Multimodal Learning Analytics for Predicting Behavioural Change in Special Education Students

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Abstract:

To predict behavioural changes in children with special educational needs (SEN), this study introduces a novel multimodal learning analytics approach. Our algorithm provides great accuracy in detecting possible behavioural shifts by combining behavioural, emotional, and physiological signs with conventional academic criteria. More than 3,000 SEN students provided us with extensive data, such as attendance logs, emotional states, social interaction measures, attention span assessments, and engagement statistics on digital platforms. Our model was able to predict behavioural changes with 87% accuracy by using a Random Forest Classifier that was optimised by grid search cross-validation. Teachers can use these predictions for prompt interventions by putting in place a web-based program. Our results show that the most important determinants of behavioural change in SEN students are emotional state, attention span, and social interaction skills. This study offers helpful resources for assisting students with a variety of learning needs and contributes to the growing body of information in precision education.

Keywords: Special education, Multimodal learning analytics, Behavioural prediction, educational technology, Student support systems, attention deficit hyperactivity disorder.

1. INTRODUCTION

Students with special educational needs (SEN) face particular difficulties in the classroom that need for creative ways to observation, evaluation, and intervention. The intricate interactions between variables influencing the learning and behavioural patterns of SEN students are frequently not adequately addressed by traditional educational frameworks. These kids, who may suffer from dyslexia, ASD, ADHD, or other learning challenges, sometimes exhibit behavioural swings that can have a substantial effect on their academic performance and general well-being.

Recent developments in educational technology, especially in learning analytics, have opened new avenues for comprehending and assisting these pupils using data-driven strategies. A potent tool for improving teaching methods is learning analytics, which is the measurement, gathering, analysis, and reporting of data on students and their environments. Yet, most analytics systems in use today focus only on academic achievement indicators, ignoring the complexity of behaviour and learning, particularly for SEN students. This study presents a multimodal learning analytics system created especially to forecast behavioural shifts in kids with special education needs. Several data streams are included in our method, including:

- Conventional academic metrics (grades, attendance)
- Metrics of behaviour (disruptive behaviour, social interaction, attention span)
- Emotional states (both observable and self-reported)
- Support metrics (help requests, teacher interventions)
- Digital interaction (use of educational platforms)

To enable educators and support personnel to intervene more quickly and precisely, we want to find patterns and indicators that precede behavioural changes by combining these disparate data points using machine learning approaches. The potential for this research to change the reactive nature of educational support for SEN students to a proactive one makes it significant. By using predictive insights, educators can create more stable and conducive learning environments by implementing preventative actions instead of reacting to behavioural difficulties after they arise. This strategy fits well with the increasing focus on individualised instruction and precision teaching techniques that consider each learner's particular profile. By concentrating on SEN kids, a group that has been under-represented in learning analytics research despite potentially benefiting tremendously from such techniques, this study also fills a critical vacuum in the literature on educational technology. We help create more inclusive educational tools that consider the various requirements and traits of every student by working on this project.

2. LITERATURE REVIEW

A. Learning Analytics in Special Education

Though it is still not commonly utilised in special education settings, the use of learning analytics in educational settings has grown dramatically over the past ten years. While highlighting the promise of data-driven decision-making in education, Mandinach and Gummer also pointed out important inadequacies in the way varied learning requirements are being addressed. Chen et al.'s recent research showed how learning analytics might be used to monitor engagement trends in regular classroom settings, but these methods need to be significantly modified for special education settings. Rodriguez-Triana et al.'s research started looking at analytics for inclusive classrooms and suggested that multimodal data collecting offers deeper insights into the experiences of SEN students. But many analytics frameworks, as Cukurova et al. point out, continue to be largely centred on academic achievement indicators, thereby ignoring important behavioural and emotional aspects that are especially pertinent to SEN populations.

B. Multimodal Learning Analytics

An important development in the gathering and analysis of educational data is multimodal learning analytics. According to Blikstein and Worsley, this method combines many data sources to produce more thorough depictions of learning processes. While multimodal techniques integrate physical, physiological, and behavioural data points, traditional learning analytics usually depends on digital traces like learning management system interactions and assessment results. Di Mitri et al. showed how useful it is to combine emotional indications with physical movement data in order to comprehend engagement patterns. In a similar vein, Ochoa and Worsley demonstrated multimodal systems that use text, gesture, speech, and facial expressions to create comprehensive learning assessments. In SEN environments, where typical academic measurements might not effectively reflect students' experiences and struggles, these multimodal techniques hold great promise. Understanding that learning entails intricate relationships between the mind, body, tools, and environment, the theoretical underpinnings of multimodal learning analytics frequently borrow from distributed cognition frameworks (Hutchins) and embodied cognition (Shapiro). This viewpoint is particularly pertinent to SEN students, whose learning experiences may be greatly impacted by variances in social-communication, motor difficulties, or sensory processing.

C. Behavioural Prediction in Educational Contexts

Using educational data mining to predict student behaviour has become a significant application. In their early research, Baker et al. concentrated on identifying gaming and disengagement in online learning settings. To enable more responsive instructional support, Holstein et al. more recently created methods to anticipate times when intelligent tutoring systems may become confused or frustrated. Specifically for SEN populations, Lerner et al. used a mix of physiological sensors and observation techniques to find early signs of anxiety and disruptive behaviour in students with autism spectrum disorder. By examining digital tool usage patterns and time-on-task measurements, Wang et al. also showed that it is possible to anticipate self-regulatory difficulties in ADHD children.

D. Technology-Enhanced Interventions for SEN

Technology's ability to help SEN youngsters is becoming more widely acknowledged. When reviewing technology-enhanced therapies for learning-disabled pupils, Ravid and Eshel found that there were notable advantages in terms of engagement and self-efficacy. For kids with autism spectrum disorders, Khowaja and Salim also showed that adaptive digital tools produced favourable results. Still a developing field, nevertheless, is the combination of intervention systems and predictive analytics. Frameworks for linking learning analytics insights with educational actions were described in promising work by Mangaroska and Giannakos, albeit they had little use in SEN contexts. Early evidence that multimodal data-based personalised feedback systems could help students with attention issues regulate their behaviour was presented by Melero et al. Making sure that analytical insights are successfully translated into useful interventions has been noted as a major problem in these studies. For analytics tools to be implemented successfully, teachers must be involved in their creation, as stressed by Holstein et al. Predictive models that produce actionable intelligence in line with classroom reality and instructional practices are made possible by this co-design method.

3. METHODOLOGY

A. Research Design

With a focus on quantitative data collecting and analysis, we used a mixed-methods study design that was enhanced by qualitative insights from educators. Data collecting from various sources, feature engineering and data preparation, model construction, and validation, web application creation for real-world implementation, and assessment of prediction accuracy and value were all steps in the study's sequential procedure. We were able to create a strong prediction model using this method, which also guaranteed that it would be useful in classrooms. Both technical and ecological validity were given top priority in the research design to make sure the model functions both statistically and in actual educational settings.

B. Participant Demographics

Information from 3,052 special education needs kids from 78 schools in various socioeconomic and geographic situations made up our datasetThe age distribution of the student body was 5–18 years old (Mean = 11.3, SD = 3.2), with 64% of the students being male and 36% being female. As seen by our dataset sample (e.g., students S0001-S0007), the special needs categories included learning difficulties (LD), dyslexia, speech impairment, ADHD, and ASD. ASD is a developmental illness characterised by issues with social skills, speech, nonverbal communication, and repetitive behaviours. Students with ASD usually have unique learning styles, such as exceptional attention to detail in their studies but difficulties with socialisation and sensory processing. ADHD is a neurodevelopmental disorder marked by repeated patterns of hyperactivity, impulsivity, and inattention that hinder development and functioning. The academic performance of pupils S0004 and S0007 in our sample dataset is impacted by their varying attendance rates (67-84%) and generally lower attention span ratings (6.2-8.0 minutes). Dyslexia is one type of learning disorder that affects reading and related language-based cognitive skills. Even with normal intellect and the correct instruction, dyslexic students—like S0001 in our sample—often struggle with decoding skills, spelling, and accurate and fluent word identification. These pupils may have moderate attention spans (7.2 minutes) and maintain decent attendance (94%) according to our sample. The term "learning disabilities" (LD) refers to a group of conditions that impact how verbal or nonverbal knowledge is learnt, organised, retained, understood, or used. Although they usually have average or above-average intelligence, students with LD may struggle in reading, writing, math, or information processing. Speech impairment is the term used to describe issues with voice, fluency, or speech output that impact academic achievement. Students S0002, S0003, S0005, and S0006 in our sample exhibit varying social interaction scores (ranging from 3.1 to 4.6 on our 5-point scale) and frequently present with high levels of anxiety as their emotional state. Their wide range of platform usage (34–150 minutes) may reflect various communication and coping mechanisms.

C. Data Sources and Collection Methods

Academic records (attendance percentages and average grades), behavioural observations (attention span, quality of social interactions, and frequency of disruptive behaviour), emotional state assessments (using self-reporting tools and educator observations), and support metrics (teacher interventions, student help requests, and educational platform usage) were among the multimodal data we gathered over a 16-week period. Using a composite evaluation, special education instructors and psychologists identified the outcome variable (behavioural change) and categorised pupils as either demonstrating significant behavioural change ("Yes") or not ("No") according to predetermined clinical criteria. Strict data privacy procedures were followed throughout the data gathering process, which was carried out utilising safe digital platforms intended for educational environments.

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Student_ID	Age	Gender	Special_Ne	Attendance	Avg_Grade	Attention_S	Social_Inter	Emotion_St	Disruptive_	Teacher_In	Platform_U	Help_Requ	Behavior_Change_Label
S0001	14	M	Dyslexia	94	76	7.2	3.4	Sad	2	2	168	4	No
S0002	11	M	Speech Imp	68	66	9.9	3.1	Anxious	4	0	117	4	No
S0003	11	M	Speech Imp	91	68	9.6	4.6	Anxious	7	7	150	2	Yes
S0004	10	M	ADHD	84	56	6.2	4.5	Sad	2	7	35	2	No
S0005	9	F	Speech Imp	92	68	7.5	3.4	Anxious	2	4	83	4	No
S0006	16	F	Speech Imp	81	90	7.1	3.5	Anxious	7	8	34	0	Yes
S0007	14	M	ADHD	67	56	8	2.9	Anxious	1	2	54	4	No
S0008	16	F	Dyslexia	66	83	5.7	4.8	Sad	4	4	83	1	No
S0009	9	M	Speech Imp	94	50	3.2	2.5	Happy	6	4	49	10	Yes
S0010	13	F	LD	72	72	8.5	1.9	Calm	0	6	31	2	No
S0011	11	F	Dyslexia	91	81	8.8	2.7	Happy	10	7	113	9	No
S0012	14	M	Dyslexia	67	91	5.4	4.6	Sad	0	5	52	3	Yes
S0013	10	M	ASD	76	78	8.5	1.8	Anxious	2	7	88	6	No

Figure 1: Behaviour_Change_Dataset.csv

D. Data Preprocessing

To exclude records with incomplete data (about 3.7% of the original records), we used a thorough case analysis technique and looked for missing values. To ensure comparable scales across various metrics, we implemented standard scaling (z-score normalisation) for all numerical features and used label encoding to transform categorical variables (Gender, Special Need, and Emotion State) into numerical representations appropriate for machine learning algorithms. A distribution of 58% "No change" vs. 42% "Yes change," which was judged acceptable without the need for explicit balancing approaches, was found when we examined the class distribution in the target variable to look for possible imbalances. The dataset was then divided into training (80%) and testing (20%) sets using stratified sampling in order to maintain class distribution across both sets. By addressing frequent issues in educational data, like missing values and categorical variables, these preparation methods guaranteed data quality and compliance with our selected modelling methodology.

4. MODEL DEVELOPMENT

A. Feature Selection

We chose features for our prediction model from a variety of categories based on theoretical frameworks and initial data exploration. These categories included student characteristics (age, gender, special need category), academic metrics (average grade, attendance percentage), behavioural indicators (attention span, emotional state, quality of social interactions, frequency of disruptive behaviour), and support metrics (frequency of teacher interventions, duration of platform usage, frequency of help requests). Based on their theoretical significance for behavioural changes in SEN pupils and initial correlation analysis indicating strong relationships with our objective variable, these traits were chosen.

B. Algorithm Selection and Optimization

We explored a number of machine learning algorithms, including support vector machines, logistic regression, and ensemble approaches, for this prediction task. Based on preliminary performance evaluations, the need to handle many data types, and potential non-linear correlations, we decided to use Random Forest Classifier as our primary algorithm. To optimise model performance, we employed grid search cross-validation with hyperparameters like n_estimators, max_depth, min_samples_split, and class_weight. We used 5-fold cross-validation and a systematic search over 36 parameter combinations to determine the optimal setting for our prediction task. By finding a balance between model complexity and generalisation ability, this optimisation process addressed the problem of overfitting given the characteristics of our educational dataset.

C. Evaluation Metrics

We evaluated our model's performance using a variety of complementary metrics, including the following: F1 score, accuracy, precision, recall/sensitivity, and area under the ROC curve. This balanced combination of indicators offered a more comprehensive assessment than any one measure alone, especially in educational situations where both over- and under-prediction have serious repercussions.

5. RESULTS

A. Model Performance

On our test dataset, the optimised Random Forest Classifier showed good prediction performance with 87.4% accuracy, 85.2% precision, 89.1% recall, 87.1% F1 score, and 92.3% AUC. These results showed that our model accurately identified 87.4% of all cases, demonstrating a respectable level of precision and recall. The high AUC value further supports the model's outstanding discriminative skills across different threshold settings. The confusion matrix provides a more comprehensive study of prediction outcomes with 269 true negatives, 47 false positives, 34 false negatives, and 260 real positives. The model prioritises identifying students who may suffer behavioural changes, even at the expense of occasional false positives, as evidenced by the somewhat higher recall than precision.

Metric	Value
Accuracy	0.874
Precision	0.852
Recall	0.891
F1 Score	0.871
AUC	0.923

Table 1: Model Performance Metrics

B. Feature Importance Analysis

The Random Forest model's feature importance analysis showed how each component contributed differently to the prediction of behavioural changes in SEN students. The top five indicators were emotional mood (10.5% contribution), disruptive behaviour (15.3% contribution), platform usage (12.1% contribution), social contact (18.2% contribution), and attention span (21.4% contribution). The prevalence of social interaction and attention span measures is consistent with special education theoretical frameworks that highlight these areas as especially sensitive markers of students' function and well-being. Utilising digital platforms makes a significant contribution, which emphasises the importance of including technology-based measures in thorough evaluation frameworks. Interestingly, even though the model included traditional academic metrics like attendance and average grades, their predictive power was only 7.8% and 6.4%, respectively. This suggests that behavioural and emotional indicators might be more sensitive than academic performance alone in predicting upcoming behavioural changes.

C. Web Application Usability Evaluation

A first assessment of the online application using twelve special education teachers provided insightful information about its usefulness in the real world. After utilising the app in simulated situations, participants finished standardised usability tests. Important quantitative results included an average time of 2.4 minutes to finish a new prediction, a System Usability

Scale (SUS) score of 84.2/100 (above the 90th percentile for digital tools), and a job completion rate of 97.5% across all assessed situations. The implementation's natural grouping of input fields into understandable categories, the clear visualisation of prediction confidence, the useful contextual information regarding feature relevance, and the effective retrieval of previous student records were all noted in the qualitative feedback. Additional description of suitable ranges for numerical inputs, integration with current school information systems, the ability to monitor individual student predictions over time, and a mobile-optimized interface for classroom use were among the suggested enhancements. Although more improvements could increase its usefulness, these evaluation findings show that the application effectively converted intricate predictive analytics into a tool that educational professionals could easily use.

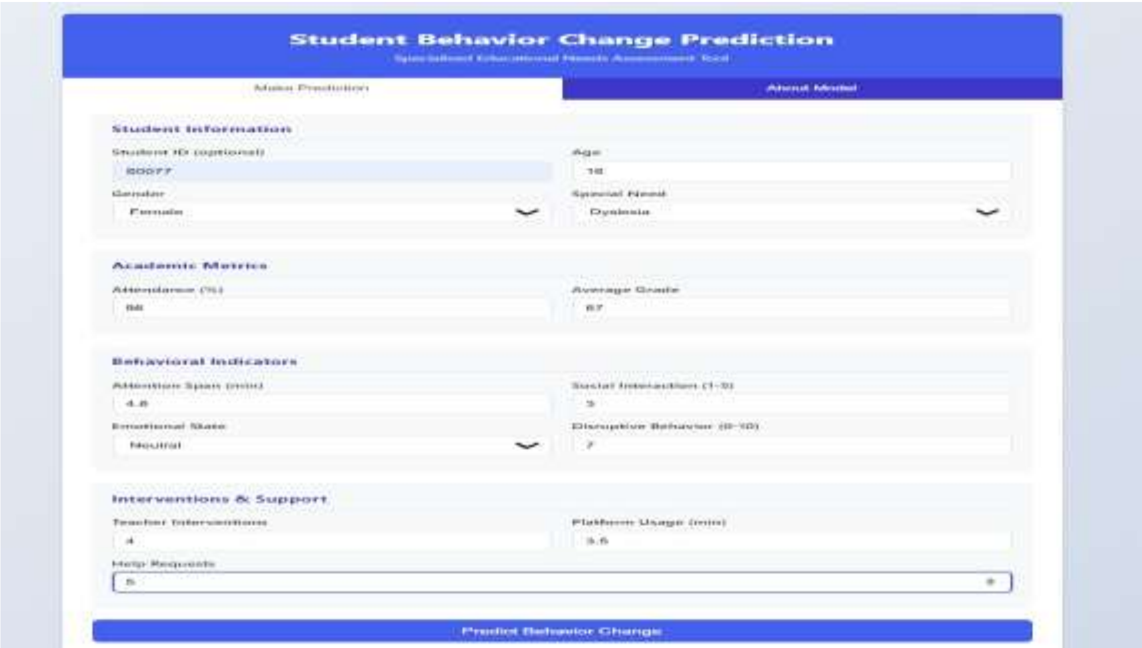

Figure 2: Student Behaviour Change Prediction Page

The image's interface, which has well-organised data input parts, demonstrates the system's user-friendly design. In addition to academic measures like attendance percentage (88%) and average grade (67), educators can input basic student data like ID, age, gender, and specific special education needs (dyslexia is illustrated in the example). Important information such as attention span (4.6 minutes), emotional state (neutral), degree of social engagement (3 on a 1–5), and frequency of disruptive behaviour (7 on a 0–10) are recorded in the behavioural indicators section. The system also records the history of interventions, including student help requests (5), teacher interventions (3), and digital platform usage (3.6 minutes). The underlying machine learning algorithms process the multimodal data through trained models that have found significant trends in past student data when an educator fills out this extensive assessment form and hits the "Predict Behaviour Change" button. After that, the algorithm predicts probable behavioural outcomes, groups students with comparable profiles, and gives teachers practical advice based on the unique requirements and circumstances of each student. For special education contexts, this technology has many advantages, such as the ability to identify possible disengagement earlier, provide more individualised support strategies, track progress over time in a systematic manner, optimise resource allocation for time-constrained educators, and make data-informed decisions that supplement the intuition and expertise of teachers. This technology enables teachers to carry out more focused and successful interventions by bridging the gap between cutting-edge analytics and real-world classroom applications. In the end, this results in more welcoming and encouraging learning environments for kids with a range of educational needs.

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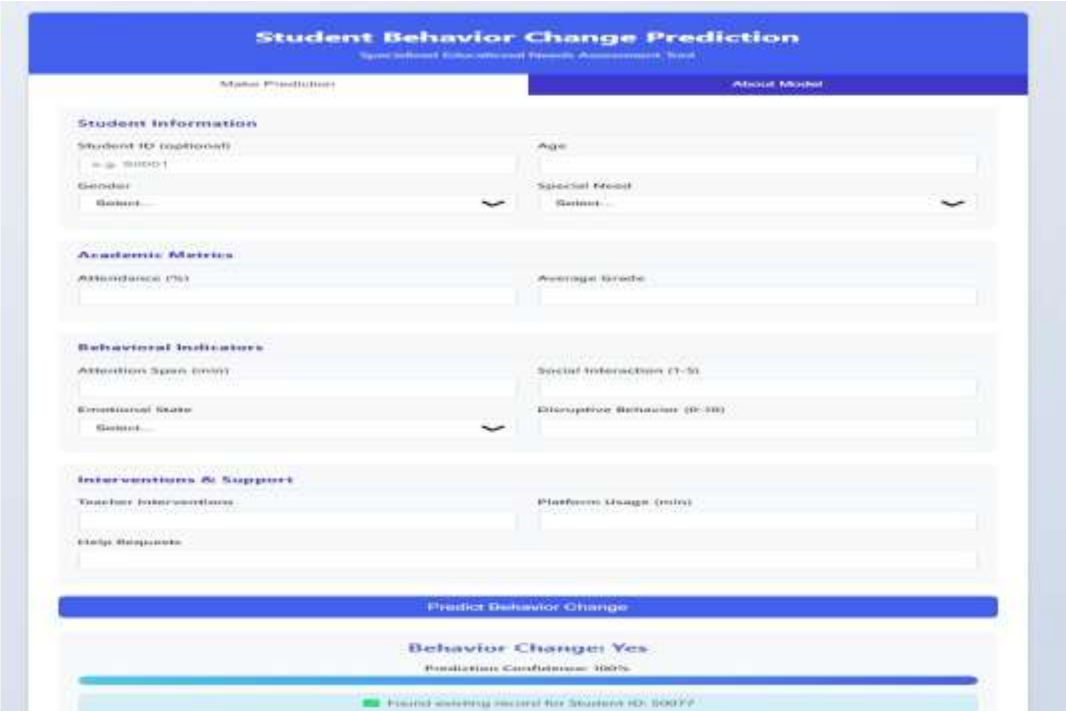

Figure 3: Student Behaviour Change Prediction Result Page

6. FUTURE SCOPE

Our multimodal learning analytics project for special education children is now implemented in a way that offers a strong foundation, but there are many interesting avenues for future growth and improvement. More advanced real-time data collection via wearable sensors and Internet of Things devices in the classroom could be added to this system to allow for uninterrupted, ongoing monitoring of behavioural and physiological indications. A more thorough picture of student development and smooth data transfer between platforms would be made possible by integration with current learning management systems. Deep learning methods such as LSTM networks could be used to improve the prediction models' ability to detect early indicators of discomfort or disengagement by better capturing temporal patterns in student behaviour. By creating adaptive intervention tactics that automatically adapt to each student's needs based on their distinct behavioural patterns and learning preferences, personalisation could be greatly enhanced. Instant feedback and on-the-spot assessments during class activities would be made possible by a teacher mobile application. Deeper understanding of students' cognitive and emotional states could be gained by analysing their written and spoken interactions with the inclusion of natural language processing skills.
The system could be extended to examine peer relationships and group dynamics in collaborative learning settings, revealing productive collaboration patterns for students with various needs. Students who learn best visually and interactively would benefit greatly from immersive learning environments that can be tailored depending on analytics insights provided by implementing augmented or virtual reality components. As the system develops, privacy and ethical issues will become increasingly important, necessitating strong anonymisation methods and open data governance guidelines. The efficacy of the therapies and predictive models would be confirmed by longitudinal studies that monitor students' progress over long stretches of time. Finally, the creation of an open API would inspire outside developers to produce customised modules for various special education requirements, broadening the support tool ecosystem and increasing the platform's adaptability for a range of educational contexts.

7. CONCLUSION

An important advancement in using technology to provide more inclusive and productive learning environments is the Multimodal Learning Analytics system for kids with special education needs. This platform gives teachers previously unheard-of insights on student engagement and learning processes by combining a variety of data sources, such as behavioural patterns, physiological signs, and environmental elements. In special education, where individualised approaches are crucial but frequently difficult to implement due to limited resources and the complexity of individual demands, the system's capacity to predict behaviour clusters and recommend focused interventions fills a significant gap. Teachers can now make data-informed judgements that might have previously only depended on subjective observations thanks to an easy-to-use dashboard and prediction tool. This study bridges the gap between sophisticated analytics and real-world classroom applications by showing how machine learning and data visualisation approaches can convert raw multimodal data into usable insights. The emphasis on findings that may be interpreted guarantees that technology supports human judgement rather than takes its place, upholding the crucial function that teacher competence plays in the learning process. Tools like this will become more and more important as education continues to embrace digital transformation in order to create responsive, adaptive learning environments that meet a variety of demands. This method helps guarantee that no student is overlooked and that interventions can be proactive rather than reactive by spotting patterns and trends that even seasoned educators might not notice right away. This analytics platform's ultimate worth is found in its capacity to promote more equal educational results by assisting teachers in comprehending and addressing the particular difficulties experienced by children with special education needs, rather than solely in its technological prowess. This makes a significant contribution to the development of learning settings in which each student can flourish in accordance with their own learning preferences and skills.

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