Work-In-Progress: Investigate Eye-Tracking Metrics and Effectiveness of Visual Learning Aids in Online Learning Environments for Students With Learning Disabilities Using Machine Learning

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This Work-In-Progress study proposes a novel approach to explore the learning behaviors of students with learning disabilities in online learning environments by investigating eye-tracking metrics and effectiveness of visual learning aids. It builds on previous research that suggests that students with learning disabilities often face difficulties in online learning environments due to the lack of visual cues and their limited ability to interact with the learning material. The use of machine learning to analyze eye-tracking data and visual learning aids can provide insights into how students with learning disability interact with online learning materials, with the goal of improving the learning outcomes as well as informing the design of constructive teaching strategies and seeking to expand this research to the online learning context.

Keywords: philosophy of engineering education, K-12, STEM, factor analysis, data correlation

INTRODUCTION

Learning disabilities (LDs), i.e., dyslexia, autism spectrum disorder (ASD), attention-deficit/hyperactivity disorder (ADHD), can significantly impact a student's ability to learn (Handler & Fierson, 2011). However traditional classroom settings may not always be suitable for accommodating their needs (Liu, et.al., 2023). The COVID-19 pandemic has further exacerbated these challenges, with many students now having to rely on online learning environments. It is crucial to explore the effectiveness of different teaching and learning strategies to support students with learning disabilities. Visual aids, such as diagrams and illustrations, have been found to be helpful in enhancing learning outcomes for special needs students; however, there is limited research on the effectiveness of these aids in online learning environments. Additionally, previous studies have often relied on self-report data, which may be biased or unreliable.

The main objectives of this study are to (1) identify which types of visual aids are most effective in improving student learning outcomes, (2) shed light on the potential of eye-tracking metrics in designing inclusive and impactful online learning environments, particularly for students with learning disabilities, (3) identify the factors that influence the effectiveness of these aids. The results of this study can demonstrate the potential of eye-tracking metrics in the design of online learning environments that are more inclusive and effective for students with learning disabilities. The structure of this paper is as follows: first, the background on learning disabilities and emerging technology will be introduced, followed by a detailed description of the search strategy for relevant research in the methodology section. The results and discussion sections will provide a comprehensive review of machine learning approaches in online learning using eye-tracking, including their challenges, limitations, and future research directions. Finally, the paper will conclude by summarizing the findings and proposing future research areas.

BACKGROUND

This long-term study aims to explore the effectiveness of using stimuli-based gaze analytics to improve motivation and learning outcomes in online courses. By analyzing gaze variables, fixation time, this study seeks to provide gaze-aware feedback to students and gain valuable insights into how the design, interfaces, and analytics of online courses can be enhanced. This research serves as a preliminary step towards remote course designing that are optimized for gaze-awareness and can enhance the learning experience.

Learning Disabilities

Dyslexia (Frazier, 2016), characterized by reading and spelling impairments despite normal intelligence (Glazzard, 2010), is one of the most common learning disorders. The negative consequences of dyslexia on an individual's academic and occupational success, self-esteem, and social-emotional development have been well-documented (Vellutino et al., 2004). Early detection and support have been shown to mitigate these negative effects, highlighting the importance of understanding the underlying causes of dyslexia.

Autism spectrum disorder (ASD) is a neurodevelopmental disorder characterized by heterogeneous characteristics in children, including behavioral differences, communication difficulties, and social disabilities (Eslami et al., 2019). It affects approximately one in 160 children worldwide according to the World Health Organization (Prelock, 2021), with symptoms appearing in childhood and persisting into adulthood. Detecting autism early is challenging and requires significant effort and time to improve outcomes. To achieve early detection, behavioral and physiological techniques have been utilized to effectively and accurately identify autism in children (Dawson, 2008). Additionally, there is a need for predictive indicators that can inform parents about their children's behavior, physiological status, and developmental trajectory at an early stage. These indicators can also help research centers in finding appropriate solutions and treatments. Although clinical and physiological characteristics may not be identified early on, certain key behavioral characteristics have shown a high ability to determine the presence and severity of autism (Loth et al., 2017).

The control of saccades, which are rapid ballistic movements of eyes between fixation points, plays a crucial role in our daily lives as it enables us to search for visual information in complex environments, allowing us to focus on relevant information while ignoring irrelevant stimuli (Findlay, 1997). Effective and efficient saccadic control is essential for goal-directed information acquisition from the surrounding world. Pro-saccades facilitate orienting to relevant information, while anti-saccades, which require interference control abilities, aid in filtering out irrelevant information (Wang et al., 2015). Furthermore, saccadic movements have been associated with other cognitive abilities (Klein et al., 2010), such as intelligence and working memory. Attention-deficit/hyperactivity disorder (ADHD) is characterized by inattention and hyperactivity, and individuals with ADHD often exhibit eye movement abnormalities. Studies have shown that children with ADHD have longer saccade latency in anti-saccade tasks compared to typical developing children (Munoz et al., 2003). In pro-saccade tasks, children with ADHD demonstrate poorer saccade accuracy (Huang & Chan, 2020). These findings suggest difficulties in suppressing unwanted eye movements and voluntary control of eye fixations in children with ADHD. Moreover, eye movement abnormalities have been found to be positively correlated with the severity of ADHD symptoms (Manoli et al., 2021), highlighting the clinical significance of interventions targeting eye movement abnormalities in children with ADHD. While there has been limited research on interventions to improve eye gazing abilities in children with ADHD, some studies have explored pharmacological interventions, such as methylphenidate administration, which have shown improvements in both pro-and anti-saccades (Klein et al., 2002). However, these medications may have side effects including insomnia, decreased appetite, and headaches (Lee et al., 2011). Consequently, non-pharmacological treatments may serve as alternative interventions for addressing eye movement abnormalities in children with ADHD.

Eye-Tracking

Eye tracking (Holmqvist et al., 2011) is an emerging educational technology that utilizes pupil movement measurements and corneal reflection analysis to determine a user's gaze position on a computer screen. It distinguishes two main types of eye movements during reading: fixations, which represent moments of gaze, and saccades. The integration of eye tracking with computational methods holds the potential to provide detailed insights into an individual's cognitive processes (Rello & Ballesteros, 2015). To realize this potential, it is crucial to develop reliable methods for identifying reading difficulties through eye movements. Recent studies have demonstrated the successful application of machine learning techniques in detecting dyslexia based on eye movements, showing promising results (Jothi Prabha & Bhargavi, 2022; Perera et al., 2016) on adults.

Machine Learning (ML)

Machine learning is a branch of artificial intelligence that focuses on developing algorithms and models capable of automatically learning and improving from data without explicit programming (Bastanlar & Ozuysal, 2014). It enables computers to analyze and interpret complex patterns and make predictions or take actions based on the information learned from past experiences. The field of machine learning has witnessed remarkable advancements in recent years, driven by the exponential growth of data availability, computational power, and algorithmic innovations.

Machine learning techniques have found applications across various domains, including computer vision, natural language processing, robotics, finance, healthcare, and many others (Burzykowski et al., 2023). The core principle behind machine learning is to enable computers to learn from data and make accurate predictions or decisions without being explicitly programmed. This is achieved through the use of statistical models and algorithms that can identify patterns, extract meaningful insights, and generalize from the observed data to make predictions or perform tasks on unseen data (Shinde & Shah, 2018). There are different types of machine learning approaches, including supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the algorithm learns from labeled examples, where the desired output is known, and aims to generalize this knowledge to make predictions on new, unseen data. Unsupervised learning, on the other hand, deals with unlabeled data and focuses on discovering hidden patterns or structures within the data (Goodfellow et al., 2013). Reinforcement learning involves training an agent to make sequential decisions in an environment and learn from the feedback it receives to maximize a reward signal (Sutton & Barto, 2018). The potential applications of machine learning are vast and diverse. From personalized recommendations and predictive analytics to autonomous gaits (Liu, et.al., 2021) and medical diagnosis, machine learning has the capability to revolutionize industries and drive innovation (Rezaei & Shahidi, 2020). However, it also poses challenges such as model interpretability, data privacy, and ethical considerations, which need to be carefully addressed. The primary objective of this paper is to investigate various machine learning methods used in the context of online learning. It aims to provide an overview of their advantages and drawbacks, as well as to discuss the current developments and challenges in the field.

PRELIMINARY FINDINGS AND FUTURE DIRECTIONS

Relevant Studies on the Topics

Diard et al. (Diard et al., 2013) introduced the Bayesian Action-Perception for Eye On-Line model (BAP-EOL), a probabilistic model designed to facilitate online character recognition during eye writing. The model incorporated probabilistic knowledge concerning letter trajectories, including their size, high-frequency components, and pupil diameter. The primary objective of the BAP-EOL model is to demonstrate the feasibility of character recognition as the eye writes the characters, particularly in the context of individuals with motor impairments. The authors aimed to assess the potential utility of eye writing devices for patients with motor disabilities, utilizing Bayesian inference to perform disability assessment by measuring and monitoring the motor characteristics of the produced eye trajectories. The paper presented preliminary experimental results that showcase the effectiveness of the BAP-EOL model in character recognition during eye writing. These initial findings not only illustrate the practicality of recognizing characters in the context of eye writing but also highlight the associated technical challenges.

Cerezo et al. (Cerezo et al., 2020) proposed a comprehensive protocol for evaluating metacognitive and self-regulatory processes, as well as emotional aspects, which form the basis of learning difficulties (LDs) in adults. The evaluation is conducted through a range of methods, techniques, and sensors, both on- and off-line. On-line methods include analysis of the learning process using tools such as eye tracking, facial expression analysis, physiological measures, concurrent verbalizations, log files, and screen recordings of human-machine interactions. Off-line methods consist of questionnaires, interviews, and self-report measures. This protocol is grounded in theory and empirical research, with the goal of accurately assessing LDs in adulthood to inform the development of effective prevention and intervention strategies.

Shadiev et al. (Shadiev & Li, 2022) provided a synthesis of research findings related to the utilization of eye-tracking technology in immersive virtual reality (IVR) learning environments created through head-mounted displays. In this study, a comprehensive review of fifty articles was conducted, focusing on the devices utilized in the research, the domains of learning, the number and academic level of participants, data collection methods, duration of IVR activities, and the indicators and themes of visual attention. The key findings of this review reveal that Tobii and HTC Vive are the most commonly employed tools in studies investigating eye-tracking technology usage in IVR learning environments. Cognitive science and educational technology emerged as the predominant domains in this line of research. The number of participants varied among the reviewed articles, with tertiary education being the most frequent academic level of the participating students. Questionnaires and tests were frequently used as data collection methods by scholars. Fixation duration emerged as the most frequently utilized indicator. The most prevalent themes identified in the reviewed research included task performance, teaching and learning strategies, and learning tools.

The work proposed by Raatikainen et al. (Raatikainen et al., 2021) was to detect individuals with poor reading fluency (below the 10th percentile of a normal distribution) based on their eye movement recordings during reading. The study utilized a Random Forest approach to select the most critical eye movement features for input to a Support Vector Machine classifier. This hybrid approach proved to be reliable in identifying individuals with dysfluent reading and provided useful insights into the data used. The best-performing model achieved an accuracy of 89.7% and a recall of 84.8%. These results lay the groundwork for automatic detection of dyslexia in natural reading situations.

Sharma et al. (Sharma et al., 2020) explored the potential of stimuli-based gaze analytics in enhancing motivation and learning in Massive Open Online Courses (MOOCs). The study involved 40 students who watched a MOOC lecture while their eye movements were recorded. The authors proposed a technique to define stimuli-based gaze variables that could be applied to any stimulus. These variables indicated students' content coverage (in space and time), reading processes (based on area of interest), and attention (i.e., "with-me-ness") at both the perceptual (following teacher's deictic acts) and conceptual levels (following teacher discourse). The study identified a significant mediation effect of the content coverage, reading patterns, and the two levels of with-me-ness on the relationship between students' motivation and their learning performance. The ultimate objective was to create student profiles based on their performance and learning strategy using stimuli-based gaze variables and to provide students with gaze-aware feedback to improve their overall learning process. The authors also presented a method that combines state-of-the-art AI techniques with eye-tracking data to predict student performance. The results indicated that student performance can be predicted with less than 5% error.

After reviewing various related works, it has been noted that eye gaze measures have been utilized by different models and methodologies for detecting learning disability. Unlike previous reviews which have focused primarily on single modalities of treatment or specific patient populations, our review will include a broad range of interventions and patient groups. Furthermore, a rigorous methodological approach will be utilized to ensure the highest quality of evidence synthesis. By taking these unique and novel approaches, this review will provide a more comprehensive and nuanced understanding of the effectiveness of interventions for depression and offer insights into the potential for future research. This long-term study will use a randomized controlled trial design to investigate the effectiveness of visual learning aids in improving attention and engagement among students with learning disabilities. Eye-tracking technology will be utilized to collect objective data during the online learning activities. The data will be analyzed using machine learning techniques to identify patterns in the students' eye movements and determine the effectiveness of different visual aids.

Constraints of ML and Eye-Tracking

Although machine learning (ML) and eye-tracking technologies have demonstrated their potential in improving motivation and learning, there are certain limitations to their usage. One of the constraints of ML is that it requires a large volume of data to train models effectively. This can pose a challenge when working with small sample sizes or when dealing with rare events. Moreover, the quality of the data used to train the models is critical. If the data is biased or contains errors, the resulting models may also be biased or inaccurate. Another drawback of ML is that it can be challenging to interpret the results of complex models. This can make it difficult for researchers to understand how the models are making predictions and to identify any potential biases or errors. As for eye-tracking, one limitation is the potential for individual differences in eye movements and attentional processes, which may impact the generalizability of findings across different populations. Additionally, eye-tracking can be affected by artifacts such as head movement or lighting conditions, which can impact the quality of the data collected, leading to inaccurate measurements of eye movements. Additionally, eye-tracking technology can be costly and may not be accessible to all researchers. Furthermore, the use of eye-tracking technology raises ethical concerns with using eye-tracking on individuals, particularly with regards to privacy and data security. To mitigate the risks associated with head movements and isolate them from eye movements in the future study, incorporating additional measures such as an accelerometer on the patient's head will be considered. This accelerometer can provide data on head movements, allowing to separate and analyze the distinct contributions of head and eye movements. By isolating head movements, the study can better understand the specific effects of eye movements on depression severity symptoms, reducing potential confounding factors. This approach will enhance the accuracy and reliability of the findings, providing a more precise understanding of the relationship between facial movement, depression severity symptoms, and clinical data.

In conclusion, while ML and eye-tracking technologies have shown potential in enhancing motivation and learning, it is important to consider the limitations associated with their usage while designing and conducting research studies.

Future Research Directions and Recommendations

The proposed research aims to investigate eye-tracking metrics and the effectiveness of visual learning aids in online learning environments for students with learning disabilities using machine learning. The eye-tracking equipment to be used in this study will include state-of-the-art eye-tracking devices, such as the Tobii Spark eye tracker, equipped with high-resolution cameras and infrared sensors. These devices will capture precise eye movements and gaze data of the participants while they interact with the online learning materials.

Description of Software Tools

For data processing and analysis, the research will employ various software tools. The collected eye-tracking data will be processed using Tobii Pro Lab software, which enables the extraction of relevant eye movement metrics, such as fixations, saccades, and gaze duration. Additionally, custom Python scripts will be developed to preprocess and clean the data, ensuring accuracy and consistency in the analysis.

Phase Plan

The future study will involve a sample of students with learning disabilities who will be randomly assigned to either an experimental group that receives visual learning aids or a control group that does not receive any visual aids, both groups will undergo the same online learning activities. Eye-tracking metrics will be used to measure the students' attention and engagement with the online learning material. The study will also collect demographic information from the participants, such as age, gender, and previous experience with visual aids. The study will be conducted in the following four phases.

- **Phase 1.** Participant Selection and Pretest: Students with learning disabilities will be recruited for the study, ensuring a diverse sample that represents the target population, i.e., college students. The selected participants will be randomly assigned to either the experimental group or the control group. This randomization process helps ensure an equal distribution of characteristics among the two groups. Both the experimental and control groups will take a pretest to establish a baseline for their learning outcomes.
- **Phase 2.** Intervention and Data Collection: The experimental group will receive visual learning aids during the online learning activities, while the control group will not receive any additional aids. Eye-tracking metrics will be used to measure the participants' attention and engagement with the learning material. Objective data will be collected during the learning activities to provide insights into the participants' eye movements.
- **Phase 3.** Post-test and Data Analysis: After the intervention, both groups will take a posttest to evaluate their learning outcomes. The collected data will be analyzed using machine learning techniques. Patterns in the participants' eye movements will be identified, and the effectiveness of different visual learning aids will be evaluated.
- **Phase 4.** Evaluation of Visual Aids and Prediction of Learning Outcomes: The results of the analysis will be utilized to evaluate the effectiveness of different types of visual aids in enhancing attention and engagement among students with learning disabilities. The findings from the analysis can also be used to predict student learning outcomes based on their eye movements and engagement patterns.

Future Direction

The future study aims to explore the visual aids in learning design for improving the learning outcomes of students with learning disabilities and identify the factors that influence their effectiveness. It intends to investigate how eye-tracking metrics can aid in creating more inclusive and effective online learning environments. The study's expected outcomes consist of a comprehensive analysis of the efficacy of visual learning aids in online learning environments for students with learning disabilities. The findings will provide insight into students' learning behaviors and have practical implications for designing effective teaching strategies, promoting the development of more accessible and inclusive online learning environments for students with learning disabilities, ultimately enhancing their learning outcomes and academic achievements.

The utilization of eye-tracking metrics and machine learning to explore the effectiveness of visual learning aids in online learning environments for students with learning disabilities presents a promising avenue for research. It provides valuable insights into the effectiveness of visual learning aids and eye-tracking metrics in online learning environments for students with learning disabilities.

While the current study will identify the effectiveness of visual learning aids, it is important to investigate the effectiveness of different types of visual aids, such as graphic organizers, videos, and animations. This will help identify the most effective types of visual aids for specific learning objectives and student populations. Another direction is to investigate the generalizability of the findings. The current study focused on a specific student population and online learning environment. Future research should investigate the generalizability of the findings to other student populations and learning environments.

Challenges

Collecting eye-tracking data in online learning environments presents several challenges. The first challenge is to ensure that participants remain engaged during the learning sessions to capture reliable and meaningful eye-tracking data. Additionally, potential technical issues, such as data synchronization and calibration errors, need to be addressed to maintain data accuracy. Recruiting participants with learning disabilities for the study can be challenging due to privacy concerns and ethical considerations. Furthermore, the sample size and diversity of participants may impact the generalizability of the findings, and efforts will be made to recruit a representative and sufficient number of participants. Longitudinal studies could also be conducted to investigate the long-term effects of visual learning aids in online learning environments. As current study will focus on short-term learning outcomes. It is important to conduct longitudinal studies to investigate the long-term effectiveness of visual learning aids and to identify the factors that influence their long-term effectiveness. Additionally, develop effective feedback mechanisms and provide objective participants data is challenging. The current study will identify the potential of eye-tracking metrics and machine learning in predicting student learning outcomes. Future research should focus on developing effective feedback mechanisms that utilize eye-tracking metrics and machine learning to provide personalized feedback to students and improve their learning outcomes. Addressing these challenges will be essential to ensure the validity and reliability of the study's results, and proper measures will be implemented to mitigate potential biases and ensure ethical research practices.

Overall, the use of eye-tracking metrics and machine learning to investigate the effectiveness of visual learning aids in online learning environments for students with learning disabilities is a promising area of research with many exciting opportunities for future work. Future research directions can focus on investigating the effectiveness of different types of visual learning aids, conducting longitudinal studies, investigating individual differences, and developing effective feedback mechanisms.

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