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A Multimodal Affect Recognition Adaptive Learning System for Individuals with Intellectual Disabilities

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ABSTRACT
Educational tools using Artificial Intelligence (AIEd) have been implemented to provide automated learning support for typical students. This innovative field focuses on using data and machine learning to detect a student's emotional state, with the goal of shifting them from unproductive emotions to more positive, learning-enhancing ones like engagement. However, AIEd systems that include emotion recognition often overlook students with intellectual disabilities. Our system employs multimodal sensor data and machine learning to identify three key emotional states related to learning (engagement, frustration, boredom). It then adjusts the educational content to keep the student in an ideal emotional state, optimizing learning effectiveness. To evaluate this adaptive learning system, we conducted studies with 67 participants aged 6 to 18, who served as their own controls, in sessions that used the system. These sessions alternated between using the system for both emotional state detection and learning progress to choose content (intervention) and relying solely on learning progress (control) for content selection. Remarkably, a lack of boredom was most strongly linked to better learning outcomes, while both frustration and engagement also showed positive correlations with achievement. Sessions using the intervention showed significantly more engagement and less boredom compared to control sessions, although there was no significant difference in achievement. These results indicate that customizing activities based on the learner's emotional state can boost engagement and foster emotions that are beneficial for learning. Nevertheless, longer-term studies are needed to assess the impact on actual learning achievements.

Key words: Artificial Intelligence, multimodal sensor data, intellectual disabilities, adaptive learning system, machine learning

INTRODUCTION

The term "intellectual disabilities" (ID) is now internationally recognized, replacing outdated labels such as "learning disabilities" and "mental retardation" (Schalock, 2010). To diagnose ID, three key criteria must be fulfilled: an IQ under 70 indicating intellectual impairment, significant difficulties in everyday living skills, and the condition's emergence before 18 years of age. Although IQ scores offer a theoretical framework for categorization, in practice, the American Association on Intellectual and Developmental Disabilities suggests that the actual distinction comes from the varying levels of support each individual requires (Luckasson, 2002). Students with ID are often deprived of suitable, accessible, and engaging

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educational experiences (Taub, 2017). In this context, Artificial Intelligence tools for education (AIEd) emerge as a promising solution, providing tailor-made educational approaches that cater to the unique learning needs of students with ID (Baker, 2010). This transcends traditional, inflexible teaching methods (Nesta, 2019). A pioneering aspect of AIEd is affect recognition, which aims to improve learning outcomes by identifying and altering a student's emotional state, guiding them from negative emotions like boredom or frustration to positive ones such as engagement or enjoyment (du Boulay, 2018; Kort, 2001).

Recent studies emphasize the growing interest in affect recognition, pinpointing more than 20 emotional states through different physiological indicators (Aslan, 2019). Applications of AIEd encompass providing teachers with immediate feedback on student engagement, delivering assistance akin to that of human tutors (Thompson, 2017), and customizing educational content according to the emotional condition of the learner (Grawemeyer, 2017). These methods have demonstrated promise in enhancing educational results and diminishing adverse behaviors (Colley, 2013; Craig, 2004).

Within the context of teaching students with Intellectual Disabilities (ID), where varied educational approaches are crucial, AIEd stands out as a significant method for catering to each student's unique learning requirements (Cukurova, 2019). Online educational platforms can provide multimedia tools and flexible timetables, facilitating tailored teaching experiences (Rose, 2007). Nonetheless, the progress in AIEd technology specifically for students with ID is not as advanced as for typical learners, underscoring the necessity for further research and development in this field. Personalizing learning environments for individuals with multiple disabilities, including ID, can be realized using ontological models and adaptive personalization based on fundamental machine learning principles (Nganji, 2017; Bertini, 2003). Although some research indicates improved engagement and learning efficiency, there's a notable lack of consideration for the emotional states of learners in these personalization efforts. Acknowledging that engagement improves when educational activities are aligned with a student's personal needs and emotional states highlights the critical role of incorporating emotional aspects into AIEd for individuals with ID.

This project employed an innovative approach to explore the impact of a system customizing learning activities based on learners' needs and emotional states. The adaptive learning system aimed to identify three affective states (engagement, boredom, and frustration) using a pedagogical framework integrating Csikszentmihalyi's Theory of Flow and Vygotsky's Zone of Proximal Development (Nakamura, 2009). For students with intellectual disabilities, particularly those with autism, unique expressions of affective states required a tailored approach (Orekhova, 2014). Machine learning algorithms were trained on multimodal data, including facial expressions, eye gaze, body pose, voice input, gestures, and interaction with learning materials (Chickerur, 2015; D'Mello, 2010).

Models for each modality were trained and validated using cross-validation methods. A multimodal fusion scheme was employed for an overall understanding of learners' affective states (Basawapatna, 2013). The adaptation of the learning process depended on the learner's affective state, utilizing learning graphs to adjust challenge levels (Tsatsou, 2018). Persistent states of boredom or frustration triggered interventions to maintain the learner in a state of flow. The study aimed to evaluate the effectiveness of the adaptive learning system in maximizing engagement and learning for school-aged children with intellectual disabilities (Figure 1), testing hypotheses related to the automatic identification of affective states and the positive impact of the system on engagement and learning achievement (Hamari, 2016).

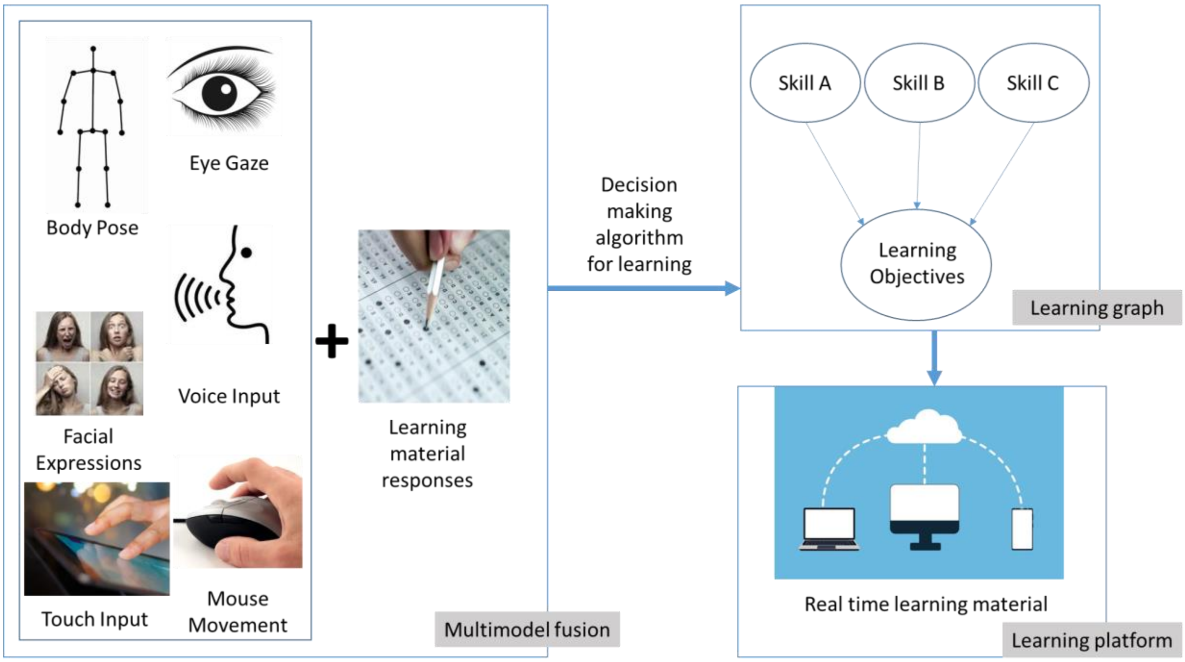

Figure 1: Adaptive Learning system

MATERIALS AND METHODS

Sessions

We adopted a within-subjects repeated measures approach in this study, where every participant took part in both the intervention (A) and control (B) sessions. During the intervention (A) sessions, the learning model was applied as initially intended, using both affect and achievement data to tailor the delivery of educational content. In contrast, the control (B) sessions relied exclusively on achievement data to present learning materials.

This methodology presented numerous benefits. Each participant acted as their own control, which effectively managed the variability inherent in a diverse group of participants. The design was flexible enough to meet the needs of both teachers and students, allowing for adjustments in the duration and scheduling of sessions to suit classroom routines and individual learner commitments. By alternating the sequence of the conditions, we reduced the order effect that might arise from consistently presenting one condition before the other. This approach also streamlined the number of test sessions required, thereby reducing potential biases.

The criteria for participation in the study focused on individuals aged 6 to 18 who had intellectual disabilities (ID) or were on the autistic spectrum (ASC), and who were performing considerably below their peer group. Participants were selected by teachers who identified students who would likely benefit from the system, with participation dependent on the approval of parents or caregivers. In total, 85 participants took part in at least one control (B) session, and their data was used for the study's analysis. Based on their school records, these participants were divided into three categories: those with ID, those primarily diagnosed with autism (ASC), and those with ID as well as some autistic traits (ID/ASC).

Intervention

Teachers selected and arranged educational content from a resource pool to create customized Learning Activities and Learning Graphs, which mirrored specific lessons found in conventional educational settings. Learning Graphs, similar to lesson plans, were composed of specific learning objectives broken down into Smart Learning Atoms—compact, standalone knowledge units (Boulton, 2019). These modular elements enabled the flexible creation of new courses or tailored learning pathways, enhancing personalization and allowing quick adjustment to changes in emotion recognition and content delivery (Ocumpaugh, 2012). The content library, collaboratively maintained by educators, was designed to support students with limited verbal skills and to enable the sharing of materials across different countries.

The Learning Objectives incorporated within the Learning Graphs at various test locations were diverse, covering areas like navigation, sequencing, vocabulary, understanding cause and effect, attention, language, mathematics, and social skills (Porayska-Pomsta, 2018). These Learning Graphs were customized to match the support needs of the students and the specific conditions at each test location, taking into account factors such as the availability of the NAO robot platform agent.

Outcome Measures

During each session, the participant's emotional state, which included feelings of frustration, engagement, or boredom, was assessed using affective state recognition technology. This involved employing a late multimodal fusion technique, where the selection of modalities was based on the user's profile. The likelihood of each affective state being present was calculated from each modality and averaged, resulting in a score between 0 and 1 for each state, with 1 indicating a complete presence of the identified emotion. The primary affective state for a given set of multimodal sensor data was then identified by choosing the state with the highest average probability score.

The software also measured learning progress by calculating an achievement value. This value represented the overall level of skill or knowledge the learner had gained through the activities designed to meet a specific educational goal. It was determined based on the learner's correct and incorrect responses during these activities, with the score ranging from -1 to 1.

Procedure

Teachers and the research team recommended involving each participant in 14 sessions, with half designated as intervention sessions. To mitigate the order effect, teachers were instructed to alternate sessions between the two conditions in sets of three, for instance, AAA BBB AAA BBB, while half of the participants experienced a reversed order (BBB AAA BBB AAA). Teachers were encouraged to conclude sessions at their discretion, aiming to stay within a 30-minute timeframe to balance data collection robustness and practicality. While technical issues and participant absences occasionally disrupted the prescribed pattern, the alternation between conditions was consistently maintained. Participants engaged with learning graphs selected by their teachers, using devices such as laptops, tablets, or NAO robots.

Analysis

Data retrieved from the MongoDB database included affective state and achievement files for each session. The system generated performance values multiple times per minute for each session. Post testing spreadsheets from testing partners were used to identify relevant data lines. Averages were calculated for each session, yielding a single value for engagement, boredom, frustration, and achievement. Statistical analysis employed multilevel modeling, considering participant-level nested data and controlling for intervention effects (Wang, 2009). Subgroups (ID, ASC, ID/ASC) were analyzed separately. Tobit models were used to account for the ceiling effect in achievement data (Barros, 2018). Akaike Information Criterion guided model fitting and variable selection (Vrieze, 2012). Age, gender, and level of intellectual disability were included in the analysis (Bozdogan, 1987).

Final model specification took the forms:

A. $\text{Inachievement}_{ij} = \beta_0 + \beta_2 \text{age}_{ij} + \beta_3 \text{female}_{ij} + \beta_4 \text{Inengaged}_{ij} + \beta_5 \text{Infrustrated}_{ij} + \beta_6 \text{intervention}_{ij} + \beta_7 \text{mild}_{ij} + \beta_8 \text{moderate}_{ij} + \beta_9 \text{severe}_{ij} + \mu_{io} + \mu_{i1} \text{Inengaged}_{ij} + \varepsilon_{ij.}$

B. $\text{Inachievement}_{ij} = \beta_0 + \beta_2 \text{age}_{ij} + \beta_3 \text{female}_{ij} + \beta_4 \text{Inengaged}_{ij} + \beta_5 \text{Inbored}_{ij} + \beta_6 \text{intervention}_{ij} + \beta_7 \text{mild}_{ij} + \beta_8 \text{moderate}_{ij} + \beta_9 \text{severe}_{ij} + \mu_{i0} + \mu_{i1} \text{Inengaged}_{ij} + \varepsilon_{ij.}$

C. $\text{Inachievement}_{ij} = \beta_0 + \beta_2 \text{age}_{ij} + \beta_3 \text{female}_{ij} + \beta_4 \text{Inengaged}_{ij} + \beta_5 \text{Inbored}_{ij} + \beta_6 \text{intervention}_{ij} + \beta_7 \text{mild}_{ij} + \beta_8 \text{moderate}_{ij} + \beta_9 \text{severe}_{ij} + \mu_{i0} + \mu_{i1} \text{Inbored}_{ij} + \varepsilon_{ij.}$

In the regression model, the dependent variable ln achievement signifies the natural logarithm of the achievement for participant i in session j. The independent variables, age, and the natural logarithm of the proportion of time spent in affective states, were treated as continuous variables. Levels of intellectual disability (ID) and gender were represented as binary variables.

To test the individual significance of fixed effect coefficients, Wald z tests were conducted under the central limit theorem, following the methodology by Bolker (2009). However, it is advisable to interpret resultant p-values cautiously, given the experimental and subjective nature of the study design, as recommended by Johansson (2011).

Addressing the hypothesis that this method positively influenced engagement and learning achievement, mean scores for engagement and achievement were computed for each participant. As these data satisfied the requirements for parametric analysis, a related t-test was employed to compare scores between the two conditions.

RESULTS

The analysis of three models for the entire group (85 participants) using the Akaike Information Criterion (Table 1) revealed that the model considering both time spent engaged and frustrated was the most fitting. In Model A, a positive relationship between both engagement and frustration with achievement was observed, meaning that increases in engagement and frustration correlated with higher achievement. Additionally, a significant variation among participants in achievement related to the time spent engaged was noted. Model B showed that more time spent bored correlated with lower achievements, a trend also seen in Model C. Across all three models, having a severe disability consistently correlated with lower achievement compared to those without any intellectual disability (ID). Age and gender did not notably influence achievement in any model.

The intervention was linked to increased achievement in participants. However, subgroup analysis mirrored the main findings without showing any significant deviations. Although the intervention had a positive but not statistically significant impact on achievement, an analysis of means showed that during intervention sessions, participants spent a significantly higher proportion of time engaged and significantly less time bored compared to control sessions. This was true for the entire group. No notable differences in time spent frustrated or in achievement scores were seen between the two conditions.

Table 1: Participants characteristics (Mean ± SD)

		Total (N=85)	ID (N=27)	ASC (N=28)	ID/ASC (N=30)
Age in years		11.4±1.8	10.3±1.1	10.9±2.6	12.6±2.2
Gender	Male	58±11.4	16±3.9	18±2.3	22±4.5
	Female	27±6.9	11±1.1	10±1.17	8±0.25
Intellectual Disability Level	None	9±1.3	0	7±1.76	0
	Mild	28±2.6	18±2.1	10±2.6	2±0.23
	Moderate	32±5.7	5±4.5	8±2.4	12±5.3
	Severe	16±3.7	4±1.0	3±1.1	16±3.2

This trend continued for participants with ID and those with both ID and ASC, where intervention sessions showed significant increases in engagement and decreases in boredom compared to control sessions. However, no significant differences in frustration or achievement scores were observed for these groups, although achievement scores were higher in the intervention condition. For participants with only ASC, the average time spent engaged was greater in the intervention condition, but this difference wasn't statistically significant.

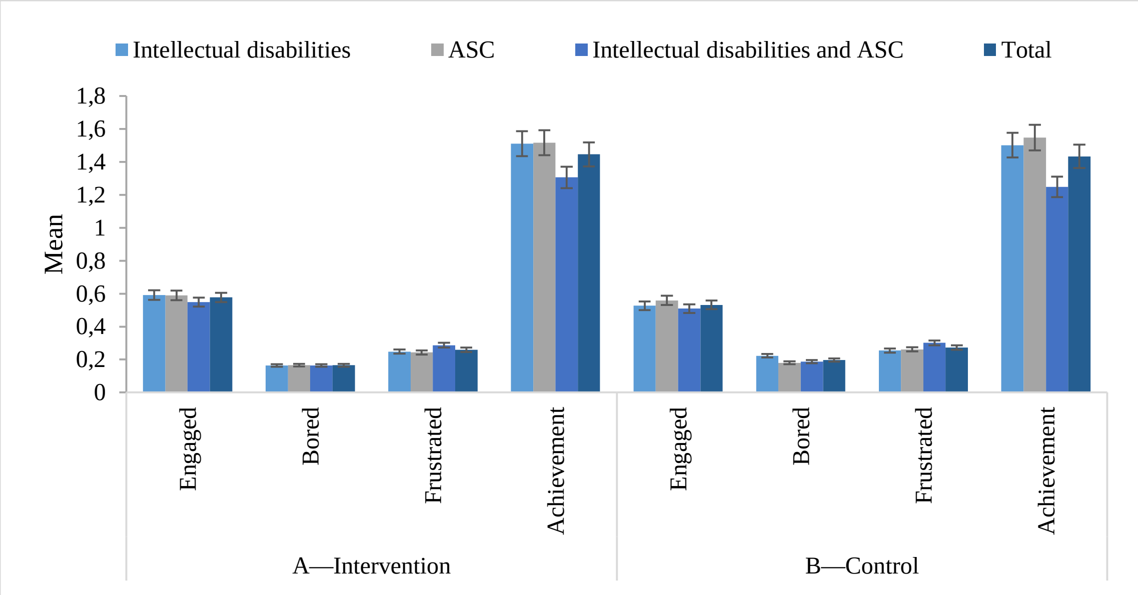

Diagram 1: Means ± SD of Group A: Intervention and Group B: Control

DISCUSSION

The study's findings, supported by multilevel modeling, confirm that sensor data effectively discern three distinct emotional states, each showing a significant link to achievement, regardless of the experimental setting. Notably, the absence of boredom has the strongest correlation with achievement, while states of frustration and engagement also show positive associations with learning outcomes. This consistency across different subgroups (ID, ID/ASC, ASC) enhances the model's credibility.

It's important to recognize that these results represent the system's interpretation of the learner's emotional state. Although the initial validation used a limited dataset and lacked teacher-rated emotional comparisons, the intervention sessions revealed that the detected emotional states impacted how learning materials were presented. Intriguingly, the model reveals that these emotional state-achievement relationships remain stable even without the system actively modifying material presentation based on these states. This indicates that the algorithm independently identifies emotional states linked to achievement, but how these align with human-observed states of engagement, frustration, and boredom is yet unclear. The observed inverse relationship between boredom and achievement echoes previous research on this emotional state's importance. The constructive role of frustration aligns with D'Mello and Graesser's (2012) theory, which posits that temporary frustration from cognitive challenges can enhance learning, potentially leading to disengagement (boredom) if prolonged.

Differentiating frustration from engagement can be challenging due to overlapping indicators in affective recognition, such as eye movements (Scheiter, 2019). Including additional physiological and conversational cues could provide a more rounded understanding. The study's data summarization approach might have concealed brief emotional states, and the intricate dynamics of these emotions during learning activities weren't fully explored. Despite the general applicability of the three identified emotional states across groups, learners with severe ID showed lower achievement levels. The hypothesis was partly supported the system increased engagement but did not significantly boost achievement, particularly among participants with limited exposure. This observation of emotional improvement without corresponding performance gains is consistent with previous findings (Aist, 2002). Extended exposure might better reveal the system's effectiveness. Limitations like a constrained range of learning materials and a potential ceiling effect might have influenced the results (Wang, 2019). Learners with autism could require customized affect detection approaches due to unique emotional responses (Sumi, 2018). Additional physiological data and conversational indicators could enhance the range of modalities employed in this study (D'Mello, 2017).

This study is a pioneering investigation into an adaptive learning system using multimodal affect recognition for individuals with ID. It successfully identified three key emotional states, with a notable finding that reduced boredom closely correlates with higher achievement (Yadegaridehkordi, 2019). Both frustration and engagement were positively related to achievement. These outcomes are in line with research suggesting that personalized activities tailored to learners' emotional states enhance engagement (Athanasiadis, 2017). However, the study did not find a significant difference in achievement when adaptations considered both affective states and achievement versus achievement alone. Future research should focus on refining machine learning techniques and diversifying learning content. Nonetheless, the study indicates that an affect recognition-based adaptive learning system has potential in aiding teachers of students with ID, enabling real-time response to emotional states and helping teachers to effectively support all students in reaching their full potential (Nakamura, 2002).

CONFLICT OF INTEREST

All authors declare no conflicts of interest related to the publication of this work.

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