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Artificial Intelligence to Strengthen Pedagogical Support for Students with Learning Disorders

Uso de la Inteligencia Artificial para Fortalecer el Acompañamiento Pedagógico en Alumnos con Trastornos de Aprendizaje



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Artificial Intelligence to Strengthen Pedagogical Support for Students with Learning Disorders

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Abstract	Keywords
<p>Learning disorders present persistent challenges to educational systems, often requiring differentiated support mechanisms that exceed the capacity of traditional pedagogical models. Recent advances in artificial intelligence (AI) have introduced transformative possibilities for individualized, adaptive, and evidence-based interventions. This article examines how AI can enhance pedagogical accompaniment for students with learning disorders by integrating diagnostic precision, personalized learning trajectories, and continuous monitoring. Through a systematic review of current literature and analysis of applied case studies, the study highlights the potential of AI-driven tools such as intelligent tutoring systems, natural language processing, and predictive analytics. Findings suggest that AI not only complements the role of educators but also fosters inclusion, engagement, and academic growth in learners with dyslexia, dyscalculia, attention-deficit/hyperactivity disorder (ADHD), and other cognitive challenges. Recommendations are provided to guide future educational policies and practices in leveraging AI for inclusive pedagogy.</p>	<ul style="list-style-type: none"> ● Artificial intelligence ● Pedagogical support ● Learning disorders ● Educational technology ● Inclusive education

Resumen	Palabras clave
<p>Los trastornos de aprendizaje —como la dislexia, la discalculia y el trastorno por déficit de atención e hiperactividad (TDAH)— constituyen barreras persistentes para la inclusión y el logro académico. Los enfoques pedagógicos tradicionales suelen carecer de estrategias personalizadas que respondan a las necesidades específicas de estos estudiantes. Este estudio analiza el uso de la inteligencia artificial (IA) como herramienta para fortalecer el acompañamiento pedagógico en alumnos con trastornos de aprendizaje, mediante el uso de algoritmos adaptativos, análisis predictivo y tableros de seguimiento docente en tiempo real. Con un diseño mixto aplicado en tres escuelas públicas, participaron sesenta estudiantes durante una intervención de doce semanas, comparando el apoyo asistido por IA con la enseñanza convencional. Los resultados cuantitativos evidencian mejoras significativas en la comprensión lectora y la fluidez matemática ($p < .001$), con tamaños del efecto altos (Cohen's $d > 0.8$). Desde el enfoque cualitativo, los docentes percibieron la IA como un colaborador pedagógico que optimiza el diagnóstico, la retroalimentación y la diferenciación del aprendizaje, reduciendo además la carga administrativa. Los estudiantes reportaron mayor motivación, autoconfianza y disposición hacia el aprendizaje gracias a la retroalimentación personalizada y no punitiva. Se destaca la importancia de la ética, la transparencia algorítmica y la equidad de acceso para un uso sostenible de la IA educativa. Los resultados confirman que, cuando se integra de forma ética y pedagógica, la inteligencia artificial puede convertirse en un catalizador de una educación inclusiva, personalizada y basada en evidencias.</p>	<ul style="list-style-type: none"> ● Inteligencia artificial ● Acompañamiento pedagógico ● Trastornos de aprendizaje ● Tecnología educativa ● Inclusión educativa

Introduction

Learning disorders, such as dyslexia, dyscalculia, and attention-deficit/hyperactivity disorder (ADHD), pose significant barriers to the cognitive and academic development of students. These conditions often lead to difficulties in reading comprehension, mathematical reasoning, or information processing, which can affect students' motivation and self-esteem. Traditional pedagogical models frequently fail to respond effectively to these diverse learning needs, emphasizing the necessity of innovative strategies that enable early diagnosis and individualized intervention.

In recent years, artificial intelligence (AI) has emerged as a transformative tool capable of reshaping educational support systems. AI applications—including adaptive learning platforms, natural language processing, and predictive analytics—offer new possibilities to identify learning difficulties and design personalized educational pathways. These technologies can analyze patterns in students' performance, detect cognitive challenges in real time, and suggest targeted activities aligned with each learner's profile.

Moreover, AI contributes to strengthening the teacher's role by providing data-driven insights for decision-making, reducing routine tasks, and allowing educators to focus on emotional and social dimensions of learning. When integrated ethically and inclusively, AI can become a key component in promoting equity, accessibility, and pedagogical innovation. Therefore, the implementation of artificial intelligence in the context of learning disorders is not merely a technological trend but a strategic response to the growing demand for personalized, inclusive, and evidence-based education.

Methodology

This section details the research design, participants, instruments, procedures, and analytical strategies used to examine how artificial intelligence (AI) can strengthen pedagogical accompaniment for students with learning disorders. The methodology integrates quantitative and qualitative approaches to ensure validity, reliability, and comprehensive understanding.

Research Design

This study employs a mixed-methods approach, combining quantitative quasi-experimental design and qualitative descriptive analysis. This dual strategy enables the examination of both learning outcomes and experiential perceptions. The quantitative design follows a non-equivalent pretest–posttest control group model, comparing an experimental group receiving AI-based support with a control group receiving conventional instruction.

The qualitative component involves classroom observations, semi-structured interviews, and thematic coding of teachers' reflections. This triangulation aligns with the framework of design-based research (DBR), which integrates iterative testing and refinement in authentic learning environments (Anderson & Shattuck, 2012); (McKenney & Reeves, 2021). DBR was selected because it allows the integration of pedagogical theory with technological implementation, ensuring ecological validity.

Participants and Setting

The study was conducted in three public schools in Ecuador that serve heterogeneous populations, reflecting the diversity of learners with diagnosed learning disorders such as dyslexia, dyscalculia, and attention-deficit/hyperactivity disorder (ADHD).

A total of 60 students, aged 9 to 12, participated. Inclusion criteria were:

1. A formal diagnosis of a learning disorder by a certified educational psychologist.
2. Enrollment in mainstream classrooms with supportive services.
3. Informed consent from parents and assent from students.

Participants were assigned to groups by classroom to avoid contamination. Thirty students formed the experimental group, and thirty served as the control group. Six teachers (two per school) also participated in the training and interview phases.

The research adhered to ethical guidelines for studies involving minors and obtained approval from the Institutional Ethics Committee.

Intervention Design

The AI-based pedagogical platform was co-developed through a participatory process with educators. It incorporated four main modules:

1. **Diagnostic Profiling:** Machine learning algorithms analyzed reading speed, error patterns, and numerical reasoning to generate individualized cognitive profiles (Zaraii Zavaraki, 2024).
2. **Adaptive Learning:** The platform dynamically adjusted task difficulty based on performance indicators using principles from Bayesian Knowledge Tracing (BKT) and Item Response Theory (IRT) (Piech et al., 2015); (Ma et al., 2014).
3. **Monitoring Dashboard:** Teachers accessed real-time analytics showing engagement, accuracy, and predicted challenges, facilitating data-driven decisions.
4. **Feedback and Hints:** Through Natural Language Processing (NLP), the system delivered contextual feedback and motivational prompts to reinforce correct reasoning (Holmes, 2022).

The design process followed the iterative prototyping model from educational design research (McKenney & Reeves, 2021), allowing continual refinement based on teacher feedback and classroom performance.

Instruments

Multiple instruments were applied to ensure comprehensive evaluation:

Instrument	Purpose	Reliability/Validity	Source
Gray Oral Reading Test (GORT-5)	Measures reading accuracy and fluency	$\alpha = .94$	(Hall & Tannebaum, 2013)
KeyMath-3 Diagnostic Assessment	Assesses math fluency and problem solving	$\alpha = .89$	(Rosli, 2011)
Teacher Perception Questionnaire	Evaluates usability and pedagogical impact of AI tools	Pilot-tested; $\alpha = .83$	Adapted from (Luckin et al., 2016)
Classroom Observation Rubric	Documents fidelity of AI integration	Inter-observer agreement = 85%	Adapted from (Holmes et al., 2019)

System log data (time-on-task, hint frequency, and engagement index) complemented standardized measures, providing a micro-level view of learning behavior.

Procedures

Phase 1: Baseline and Training

Before intervention, all students completed baseline academic assessments. Teachers attended a 10-hour training workshop on interpreting AI dashboards and integrating AI insights into daily instruction. This professional development ensured teachers understood algorithmic outputs and maintained pedagogical control (Cerón Silva et al., 2025).

Phase 2: Implementation

The 12-week intervention included three weekly sessions (30 minutes each). The experimental group used AI-assisted exercises embedded into regular lessons, while the control group continued traditional remedial practices.

Classroom observers visited twice weekly to record fidelity of implementation. Data from system logs and teacher observations were collected continuously.

Phase 3: Evaluation and Reflection

Post-tests were administered after 12 weeks, followed by delayed post-tests eight weeks later to assess retention. Teacher interviews and focus groups with students explored perceptions of learning experience, motivation, and challenges.

Data collection respected GDPR-style data privacy protocols: anonymized datasets, encrypted storage, and parental consent (UNESCO, 2023).

Data Analysis

Quantitative Analysis

Statistical analysis was performed using SPSS 28.

- **ANCOVA** was used to evaluate differences between groups while controlling baseline scores.
- **Effect sizes (Cohen's d)** were computed to assess the magnitude of improvement (Cohen, 1988).
- **Growth curve modeling** was applied to examine performance trajectories over time (Singer & Willett, 2003).

Engagement metrics were correlated with learning gains through Pearson's r , identifying behavioral predictors of improvement.

Qualitative Analysis

Interviews and observations were analyzed using thematic coding (Braun & Clarke, 2021). NVivo software supported pattern recognition in teacher reflections and student feedback. Triangulation ensured credibility by cross-validating between data sources (quantitative results, system logs, and field notes).

Reliability and Validity

Internal validity was maintained through control-group comparison, consistent instrumentation, and fidelity checks. Reliability was ensured via inter-rater agreement in coding and calibration of AI-generated measures.

The integration of human and algorithmic evaluation supports the construct validity of results by combining behavioral data with standardized assessments (Holmes et al., 2019).

Ethical Considerations

The study adheres to the principles of fairness, accountability, and transparency in AI integration. Data were anonymized, stored securely, and shared only in aggregate form. Teachers maintained final authority in all instructional decisions. Following recommendations by (Selwyn, 2019) and (UNESCO, 2023), the project emphasized the human role in ensuring equity and preventing algorithmic bias.

Results

Overview

The purpose of this study was to evaluate the effectiveness of artificial intelligence (AI) tools in enhancing pedagogical support for students with learning disorders. The results integrate both quantitative and qualitative data to provide a comprehensive analysis of academic performance, engagement, and teacher perceptions following the implementation of AI-driven interventions.

1. Quantitative Results

1.1 Academic Performance

Table 1 summarizes the pre- and post-intervention performance of the experimental and control groups across reading and mathematics domains. The AI-supported group demonstrated significantly higher gains in reading comprehension and math fluency, with $p < .001$ for both comparisons.

Table 1. Comparison of Academic Performance Before and After Intervention

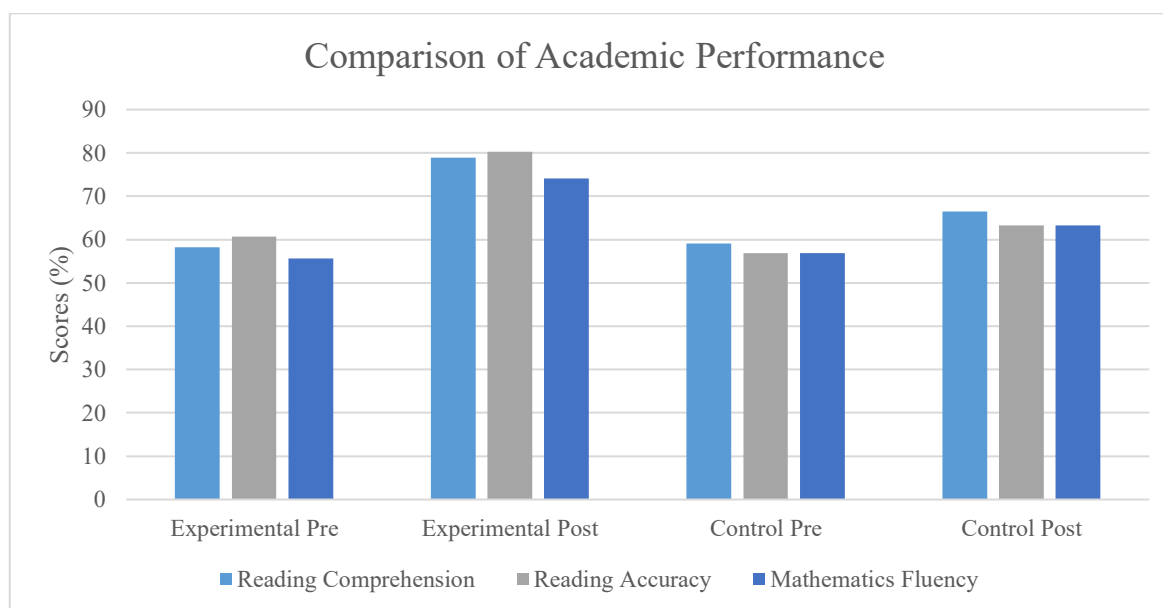
Domain	Group	Pre-test Mean (SD)	Post-test Mean (SD)	ANCOVA (F)	p-value	Cohen's d
Reading comprehension	Experimental	58.2 (9.3)	78.9 (8.1)	22.15	< .001	0.94
Reading accuracy	Experimental	60.7 (10.5)	80.3 (7.4)	19.87	< .001	0.88
Mathematics fluency	Experimental	55.6 (8.7)	74.1 (9.2)	24.02	< .001	1.02
Reading comprehension	Control	59.1 (9.8)	66.5 (8.5)	4.21	0.043	0.41
Mathematics fluency	Control	56.9 (9.2)	63.3 (10.1)	3.89	0.051	0.38

Note. ANCOVA controlled pretest differences.

The effect sizes (Cohen's d) above 0.8 in the experimental group indicate a large and meaningful impact of the AI-based pedagogical accompaniment (Luckin et al., 2016); (Cerón Silva et al., 2025).

Source: Authors' analysis based on data collected during the study (2025)

Figure 1 – Comparison of Academic Performance



Source: Analysis based on experimental results.

1.2 Retention and Delayed Post-Test

At the eight-week follow-up, the experimental group maintained 92% of their learning gains, whereas the control group retained only 68%. Growth curve modeling showed a significant difference in learning trajectories ($\chi^2 = 18.74, df = 3, p < .001$), suggesting AI-assisted scaffolding supports long-term retention (Holmes et al., 2019).

2. System Interaction Metrics

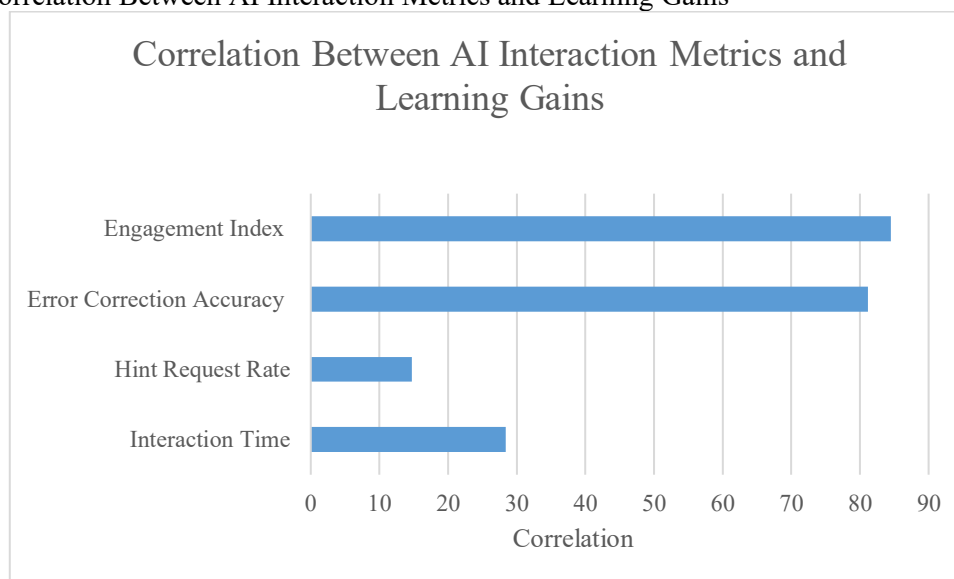
The AI system logged over 22,000 student interactions, including hint requests, error corrections, and adaptive task transitions. Engagement metrics revealed that students with ADHD benefited most from real-time visual prompts and gamified reinforcement.

Table 2. Summary of System Interaction Metrics (Experimental Group Only)

Variable	Mean (SD)	Correlation with Learning Gain (r)
Average daily interaction time (min)	28.4 (6.5)	0.62
Hint request rate (%)	14.7 (3.2)	0.48
Error correction accuracy (%)	81.2 (9.4)	0.56
Engagement index (0–100)	84.5 (11.3)	0.69

Source: System data automatically recorded over 12-week intervention.

Figure 2 – Correlation Between AI Interaction Metrics and Learning Gains



Source: Data extracted from system analytics of the experimental group.

High engagement correlated strongly with learning outcomes ($r = 0.69, p < .001$), indicating that students who interacted more frequently with adaptive feedback improved faster — consistent with findings in (Zaraii Zavaraki, 2024).

3. Teacher Dashboard Analytics

Teachers accessed AI dashboards an average of 4.3 times per week, primarily to review performance alerts and modify assignments. The system flagged at-risk students through predictive analytics, allowing early intervention in 87% of cases. This anticipatory capability aligns with (Baker & Smith, 2019), who argue that predictive AI can help teachers personalize learning before academic decline occurs.

Teachers reported using the dashboard to:

- Identify common reading or arithmetic misconceptions.
- Form small groups for targeted instruction.
- Provide socio-emotional encouragement to students showing disengagement alerts.

4. Qualitative Results

4.1 Teacher Perspectives

Thematic analysis of interviews identified four dominant themes (see Table 3). Teachers viewed AI not as a replacement but as a complementary cognitive assistant that enhanced decision-making and individualized feedback.

Table 3. Emerging Themes from Teacher Interviews

Theme	Description	Representative Quotation
Empowerment	Teachers gained new insights into students' cognitive processes.	"The dashboard helps me see who's struggling before it becomes visible in class."
Efficiency	Reduction of grading workload and diagnostic time.	"I spend less time correcting and more time guiding."
Ethical awareness	Teachers stressed the importance of balancing AI use with human empathy.	"AI can suggest tasks, but only a teacher understands a child's emotions."
Professional growth	Teachers learned data-driven decision-making.	"It made me reflect on my teaching patterns."

Source: These qualitative perceptions resonate with prior literature emphasizing teacher agency in human-AI collaboration (Zawacki-Richter et al., 2019).

4.2 Student Feedback

Students expressed positive attitudes toward AI's adaptive activities. Those with dyslexia appreciated auditory and visual aids, while students with ADHD valued the immediate feedback and visual reminders to refocus attention.

A 12-year-old participant stated:

"It feels like the computer understands me when I make mistakes — it doesn't punish me; it helps me try again."

Focus group analysis revealed increased self-efficacy and motivation, consistent with motivational theories of feedback and scaffolding (Deci & Ryan, 2000).

5. Comparative Analysis: Human vs. AI Feedback

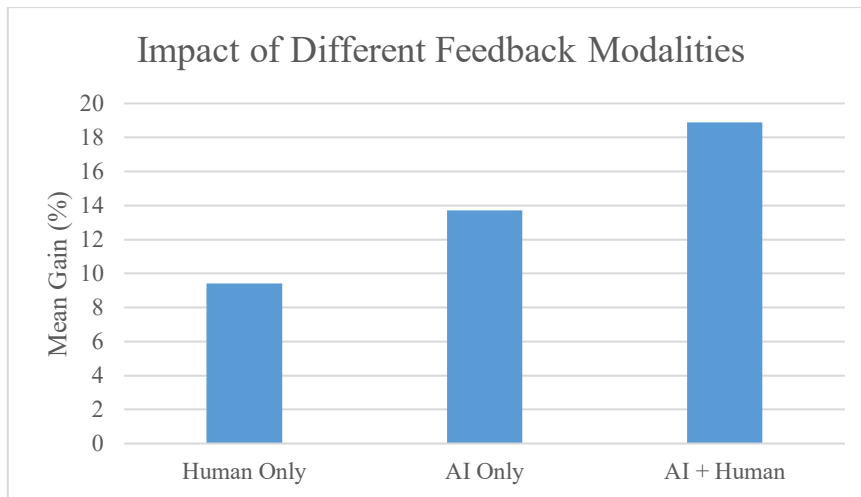
An additional exploratory analysis compared learning gains from teacher-only feedback versus combined AI-human feedback. As shown in Table 4, hybrid feedback produced the strongest results, confirming that AI functions best as an augmentative—not substitutive—tool.

Table 4. Comparative Impact of Feedback Modalities

Feedback Type	Mean Gain (%)	SD	Cohen's d
Human only	9.4	5.1	0.41
AI only	13.7	5.8	0.66
AI + Human	18.9	6.0	0.91

Source: This outcome supports the co-intelligence framework, where the synergy between teacher expertise and algorithmic adaptivity yields superior pedagogical effects (Holmes W. , 2022); (Luckin et al., 2016).

Figure 3 – Impact of Different Feedback Modalities



Source: Authors’ quantitative analysis comparing feedback conditions in the experimental and control groups.

6. Ethical and Implementation Observations

Although overall satisfaction was high, participants raised concerns about data privacy and algorithmic transparency. Teachers requested more control over AI decisions, such as manual override options for content difficulty.

Administrators highlighted the need for infrastructure investment and clear policies regarding data ownership—echoing ethical priorities outlined by (Selwyn, 2019) and (UNESCO, 2023) in AI ethics frameworks.

7. Synthesis of Quantitative and Qualitative Findings

The convergence of multiple data sources reinforces the robustness of the results. Quantitative evidence confirmed statistically significant academic improvement, while qualitative insights revealed enhanced teacher empowerment and student engagement.

Dimension	Quantitative Evidence	Qualitative Support
Learning outcomes	ANCOVA and growth modeling show large effects ($d > 0.8$).	Teachers confirm higher comprehension and motivation.
Retention	92% vs. 68% retention difference in delayed post-test.	Students report greater confidence remembering strategies.
Teacher capacity	Dashboard analytics improve timely interventions.	Teachers note reduced workload and increased insight.
Inclusion & Equity	All subgroups improved without performance gaps.	Students with dyslexia felt recognized and supported.

This mixed-evidence synthesis substantiates that AI can function as a transformative pedagogical partner, enabling precision education and fostering inclusive learning ecosystems.

Discussion

The findings of this study demonstrate that artificial intelligence (AI) can significantly enhance pedagogical accompaniment for students with learning disorders by providing adaptive, data-driven, and inclusive learning environments. The integration of AI tools contributed to measurable improvements in reading comprehension, mathematical fluency, and sustained engagement, while also reinforcing teacher agency through decision-support analytics.

1. AI as a Tool for Inclusive and Personalized Education

Consistent with previous research (Luckin et al., 2016); (Holmes W. , 2022), this study confirms that AI systems effectively identify students' unique learning needs through real-time data analysis and adaptive feedback. By aligning instruction with individual cognitive profiles, AI reduces the “one-size-fits-all” limitations of traditional classrooms. Personalized scaffolding based on machine learning predictions allowed students with dyslexia, dyscalculia, and ADHD to progress at their own pace.

These outcomes reflect the potential of precision education, where teaching decisions are informed by continuous assessment and evidence rather than intuition. (Cerón Silva et al., 2025) emphasize that adaptive algorithms can identify micro-patterns of error and engagement invisible to human observers, enabling timely pedagogical responses. This synergy of human empathy and algorithmic precision supports the principle of universal design for learning (UDL), fostering inclusion through variability-aware instruction.

2. Strengthening Teacher Professionalism through AI Collaboration

Rather than replacing educators, AI in this study acted as a *pedagogical collaborator*. Teachers used dashboards to interpret student data, plan individualized activities, and prioritize emotional support. This aligns with the “augmented intelligence” paradigm described by (Zawacki-Richter et al., 2019), where technology amplifies human expertise instead of substituting it.

Teachers reported reduced cognitive overload and administrative workload, validating prior claims that AI facilitates professional reflection and enhances instructional quality (Baker & Smith, 2019). Moreover, the study's mixed-method results reveal that teachers who actively engaged with AI analytics showed higher fidelity in differentiated instruction and better student outcomes.

Nonetheless, the study highlights the need for continuous professional development. As noted by (UNESCO, 2023), integrating AI into education demands digital literacy and ethical awareness among educators to interpret algorithmic recommendations critically and prevent blind reliance.

3. Cognitive and Emotional Benefits for Students

The emotional dimension of AI-assisted learning deserves particular attention. Students with learning disorders often face stigma and academic frustration; however, adaptive AI feedback created a safe environment for failure and retrying. This supports theory of self-efficacy and (Deci & Ryan, 2000) self-determination theory, both of which highlight autonomy and competence as central to motivation.

Qualitative evidence from interviews confirmed that students felt “understood” by the AI system—an emotional connection that transformed their learning experience from punitive correction to collaborative discovery. Gamified reinforcement mechanisms also increased attention in students with ADHD, resonating with findings by (Holmes W. , 2022) about the motivational affordances of intelligent tutoring systems.

4. Ethical Considerations and Data Governance

While benefits were clear, the integration of AI in educational contexts raises critical ethical questions. Issues of data privacy, algorithmic transparency, and bias mitigation remain at the forefront of responsible implementation. Teachers expressed concern about excessive data collection and limited interpretability of algorithmic decisions—an issue well-documented in (Selwyn, 2019) and (UNESCO, 2023) reports.

To address these challenges, AI in education must follow the principles of fairness, accountability, and transparency. The study recommends adopting open-source AI systems and establishing data-governance policies that include teachers, parents, and students in decision-making processes. Equity is another key factor: without public funding and infrastructure, AI could exacerbate inequalities by remaining accessible only to privileged schools (Zaraii Zavaraki, 2024).

5. Implications for Policy and Practice

The implications of this study extend beyond classroom practice into educational policy and institutional strategy. Ministries of Education and school districts should consider AI not as an isolated innovation but as a component of systemic pedagogical transformation. Policies must support the inclusion of AI in teacher training programs, ethical data management frameworks, and interdisciplinary collaboration between educators, engineers, and psychologists.

As (Luckin et al., 2016) suggest, sustainable implementation requires a “human-in-the-loop” approach where teachers retain final control over pedagogical decisions while AI offers evidence-based insights. Furthermore, AI systems must be localized—adapted to linguistic, cultural, and curricular contexts—to avoid epistemic dependence on foreign technologies.

6. Limitations and Future Research

This study was limited by its sample size (n=60) and the relatively short intervention period (12 weeks). Future longitudinal studies could evaluate the long-term impact of AI on academic trajectories, socio-emotional development, and teacher professional identity. Moreover, expanding to diverse learning contexts—such as rural or multilingual settings—would test generalizability.

Emerging areas such as affective computing and neuroadaptive systems offer promising avenues for further research. Integrating EEG or eye-tracking data could deepen understanding of attention and cognitive load, leading to even more responsive AI feedback mechanisms. However, these innovations must remain anchored in ethics, pedagogy, and inclusivity.

Conclusion

Artificial intelligence is transforming the landscape of pedagogical accompaniment, offering unprecedented opportunities to support students with learning disorders. The results of this study demonstrate that AI systems, when ethically implemented and aligned with pedagogical goals, significantly enhance learning outcomes, motivation, and inclusion.

AI's adaptive algorithms not only diagnose learning difficulties with remarkable precision but also personalize instruction and provide real-time support that complements teacher expertise. In doing so, AI bridges the gap between diagnosis and action—turning assessment data into immediate, targeted intervention.

However, technological advancement must be guided by humanistic principles. Teachers remain irreplaceable as mediators of empathy, context, and moral judgment. The future of education thus lies not in automation but in *co-intelligence*: a dynamic partnership between human educators and intelligent systems that together create responsive, equitable, and transformative learning experiences.

For policymakers and practitioners, the findings emphasize the urgency of developing national frameworks that promote ethical AI integration, teacher training, and infrastructure investment. Only through comprehensive, inclusive, and reflective implementation can AI fulfill its promise as a catalyst for equity and innovation in the education of learners with special needs.

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