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The Digital Inclusion Ecosystem: AI, Adaptive Platforms, and New Pedagogical Challenges for the Italian School System

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Abstract: This paper analyzes the transformative potential of Artificial Intelligence (AI) and Open Educational Resources (OER) in promoting school inclusion, with particular reference to the Italian context. Through dialogue with leading technology acceptance models and teacher competence frameworks (DigCompEdu), it examines how the integration of Adaptive Learning and Learning Analytics systems can address Special Educational Needs (SEN) according to the Universal Design for Learning (UDL) perspective. A quasi-experimental study conducted on a sample of 62 primary school students is presented, aimed at evaluating the impact of an adaptive platform on learning and self-efficacy. The results show a significant improvement in the experimental group (d = 0.91), with particularly significant effects for students with SEN/DSA (d = 1.12), and a significant increase in perceived self-efficacy (d = 1.05).

Keywords: SEN; SLD; Inclusion; Adaptive Learning; Primary School.

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1. Introduction: the challenge of digital inclusion in the Italian context

Italy represents a paradigmatic case in the international landscape regarding the protection of the right to education. The path toward inclusion is the result of a long legislative and cultural evolution: from the medical-segregating model of "special classes" of the first half of the twentieth century to the social model, initiated by Laws 118/1971 and 517/1977, which abolished special classes, sanctioning the entry of students with disabilities into mainstream schools and inaugurating the process of integration (Canevaro, 2013).

Law 104/1992 consolidated this approach, introducing the Individualized Educational Plan (PEI) as a key tool for comprehensive care. However, it is in the 21st century that the paradigm shifts toward full-fledged inclusion: Law 170/2010 recognized Specific Learning Disabilities (SLD), legitimizing the use of compensatory tools and dispensatory measures, while the Ministerial Directive of December 27, 2012, extended the scope of educational responsibility to Special Educational Needs (SEN), including socioeconomic, linguistic, and cultural disadvantage (Cottini, 2017).

[1] Francesco Del Sorbo wrote paragraphs 2, 4, 5 and 6; Rosa Indellicato wrote paragraphs 1, 3 and 7.

From an international perspective, inclusion is now defined as a systemic process of removing barriers to learning and participation (Ainscow, 2020), aimed at the structural transformation of educational contexts. In this scenario, the contemporary challenge is represented by digital inclusion: it is no longer a matter of integrating technologies into teaching, but rather of designing educational ecosystems capable of using AI to respond to the variability of learning profiles (UNESCO, 2023).

This approach requires a transition toward models of "bio-psycho-social inclusion" in which technology mediates educational processes (Ianes, 2005; Rivoltella, 2021). Within this framework, this paper aims to investigate the role of adaptive systems in promoting inclusive practices, integrating theoretical analysis, empirical evidence, and comparison with recent international literature.

2. Learning Analytics, Adaptive Learning and school inclusion

Scientific literature distinguishes two complementary areas that structure the inclusive digital ecosystem: Learning Analytics (LA) and Adaptive Learning (AL) systems (Siemens, 2013; Vivanet, 2023).

Learning Analytics represents the descriptive and predictive dimension of the digital ecosystem: through the collection and analysis of student-generated data (interaction times, error patterns, navigation paths), they allow for understanding learning processes and the early identification of risk situations. Adaptive Learning Systems, on the other hand, constitute the operational and transformative dimension, as they use this data to dynamically modify the learning environment, adapting content, pace, and presentation methods to the characteristics of the individual student.

In the inclusive school context, LA allows for monitoring the "digital traces" of students with learning disabilities, identifying recurring error patterns early; AL intervenes, on the operational level, in the adaptive regulation of cognitive load (Vivanet, 2023). The effectiveness of these systems lies in their ability to operationalize the principles of Universal Design for Learning (UDL): by providing multiple modes of representation and action, AI enables dynamic scaffolding tailored to the student's zone of proximal development (Rose & Meyer, 2002).

Unlike traditional assistive technologies, which rely on static rules and compensatory interventions, adaptive systems use probabilistic and predictive models to support the development of autonomous skills (Luckin, 2018; Vassilaki et al., 2023). This distinction is not merely technical, but implies a different conception of learning: from a process to be compensated to a process to be enhanced in a personalized manner.

Integrating AL into the classroom significantly reduces the risk of social stigmatization, as personalization becomes a "discreet" practice, widespread across the entire class, normalizing the use of supports that would otherwise identify students with SEN as "different" (Florian, 2014; Limone & Toto, 2022). However, this raises significant issues of algorithmic governance: model transparency (Explainable AI) is a necessary condition for teachers to maintain their professional agency and not be reduced to mere executors of algorithmic prescriptions (Holmes et al., 2023; Khosravi et al., 2024).

It is essential that systems are designed according to the principles of Privacy by Design, avoiding discriminatory profiling that could crystallize labels on students (Williamson & Eynon, 2020). In Italy, the pedagogical debate emphasizes that the governance of educational data must be understood as a pedagogical guarantee and not exclusively as a bureaucratic requirement (Fiorucci & Bevilacqua, 2025).

Teacher professionalism is challenged by institutional resistance and technocratic pressures. The literature highlights that digital readiness does not depend on seniority, but rather on the perception of professional self-efficacy (Bandura, 1997; Limone & Toto, 2022). Teachers who are "critical mediators" are those who use learning outcomes data to monitor student progress, maintaining a central role in human relationships and using authentic assessment (Performance-Based Assessment) as a pedagogical anchor (Rivoltella, 2021).

3. Adaptive technologies and teacher professionalism

The integration of Adaptive Learning systems into school contexts requires a profound redefinition of the teaching profession. Teachers are no longer mere content providers, but assume the role of critical mediators of technology-mediated learning processes. From this perspective, digital teacher competence cannot be reduced to a technical dimension, but must include interpretative and reflective skills on the data produced by Learning Analytics.

The DigCompEdu framework highlights how professional competence is articulated in the ability to use data to support informed teaching decisions (Redecker, 2017). However, recent studies emphasize that this competence requires a specific pedagogical data literacy, understood as the ability to critically interpret data while avoiding technocratic biases, i.e., the tendency to delegate to algorithms decisions that fall within the realm of the teacher's professional judgment.

In this scenario, the need for a balance between automation and teaching agency emerges: AI must be conceived as a tool to support pedagogical judgment, not as a replacement. Initial and ongoing teacher training, in this sense, represents the primary enabling factor for ensuring a critical and pedagogically sound use of adaptive technologies.

4. Materials and Methods

This study is part of an evidence-based quantitative research paradigm and adopts a quasi-experimental pretest/posttest design with a non-equivalent control group. This approach is particularly appropriate in real-world educational contexts, where complete randomization is not always feasible, but control strategies can be implemented to ensure adequate levels of internal validity.

The independent variable is the introduction of an Adaptive Learning system based on Artificial Intelligence. The dependent variables concern: a) cognitive performance (reading comprehension and logical-mathematical reasoning); b) motivational performance, with particular reference to perceived self-efficacy. The study was conducted in the 2025/2026 school year and involved 62 fourth-grade elementary school students.

Table 1. Research sample description

Group	N. students	SEN/SLD	Without diagnosis	Average age (SD)
EG (Experimental)	31	12	19	9,4 (0.3)
CG (Control)	31	11	20	9,3 (0.4)

Group assignment was based on existing classes, to preserve the ecological nature of the educational context and ensure natural teaching dynamics. To reduce the risk of selection bias, initial equivalence between groups was verified by: a) comparing pretest scores using independent-samples t-tests; b) analyzing the main control variables (age, presence of SEN/LD). The results showed no statistically significant differences between groups in the initial phase, confirming the comparability of the starting conditions.

The intervention lasted 12 weeks and took place during regular school hours. The Experimental Group (EG) used an AI-based Adaptive Learning platform, characterized by: a) dynamic adjustment of the difficulty level; b) multimodal content personalization (text, audio, visual format); c) immediate and specific feedback; d) progressive adaptive scaffolding.

The Control Group (CG) followed a traditional teaching path, using non-adaptive compensatory tools such as paper-based concept maps and standard speech synthesis. Both groups followed the same curricular content, with identical learning objectives and identical exposure times. The activities were conducted by the same teachers, who were previously trained on the intervention, in order to reduce the teacher effect.

4.1. Detection tools

Reading comprehension and logical reasoning skills were assessed using standardized tests validated in the Italian context (MT tests or equivalent instruments), selected on the basis of high reliability ($\alpha > 0.80$) and proven construct validity. The tests were administered under controlled conditions at two points: pre-test (initial phase) and post-test (at the end of the intervention).

The motivational dimension was assessed using a self-efficacy scale adapted to the primary school context, developed based on Bandura's socio-cognitive model (1997). The instrument is structured on a 5-point Likert scale and includes items relating to perceived competence, error management, and task persistence. The version used was subjected to linguistic simplification appropriate to the age of the sample. Internal consistency analysis showed high reliability ($\alpha = 0.87$). Example item: "I feel capable of solving even difficult exercises if I try hard."

For the Experimental Group, learning analytics data was collected through automatic tracking of interactions with the platform. The variables considered included: time spent on tasks, number of attempts, frequency of errors, and use of digital compensatory aids. These indicators were used as proxy variables to infer adaptation processes, learning trajectories, and changes in cognitive and metacognitive regulation.

Technically, the platform used belongs to the category of Knowledge-Based Intelligent Tutoring Systems (ITS), with an adaptive engine based on Bayesian student models (Bayesian Knowledge Tracing, BKT), which adjusts difficulty, pace, and scaffolding in real time based on observed performance (Baker & Siemens, 2022; Luckin, 2018). It should be noted that, although the parameters of the predictive model are subject to contractual confidentiality constraints by the platform provider, a recurring condition in educational field research with commercial systems (Selwyn, 2019; Holmes et al., 2023), the process indicators extracted via the analytical dashboard are accessible and interpretable by the teacher, ensuring a sufficient level of operational transparency for pedagogical monitoring. The limitation related to the partial opacity of the algorithm was therefore assumed as an ecological constraint of the research context and not as an invalidating element of the design.

4.2. Data Analysis

The data were analyzed using a combination of descriptive and inferential statistics. Specifically, the following techniques were used: independent-samples t-tests to compare EG and CG in the post-test measures; paired-samples t-tests to analyze pre-post changes within groups; and repeated-measures ANOVA (2x2: time x group) to test the interaction between intervention and change over time. Effect size was estimated using Cohen's d to assess the practical relevance of the results beyond statistical significance. The significance level was set at $p < 0.05$. The assumptions of normal distribution and homogeneity of variances were preliminarily verified.

In relation to the sample size, an a priori power analysis was conducted to verify the adequacy of the sample with respect to the study objectives. Assuming a medium-large effect size ($d = 0.70$, in line with estimates derived from the adaptive learning literature: Ma et al., 2024; Pane et al., 2017), a significance level of $\alpha = 0.05$, and a desired power of 0.80 ($1-\beta$), the minimum sample size for a two-group design is $N = 52$ (26 per group), calculated using G*Power 3.1 (Faul et al., 2007). The actual sample of 62 participants (31 per group) exceeds this minimum threshold, ensuring an estimated power of 0.85 for the main comparison. For the SEN/DSA subgroup ($n = 23$), the power is reduced to approximately 0.72, a value that constitutes a recognized limitation and is stated in the limitations section. These estimates indicate that the design has sufficient power to detect medium-sized effects, although some caution is needed when interpreting the results for smaller subgroups.

4.3. Methodological limitations of the study

The research design ensures good internal validity, ensured by the presence of a control group, pre-post measurements, the use of reliable standardized instruments, and the control of key contextual variables. External validity, although limited by the sample size, is strengthened by the high ecological nature of the real-world school context. Among the main limitations are: the lack of complete randomization; the potential influence of self-perception bias in the self-efficacy scale; the limited statistical power in the analysis of the SEN/LD subgroup (estimated at 0.72); and the dependence of learning analytics on the partial transparency of the algorithms used.

The potential novelty effect, or the tendency of students to show increased performance and motivation in response to the mere novelty of a technological tool, regardless of its intrinsic adaptive characteristics, deserves specific consideration (Clark, 1994; Selwyn, 2019). In this study, three strategies were adopted to contain this effect: first, the duration of the intervention (12 weeks) was deliberately extended beyond the 4–6 week threshold within which the novelty effect tends to dissipate in the Educational Technology literature (Tamim et al., 2011); second, teachers were trained to maintain a neutral attitude towards the presentation of the tool, avoiding emphasis that could amplify students' enthusiasm; third, the progress of the Learning Analytics over the 12 weeks, with the progressive reduction in the use of compensatory supports and the improvement in processing time efficiency, suggests a consolidated learning trajectory rather than an initial peak followed by a plateau, a pattern typical of the novelty effect. Despite these precautionary measures, it is not possible to completely rule out this effect in the absence of a long-term follow-up, which therefore represents a priority direction for future research developments.

4.4. Methodological triangulation

The integration of standardized tests, psychometric scales, and process data constitutes an advanced methodological triangulation, which represents one of the study's main strengths. This approach allows us to overcome a reductionist view of learning, offering a multidimensional analysis that connects cognitive outcomes, motivational dimensions, and learning processes. The adopted methodology therefore allows for an in-depth analysis of the impact of adaptive learning systems in inclusive contexts, contributing to the study's robustness and scientific relevance.

5. Results

Data relating to academic performance show a significant improvement in both groups, with substantial differences in terms of the magnitude of the effect and educational relevance.

Table 2. *Academic performance: pre-test/post-test comparison between groups (M = Mean; SD = Standard Deviation*

Indicator	EG Pre	EG Post	CG Pre	CG Post	Δ EG	Δ CG	d
Total sample	62,1	85,4	63,2	74,8	+23,3	+11,6	0,91
SEN/SLD sub-group	48,5	79,2	49,1	58,4	+30,7	+9,3	1,12

The data show significant improvement in both groups, with substantial differences in effect size and educational relevance. In the Experimental Group, the mean score increased from 62.1 to 85.4 (+23.3 points), while in the Control Group, it increased from 63.2 to 74.8 (+11.6 points). Inferential analysis indicates that this difference is statistically significant ($p < 0.05$), with a high effect size ($d = 0.91$), indicative of a robust impact of the intervention.

The disaggregated analysis shows even more marked effects for students with SEN/LD: the improvement of +30.7 points in the EG, compared to an increase of +9.3 in the GC, with an effect size greater than one ($d = 1.12$), indicating a very strong impact of the intervention (Baker & Siemens, 2022), rarely observed in ecologically valid educational contexts. This data suggests that the effectiveness of adaptive learning increases as the variability of learning profiles increases. From a pedagogical perspective, these data indicate that: dynamic regulation of difficulty prevents both cognitive overload and understimulation; immediate feedback interrupts error processes early; and continuous personalization enables cumulative and progressive learning. Taken together, these elements establish adaptive learning as a regulated scaffolding device, consistent with the theory of the zone of proximal development (Vygotsky, 1974), in which support is modulated based on the student's actual performance.

Table 3. *Perceived self-efficacy: pre-test/post-test comparison between groups*

Group	Pre	Post	Δ	d
EG (Experimental)	2,4	4,6	+2,2	1,05
CG (Control)	2,5	3,2	+0,7	0,42

The increase in self-efficacy in the EG (+2.2 points) compared to the GC (+0.7) highlights a marked effect of the intervention not only on the cognitive level, but also on the motivational level. The high effect size in the EG (d = 1.05) indicates a substantial change in students' perception of competence, while the value in the GC (d = 0.42) suggests a limited improvement, plausibly attributable to normal educational progression.

From a theoretical perspective, this result can be interpreted in light of Bandura's (1997) socio-cognitive model, according to which self-efficacy is built through mastery experiences, immediate feedback, and the perception of control over the task. Adaptive systems appear to impact all three of these dimensions: they provide tasks proportionate to the student's abilities, increasing the probability of success; they provide immediate feedback that reduces uncertainty and strengthens the link between action and outcome; They give students the perception of an educational environment that "responds" to their needs. Increasing self-efficacy takes on crucial pedagogical importance, as it correlates not only with immediate results, but also with persistence, commitment, and resilience in learning tasks.

Table 4. *Reduction of the SEN/SLD gap between the experimental group and the control group*

Group	Initial gap	Final gap	Variation
EG (Experimental)	13,6	6,2	-54%
CG (Control)	14,1	16,4	+16%

One of the most significant findings concerns the reduction in the gap between students with SEN/DSA and their peers in the EG (-54%) compared to a widening gap in the GC (+16%). This data highlights a clear divergence between the two teaching models, which can be interpreted on three levels.

On the teaching level, Adaptive Learning allows for continuous differentiation that avoids standardization of curricula: students with SEN/DSA are not forced to adapt to the pace of the class, but operate in an environment that adapts to them. On the cognitive level, the reduction in the gap suggests that the system effectively intervenes on basic processes (decoding, comprehension, elaboration), allowing access to subject content without penalties related to instrumental difficulties. On the socio-inclusive level, this finding takes on particular significance in terms of equity: it is not simply a matter of improving individual performance, but of reducing structural inequalities within the class group. In this sense, the results support a conception of inclusion as a transformation of the context rather than an adaptation of the individual, in line with Ainscow's (2020) systemic perspective.

Table 5. *Learning Analytics Analysis - Experimental Group*

Indicator	Value
Average time per task	-18% during the intervention
Use of audio media	65% → 28%
Repeated errors	-42%

Analysis of interaction data highlights significant transformations in learning trajectories. First, an improvement in cognitive efficiency is observed: students progressively become faster at processing information, indicating a shift from controlled to more automated processes. Second, a significant reduction in the use of digital compensatory tools (scaffolding fading) is observed: the support is not simply employed, but progressively internalized, which indicates a genuine development of autonomous skills and confirms the formative (and not merely compensatory) nature of the system. Third, the reduction in recurrent errors (-42%) suggests that the system is effective in interrupting dysfunctional learning patterns, implying improved metacognitive regulation, greater awareness of errors, and more stable learning. These data confirm that the intervention not only produces better final results, but also structurally modifies learning processes.

6. Discussion: towards an inclusive adaptive teaching

Taken together, the results indicate that Adaptive Learning operates as a complex, multilevel pedagogical device, capable of simultaneously impacting cognitive (performance), motivational (self-efficacy), social (gap reduction), and metacognitive (learning regulation) dimensions. The integration of Learning Analytics and adaptive systems enables an advanced form of data-informed teaching, in which pedagogical decisions are supported by empirical evidence, without replacing the teacher's interpretative role.

It is important to distinguish between Adaptive Learning systems and Generative Artificial Intelligence systems: the former operate through predictive models that regulate learning paths, while the latter (such as Large Language Models) produce dynamic content in response to contextual input. From this perspective, AI is configured not as an autonomous agent, but as an epistemic mediator capable of amplifying the educational system's ability to respond to the complexity and diversity of learning profiles.

The findings of this study are part of a rapidly evolving international landscape. A systematic review of 142 studies (2015–2025) highlights how AI enables the development of personalized, data-driven learning environments, capable of significantly improving both engagement and learning outcomes (Ma et al., 2024; Khosravi et al., 2024). The significant increase in performance observed in the Experimental Group is supported by literature that attributes three key functions to adaptive systems: dynamic difficulty adjustment, immediate feedback, and multimodal content adaptation (Pane et al., 2017; Luckin, 2018; Holmes et al., 2023).

Recent studies confirm that AI can enhance accessibility and participation for students with disabilities, improving both learning and engagement (UNESCO, 2023; Holmes et al., 2023; Ainscow, 2020). The significant reduction in the SEN/LD gap observed in this study represents empirical evidence consistent with the international trend that adaptive technologies can contribute to reducing educational inequalities (Florian, 2014; OECD, 2021).

The most recent scoping reviews on digital inclusion highlight, however, that the effectiveness of AI is not automatic, but depends on specific pedagogical and institutional conditions (Selwyn, 2019; Zawacki-Richter et al., 2019). The enabling factors identified (teacher training, institutional support, integration with theoretical frameworks such as UDL) are confirmed by the study's results, which show that the positive impact of adaptive learning does not derive from the technology itself, but from its integration into a structured and intentionally designed educational context.

In terms of its original contribution, this study offers a significant contribution in two respects. On the one hand, the centrality of inclusion as a measurable outcome: the reduction of the SEN/DSA gap represents a concrete indicator of equity, still poorly addressed in international studies (Ainscow, 2020; Florian, 2014). On the other hand, the results confirm that the effectiveness of AI cannot be reduced to cognitive performance alone, but must be interpreted multidimensionally, including motivational, metacognitive, and social dimensions (Bandura, 1997; Holmes et al., 2023).

7. Conclusions

This paper highlights how digital inclusion cannot be reduced to a technological issue, but must be interpreted as a complex pedagogical process, requiring intentional planning and informed governance of educational data. Artificial Intelligence, far from being an automatic solution, emerges as a pedagogical catalyst capable of amplifying the potential of teaching when integrated into a solid theoretical framework and reflective practices.

In this scenario, teachers assume a strategic role not as simple users of tools, but as designers and mediators of learning processes, called upon to critically interpret data and integrate it with direct pedagogical observation. The main challenge concerns striking a balance between technological innovation and the protection of student rights, particularly with regard to the protection of personal data and the prevention of forms of algorithmic labeling.

Despite the study's limitations, including its small sample size, lack of complete randomization, the limited duration of the intervention, and the potential novelty effect, this work highlights three priority directions for research and educational policy: 1) the need to invest in teacher training on the critical and pedagogically sound use of AI; 2) the importance of integrating adaptive systems into curricula in a systematic, rather than episodic, manner; and 3) the development of national guidelines for educational data governance, inspired by the principles of algorithmic fairness and transparency (Fiorucci & Bevilacqua, 2025; Khosravi et al., 2024).

Recent studies highlight how the integration of adaptive learning and explanatory AI represents one of the key development directions for ensuring transparency and fairness in digital education systems (Holmes et al., 2023; Khosravi et al., 2024). The future of inclusive education lies not in replacing pedagogy with technology, but in their critical and reflective integration. From this perspective, Adaptive Learning emerges as a point of convergence between the pedagogical tradition of inclusion and algorithmic innovation, representing one of the most promising tools for building equitable, personalized, and sustainable educational systems.

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