed artificial intelligence technologies to analyse facial expressions, and all three utilised this data to forecast students' involvement with the subject matter. Researchers used artificial intelligence (AI) tools like convolutional neural networks (CNN) (Ouherrou et al., 2019), speed-up robust features (SURF) and support vector machines (Abdul Hamid et al., 2018a), and bag of features (BOF) (Abdul Hamid et al., 2018b) to analyse the facial expressions of students in these studies, whose ages ranged from 7 to 12.

(iii) Chat robot- Due to technological advancements, a growing number of students globally are familiar with the use of chat robots, also known as smart assistants, as they become more prevalent on digital platforms related to students' life. Large corporations have been using chatbot AI technology for customer service and troubleshooting their goods; this has led to the application in education. In particular, the chatbot was utilised by two research in this study to assist SWLDs. One employed Samantha, a chatbot that communicated with students to offer resources, accessibility, and feedback according to their requirements (S. Gupta & Chen, 2022).

(iv) Context and Data Framework- The Innovation Management and Product Development course (GISP: PoliTo Data Lake), which is a popular course among all those offered in Politecnico's Master of Science programmes, serves as the basis for this case study. This course now enrols over 100 new students each semester. Alongside the GISP course, students take additional courses in project management, object-oriented programming, business planning, quality control, and data-driven application development.

(v) Classroom- Over 100 students from a diverse background attend the constructivist classroom in the 2023 academic year, which is divided into two theory classes and two lab sessions focused on teamwork each week. It is the responsibility of the instructors, professors, and trainers in this classroom to foster a collaborative environment where students actively participate in their own education. Each group consists of five members who independently oversee their work processes and enforce internal cooperation while addressing complex problems related to particular projects. The latter are frequently developed through brainstorming meetings, perhaps with the aid of outside enterprise actors. Cooperation is sought within each group using a variety of collaborative tools, including appropriate application and system development, Skype, Teams, or Zoom for synchronous communication, and Dropbox and Google Drive for data storage.

(vi) Course Delivery- Within a dynamic learning framework, the active learning methodology described in a distinctive combination of traditional and constructivist methods. According to the project work syllabus, the course structure serves as a living laboratory in this method, mirroring the project's life cycle. The weekly timetable is split in half, with half going towards project creation and the other half going towards traditional lecture-style instruction. This combination tackles two problems. It is consistent, on the one hand, with the corporate-style organisation of a university, where time is methodically controlled through labour coordination and passive interactions. Conversely, it meets the needs of processes that are driven by creativity and are mainly concerned with promoting student participation.

(vii) Assessment Management- Educators, professionals, and their support personnel may find it difficult and counterintuitive to manage a course while also improving the learning experience. Utilising questionnaires to find enduring evidence in practice, the difficulties associated with enhancing teaching and learning can be determined.

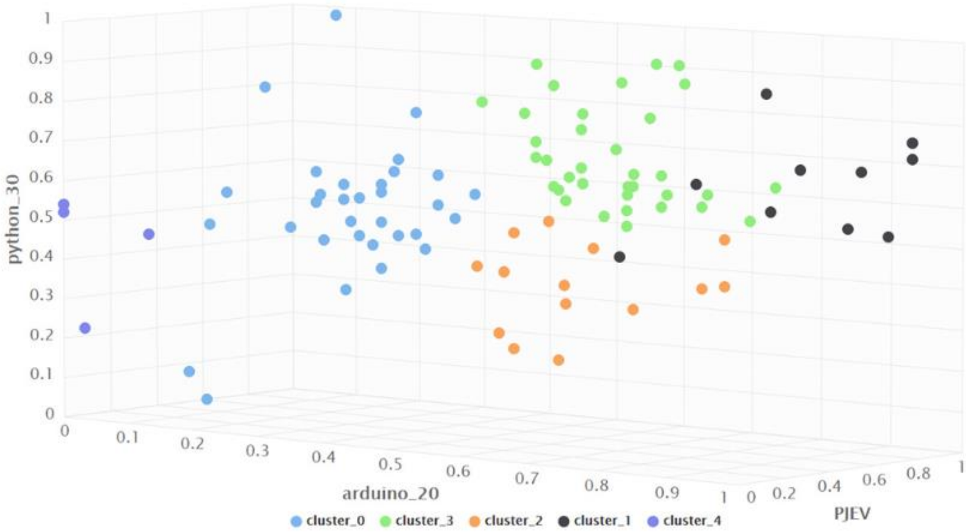

Figure 2- Cluster visualization

CONCLUSION

We discovered that several AI applications are used to support SWLDP learners' learning, and there are a variety of ways in which the technologies are combined to facilitate learning. The results of this study have demonstrated the potential of AI in supporting SWLDP learning, as the focus of this review study was to specifically identify research on how AI can be used to support the learning process of SWLDP, rather than the diagnosis or identification of a learning disability. The paucity of empirical research in this field, however, also suggests important research gaps and the need for additional studies on how AI may assist SWLDs in ways other than only detecting and diagnosing a learning disability. In order to use AI to help SWLDP learn, further study on design and development is required. Additionally, additional empirical data is required to expand our understanding of the potential of AI for SWLDP. The purpose of this aim is to demonstrate the use of particular toolkits, namely Excel, PowerBI, and RapidMiner. These are three efficient settings that allow data to be processed from various angles. The initial data representations were obtained by preprocessing using Excel; PowerBI was then utilised to visually enhance these representations. In order to provide information to particular clustering methods, RapidMiner was utilised, selecting particular association rules to describe every cluster that was discovered.

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