FROM TECHNOPHOBIA TO ETHICAL INTEGRATION: RESEARCH EVIDENCE ON TEACHER EDUCATION IN THE ERA OF AI

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ABSTRACT
This paper examines the challenges of AI-assisted education by integrating Critical AI Literacy (Veldhuis et al., 2025) with the Human-in-Command paradigm (AGID, 2024). Utilizing a mixed-methods research design involving 263 teachers, the study reveals a significant discrepancy between high conceptual familiarity with generative systems and a deficit in operational and ethical competencies. The evidence demonstrates that the fear of dehumanization reduces AI to mere automation, hindering authentic pedagogical integration. To overcome this professional impairment, we propose a Digital Affective Literacy model, essential for governing hybrid learning environments (Luckin, 2018). Transcending purely technical training, this work delineates the teacher as a pedagogical director of care, capable of orchestrating human-machine interaction while safeguarding relational responsibility and the depth of the human encounter (Andler, 2024; Ranieri et al., 2024).

KEYWORDS
Critical AI Literacy; Digital Affective Literacy; Human-in-Command; Teacher professionalism; Mixed-method research.

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1. Introduction

The pervasive evolution of generative AI is reconfiguring educational frameworks, reshaping the epistemological tenets of knowledge and classroom relational dynamics (Floridi, 2022; Miao & Holmes, 2023). Within this diffuse hybridization, computational models act as active agents of mediation rather than mere technical artifacts (Luckin, 2018). This shift challenges traditional teaching paradigms, dismantling vertical knowledge transmission and the exclusive centrality of human agency in information flows (Holmes et al., 2019; Selwyn, 2019). Consequently, the teacher-learner asymmetry is mediated by a third actor, demanding new evaluative practices that target higher-order cognitive skills and systemic redefinitions of assessment criteria (Trinchero, 2023).

As Large Language Models simulate cognitive and empathetic functions, instructional practice is squeezed between performance standardization demands and the need to preserve the pedagogical mandate's ethical authenticity (Williamson et al., 2024). Uncritical automation brings a latent risk of bureaucratization and professional alienation. The true professional loss stems not from adopting technology, but from unconditionally delegating axiological, ethical, and care-based functions to the machine (Pellerey, 2024). Therefore, investigating and reclaiming spaces of emotional conflict management and human limitation remains a priority (Andler, 2024).

Transcending the polarizations of technocentric enthusiasm and technophobic rejection requires a critical, methodologically grounded pedagogical posture (Ranieri et al., 2024). To effectively govern this change, it is essential to empirically map teachers' needs, resistances, and self-reported competencies.

This paper contributes to this inquiry through a mixed-methods empirical study analyzing teachers' experiences and perceptions regarding generative AI systems in schools.

2. Theoretical Framework

In the international scientific debate, AI literacy transcends procedural skills, such as prompt formulation or passive interface consumption. Recent research references the construct of Critical AI Literacy (Veldhuis et al., 2025), which integrates Freirean Critical Literacy with computational empowerment models (Freire, 1970). Grounded in Freire's (1970) emancipatory pedagogy, literacy is defined not as a mechanical decoding of signs, but as a political and cognitive process fostering critical consciousness. Rejecting the "banking concept" of education—where learners passively receive standardized contents—Freire advocates for a problem-posing education grounded in dialogic discourse and praxis, merging theoretical reflection with transformative action.

Applied to the digital transition, this framework overcomes technocentric approaches focused strictly on operational tool usage. Critical AI literacy qualifies as the ability to interrogate, problematize, and expose power structures, ideological biases, and economic determinisms hidden behind the apparent neutrality of generative technologies. Operating in synergy with computational empowerment, it restores democratic agency to teachers and students, transforming algorithmic comprehension into a tool for cognitive emancipation that reshapes the ethical and socio-political impact of technology in education (Long & Magerko, 2020; Singgih & Sumarni, 2025; Veldhuis et al., 2025). This model comprises three fundamental sub-dimensions:

understanding algorithmic agency based on probabilistic rather than intentional models; evaluating the social and ethical impact of data extraction and commercial surveillance; and promoting algorithmic justice by identifying and neutralizing embedded cognitive, historical, or cultural biases.

Without this critical posture, educational institutions face latent forms of epistemic violence. Algorithms often impose standardized categorization criteria that exclude or penalize minorities, undermining pedagogical personalization and equitable inclusion. Critical competence serves as an indispensable methodological device, ensuring teachers act as critical analysts capable of revealing the hidden power relations behind school automation (Ranieri et al., 2024).

2.1 The Human-in-Command Paradigm

The operational necessity for critical oversight stems from the Human-in-Command paradigm, originally formulated in the High-Level Expert Group on AI's Ethics Guidelines for Trustworthy AI (European Commission, 2019) and further elaborated in philosophical and pedagogical debate (Floridi, 2022). This principle finds institutional codification in the European Artificial Intelligence Act (Regulation EU, 2024/1689), which specifically classifies AI systems intended to be used in education and vocational training—for determining access, evaluating learning outcomes, or assessing educational levels—as high-risk applications (Annex III). For these specific use cases, the regulation legally mandates structural human oversight measures to mitigate risks to fundamental rights, autonomy, and equity. In alignment, the Italian Strategy for Artificial Intelligence 2024–2026 demands an anthropocentric approach, establishing human supervision as irreplaceable across all phases of AI

application to safeguard autonomy, transparency, and accountability (AGID, 2024).

In educational evaluation, UNESCO (2023) warns that uncritically delegating docimological functions to AI undermines systemic equity, asserting that assessment must remain a human prerogative focused on reflective and relational faculties (Noble, 2018). Consequently, teachers cannot abandon their roles to predictive algorithms or learning analytics (Siemens, 2013).

Algorithmic assessment yields only fragmented measurements based on statistical correlations (Trinchero, 2023). Conversely, the Human-in-Command paradigm dictates that machine outputs are merely drafts. They lack intrinsic pedagogical value until the teacher re-signifies and validates them considering the student's biographical history, classroom relational dynamics, and longitudinal educational goals (Selwyn, 2023; Williamson et al., 2024).

2.2 Ecology of Hybrid Learning

The convergence of critical oversight and instructional action finds a fruitful synthesis in the model of "augmented" human intelligence applied to hybrid learning. Luckin (2018), in exploring the ecology of AI-supported educational contexts, proposes a multifactorial taxonomy of intelligence. She distinguishes purely computational intelligence—a specific domain in which machines surpass humans in terms of processing speed, memory, and macroscopic data pattern recognition—from other forms of intelligence that remain structurally exclusive to the human subject: social intelligence, emotional intelligence (Goleman, 1995), metacognitive intelligence (Flavell, 1979), and deep contextual knowledge. The algorithm possesses no consciousness regarding the biological, ethical, and social meaning of the data it manipulates; it operates according to criteria of syntactic and probabilistic optimization.

Strategic cooperation within hybrid learning environments is therefore grounded in a rigorous and scientific division of pedagogical labor. The controlled delegation to AI of routine, bureaucratic, administrative, and automated assessment procedures (such as the grading of objective tests or the tracking of linear progress) frees up the teacher's time. This reclaimed time does not constitute an operational void, but rather the indispensable condition for reinvesting the teacher's cognitive and energetic resources into the educational relationship, the design of complex instructional scenarios, guidance, and active listening (Luckin, 2018).

2.3 Digital Affective Literacy and the Challenge of Simulated Empathy

The effectiveness of this ecosystem faces a significant friction point when the algorithm is trained to simulate affective language. This epistemological challenge constitutes the theoretical foundation of Digital Affective Literacy. Modern generative AI systems, powered by conversational interfaces, are designed to display a pronounced capacity for emotional mirroring and high-density synthetic personalized dialogic interaction. According to studies in cognitive science applied to complex systems, this synthetic or artificial empathy is structurally devoid of relational intentionality and bodily grounding. Nonetheless, it produces a profound psychological impact on users, generating the risk of relational illusions, emotional dependency, or cognitive passivity (Andler, 2024).

Learners tend to spontaneously attribute intentionality and emotional subjectivity to a purely computational entity (the ELIZA effect) (Weizenbaum, 1976). Algorithmic affectivity is a statistical function that cannot surrogate the depth of the embodied human encounter, which is constitutively nourished by shared vulnerability, the management of the unexpected, and the

intersubjective negotiation of meaning within the physical space of the classroom. Digital Affective Literacy is therefore defined as a second-level metacognitive and emotional competence. It provides the teacher with the theoretical and methodological tools to operate as a “pedagogical director of care” (Pellerey, 2024), capable of integrating the algorithmic artifact for its extraordinary analytical properties, while simultaneously drawing a clear boundary that preserves the relational and ethical sphere from technological intrusion.

This theoretical framework provides the foundation to interpret the technophobia emerged from the empirical research not as a mere rejection of progress, but as an indicator of an institutional training void that critical and affective literacy is called to fill.

2.4 A Framework for Assessing Teacher Self-Efficacy

Within this scenario, to assess teacher readiness regarding the integration of generative artificial intelligence, literature emphasizes the importance of models capable of connecting cognitive, attitudinal, and affective components. The framework developed by Işık, Çakır, and Korkmaz (2024), which integrates Bandura’s (1977) self-efficacy theory with classic technology acceptance models (TAM), constitutes a pivotal reference. The authors postulate that AI adoption is predicted by the dynamic interaction of four latent constructs:

1. Knowledge: defines the theoretical-conceptual dimension of literacy. It encompasses the understanding of AI principles, the ability to select appropriate tools for instructional and evaluative objectives, and proactivity in continuous professional development;
2. Practice: expresses the operational dimension of self-efficacy. It measures the perceived ability to apply generative artificial intelligence

within the school routine to design activities, generate personalized content, and optimize bureaucratic management time;

3. Anxiety: represents the affective dimension and functions as a barrier to innovation. It quantifies the emotional discomfort and ethical-pedagogical concerns associated with the introduction of AI, including feelings of professional inadequacy, potential negative effects on students, and the risk of relational dehumanization;
4. Utility: measures the expectation of perceived benefit. It detects the teacher's conviction that AI can increase professional productivity, enhance the accuracy of formative assessment, and foster student success and inclusion.

The adoption of this framework offers a robust interpretative lens to deconstruct the complex relationship between teachers' self-reported competencies and psychological resistances.

3. Research Design and Methodology

The general objective of this research is to analyze teachers' perceptions, self-efficacy levels, and professional experiences regarding the implementation of generative artificial intelligence in school contexts, to design and optimize initial and continuous training pathways. Furthermore, the research design is structured around two specific objectives: to quantify the level of conceptual familiarity and use of AI, and to map ethical concerns and the fear of dehumanization. Consistent with the descriptive-exploratory design of the inquiry, the main questions guiding the empirical process are as follows: What are the prevailing opinion profiles, levels of self-reported familiarity

(theoretical and practical), and perceptions of the utility of generative artificial intelligence within the sample of teachers? What areas of systematic agreement or disagreement are recorded regarding AI's capability to serve as an instructional and evaluative support? What emerging thematic nodes and personal narratives do respondents associate with the potential impact of AI on the embodied educational relationship and the risk of dehumanizing the school system? What ethical-operational criticalities and professional development needs emerge as most salient?

In line with the reviewed literature (Andler, 2024; Işık, Çakır & Korkmaz, 2024; Ranieri et al., 2024), the following working hypotheses are formalized: it is hypothesized that there is an asymmetry in the teachers' response profiles, characterized by higher mean frequencies in items related to theoretical knowledge of AI (conceptual familiarity) compared to lower frequencies in those related to operational application in classroom routines; it is hypothesized that the frequency distribution for items tied to the affective dimension will reveal higher agreement in areas concerning performance anxiety and the fear of a dehumanization of assessment processes.

3.1 Sample

The study adopted a non-probability convenience sampling strategy. This methodological choice was aimed at selecting subjects already embedded within institutional frameworks of pedagogical reflection and professional development, thereby maximizing the authenticity and responsiveness of the participants regarding issues of teacher professionalization.

The convenience sample comprises 263 participants enrolled in the Specialization Programs for Educational Support Activities at the University of Salerno (A.Y. 2024/2025, X Cycle). Demographically, the sample shows a

distinct prevalence of female participants (83.6%), followed by males (13.4%), and 3% who preferred not to specify (Item 1).

Chronological age data indicate a mature profile: the 40–49 age bracket forms the majority (40.3%), followed by the 30–39 group (23.9%), the 20–29 cohort (19.4%), and the 50–59 bracket (16.4%) (Item 2).

Teaching experience is heavily skewed toward low seniority, with 80.6% of participants reporting fewer than 5 years of service. Correlated with age, this highlights the "new-entry paradox", where chronologically mature professionals are only beginning to stabilize their teaching careers. The remaining sample shows higher career stability: 9.0% have taught for 5–10 years, 6.0% for 11–20 years, and 4.5% for over 20 years (Item 3).

3.2 Survey Instruments

The quantitative instrument was adapted from the scale developed by Işık, Çakır, and Korkmaz (2024). To better align with the Italian school context and the specific focus on special education trainees, structural and operational modifications were introduced. First, while the original instrument conceptualized operational ability within a single construct, we conceptually bifurcated this factor into two distinct analytical dimensions: Knowledge (9 items, capturing theoretical-conceptual familiarity and awareness) and Practice (13 items, measuring self-reported operational usage and instructional design in classroom routines). The scale also includes Anxiety (8 items) and Utility (7 items). These four domains are treated as operational analytical dimensions rather than verified latent constructs.

Second, the original 5-point Likert response format was converted into a 6-point scale (ranging from 1 = strongly disagree to 6 = strongly agree). This choice

design was selected to prevent central tendency bias and compel respondents to express a directional orientation.

To ensure semantic and content validity, the translated items underwent a standard back-translation procedure followed by panel review by three experts in experimental pedagogy. Internal consistency was evaluated across the four analytical dimensions using Cronbach's alpha, yielding satisfactory reliability coefficients: Knowledge (α=0.82), Practice (α=0.85), Anxiety (α=0.78), and Utility (α=0.81). Total score for each dimension was calculated by averaging the respective item scores.

Administered asynchronously via Google Forms, the survey included an introductory letter outlining scientific objectives and guaranteeing anonymity in compliance with privacy regulations (Legislative Decree 101/2018; Regulation EU, 2016/679).

In the qualitative phase, which served to deepen and contextualize the phenomena emerged from the questionnaire, the research instrument consisted of individual semi-structured interviews. This instrument was administered to a targeted sub-sample of 8 teachers, selected from those who had participated in the quantitative phase and had indicated at the end of the questionnaire their willingness to continue with the research process. The semi-structured format ensured that all participants were guided through the same core thematic macro-areas, thereby guaranteeing coverage of the research objectives while allowing the researcher to adapt the order of questions and delve deeper into the subjects' emerging narrative nuclei.

The interview guide was designed according to a sequential funnel logic structured into three sections: an introductory block aimed at establishing

rapport and identifying the general usage profile of digital technologies; a central section designed to qualitatively explore practical experiences, ethical concerns, and the perceived pedagogical potential in relation to instruction and assessment; and a concluding section oriented toward recommendations for future professional development pathways (Işık, Çakır & Korkmaz, 2024; Sabouret, 2020). Table 1 summarizes the main sample questions posed to the participants during the interviews.

Introductory Section	*What were the first Generative Artificial Intelligence tools you began using, and for what specific purposes?*
Central Section	*In which instructional design activities do you believe AI is truly useful, and in which areas do you prefer not to employ it?*
Concluding Section	*What specific type of training or professional development do you require to feel confident and competent in using AI within the instructional domain?*

Table 1. Sample interview questions broken down by section.

To ensure its fluidity, linguistic clarity, and temporal sustainability (estimated between 45 and 60 minutes), the interview guide was previously subjected to a pilot test on a small group of teachers who were external to the actual sample.

Participation in both phases of the study was entirely voluntary. Written informed consent was obtained prior to questionnaire administration and interview recording, explicitly detailing research objectives, data handling procedures, and the right to withdraw at any time. Data management complied

with European Union GDPR (Regulation EU 2016/679) and Italian privacy legislation (Legislative Decree 101/2018), ensuring strict pseudonymization.

3.3 Research Phases

The study adopted a convergent parallel mixed-methods design (Creswell & Plano Clark, 2011). This model is characterized by the concurrent collection and independent analysis of quantitative and qualitative data, the findings of which are subsequently compared and integrated during the triangulation phase to obtain a comprehensive understanding of the phenomenon under investigation. The process was structured across three sequential macro-phases:

1. Simultaneous Collection and Independent Analysis: A digitized questionnaire was distributed to a convenience sample of special education trainees (N=263), yielding a complete dataset with no missing data. Concurrently, semi-structured interviews were recorded and transcribed via videoconference.
2. Comparison, Integration, and Triangulation of Results: The research followed an explanatory-sequential design where the quantitative survey data collection preceded and informed the qualitative phase. From the pool of survey respondents who expressed availability for follow-up (n=42), a purposive sub-sample of 8 special education teachers was selected based on maximum variation criteria regarding age and teaching experience to capture diverse professional trajectories. Quantitative data were processed by calculating descriptive statistics, specifically focusing on percentage frequency distributions for each step of the Likert scale to map areas of agreement and disagreement. Qualitative data from the full audio-

recorded interview transcripts were examined through a manual thematic analysis following a systematic interpretative reading and coding protocol. Both authors independently performed primary open coding on the raw transcribed text to extract recurring units of meaning. Subsequently, collaborative negotiation sessions were conducted between the two researchers to compare individual codebooks, resolve interpretative discrepancies, and synthesize the final thematic framework (Benvenuto, 2018).

3. Final Interpretation: The results of both analyses were triangulated to verify their convergence, divergence, or complementarity.

4. Results

4.1 Quantitative Data Analysis

The quantitative analysis focused on descriptive percentage frequency distributions across the 4 analytical dimensions (*Knowledge, Practice, Anxiety, Utility*). To interpret response profiles, categories were grouped into overall disagreement (points 1, 2, and 3: *strongly disagree, disagree, slightly disagree*) and overall agreement (points 4, 5, and 6: *slightly agree, agree, strongly agree*). On this 6-point scale, point 3 represents a mild disagreement rather than a neutral midpoint.

Data concerning the first dimension (Knowledge) reveal a profile characterized by a marked theoretical receptivity and widespread conceptual familiarity. Item 4, designed to capture the overall self-assessment of possessing sufficient knowledge, gathers a clear orientation toward positive agreement, reaching 65.8% of the sample. An equal concentration of 29.9% is split evenly between

points 4 (slightly agree) and 5 (agree), contrasted with a small 6% of responses positioned on point 6 (strongly agree).

Motivation toward autonomous professional development is reflected in Item 9, where positive agreement reaches 59.7%, with 11.9% of responses on point 6. In line with this trend, Item 10 reveals that 60.6% of respondents maintain active and constant vigilance regarding the evolution of AI, and Item 11 confirms that for 59.7% of the subjects, tool selection remains firmly anchored to the prioritization of pedagogical and curricular goals.

However, a discrepancy divergence emerges as soon as knowledge shifts to the level of strategic discernment: in Item 7 (the ability to select the AI tool based on the criterion of maximum effectiveness relative to a specific learning objective), the cumulative disagreement band (points 1, 2, and 3) stand at 49% (with a significant 28.4% concentrated on point 3, slightly disagree), revealing that nearly half of the teachers experience a marked vulnerability in translating generic interest into intentional instructional choices. Furthermore, regarding training investment (Item 12), 64.2% of participants admit to not taking an active part in structured seminars and events on AI.

Relatively to the instrumental and logistic dimension (Practice), AI devices are perceived as accessible and efficient: Item 13 reveals that 67.2% of teachers consider AI easy to use and free from excessive operational or cognitive effort, while Item 19 records high agreement (70.6%) regarding speed in information retrieval. Consistently, Item 22 highlights that 67.2% of the sample recognizes that AI holds strong value in terms of time-saving and optimization of the bureaucratic workload—a projection of labor efficiency that consolidates in the long term in Item 23 (67.1%) and prompts 68.6% of respondents (Item 24) to

consider the introduction of such technologies as a necessary prerequisite for future professional development courses.

Critical nodes emerge when reflecting on the use of AI within instructional design. In Item 14 (the ability to design effective learning environments mediated by AI), positive agreement drops to 53.1%, indicating that the transition toward structured curricular integration represents a substantial barrier. The actual and frequent use of AI during daily lessons (Item 18) stands at 50.8%, testifying to a practice that remains extemporaneous and not yet fully institutionalized within classroom routines. Finally, Item 27 confirms that 47.7% of the sample fears that AI could compromise ultimate learning outcomes and students' educational success.

Regarding the affective-emotional dimension (Anxiety), the response distribution is highly fragmented: Item 30 (general level of emotional concern raised by AI in educational contexts) records equal concentrations on point 3 (*slightly disagree*, 26.9%) and point 4 (*slightly agree*, 26.9%).

While on one hand Item 28 shows partial confidence in the role of AI (59.7% reject the idea that AI will reduce the quality of education), on the other hand, innovation clashes with psycho-pedagogical resistance concerning the impoverishment of the learning experience. Item 29 reveals that the majority of participants (51.5%) fear that AI could demotivate students, making learning processes sterile, mechanical, and devoid of real engagement (Fredricks et al., 2004). The most consistent alarm is recorded in Item 33 (the risk of generating technological dependency and the atrophy of autonomous skills), where positive agreement reaches 52.7%. This framework justifies why 49% of the teachers (Item 32) report limiting the use of AI strictly to cases of absolute

necessity, relinquishing a proactive style of exploration due to a latent fear of the dehumanization of educational contexts.

Relatively to the dimension investigating perceived benefit (Utility), in Item 34, designed to measure the conviction that AI can foster student success, responses in the overall disagreement band total 53.7%. The majority of teachers, therefore, do not envision a direct causal link between the adoption of the machine and the improvement of student performance. A partially more favourable orientation is recorded in Item 35 (the utility of AI to improve the accuracy and quality of formative assessment), where positive agreement rises to 55.2%, supported by the recognition of the device's value as a facilitator for professional problem-solving (Item 39, 53.7%) and personal productivity (Item 40, 55.2%).

However, the most alarming data from a pedagogical standpoint is found in Item 38 (allowing students to monitor and self-assess their own learning processes via AI). In this case, positive agreement collapses to just 27.4% of the sample. This evidence demonstrates a generalized deficit in the reflective and emancipatory use of technology, which is conceived predominantly as an optimization device for the exclusive use of the teacher, rather than as a catalyst for the development of student autonomy and metacognition.

4.2 Qualitative Data Analysis

Four critical nodes regarding AI integration in education emerge from teachers' narratives:

- Dehumanization of Educational Contexts: Teachers fear the progressive replacement of embodied relational acts with machine-mediated interactions. While computationally efficient, AI is seen as a

disruptor of “pedagogical care”, risking a future where automated content delivery replaces emotional grounding and intersubjective dialogue (Ranieri et al., 2024);

- Erosion of Empathy: Algorithmic feedback is defined as cold and structurally incapable of accommodating a student’s psychological background or intrinsic motivation. Teachers worry that LLMs reduce human complexity to flat, standardized metrics, ignoring crucial qualitative variables like effort and progress;
- Cognitive Passivity: Widespread concern exists that indiscriminate access to generative tools provides shortcuts that atrophy critical thinking. This induces a form of performance sterility, as students delegate text production and problem-solving to the machine, bypassing independent thought;
- Algorithmic Inequity and Bias: AI training on standardized data replicates systemic biases, threatening inclusive education (Williamson et al., 2024). Teachers dread rigid algorithmic labelling that penalizes students with special needs, positioning human interpretation and ethical teacher mediation as the irreplaceable bulwarks safeguarding democratic equity in schools.

For a more detailed examination of these thematic nodes, please refer to Table 2, which compiles the most representative excerpts from the respondents’ statements.

The Fear of Dehumanizing Educational Contexts
My greatest fear is that artificial intelligence will become a sort of cold wall between myself and the classroom. Schooling means looking into each other’s eyes, understanding in a split second if a student is struggling or sad.

A machine merely executes commands, but it can never provide that human warmth that is indispensable for true education.
The Erosion of Empathy in Teaching and Assessment
I tried having an AI grade an assignment and generate a feedback comment: from a technical standpoint, it was flawless, yet it felt cold. The algorithm does not know who it is dealing with; it is unaware of the student's personal history or whether they might have been crying the day before. The machine only sees the final output, whereas the teacher evaluates the entire longitudinal journey.
Cognitive Passivity and Technological Dependency in Students
The students quickly figured out the shortcut and view AI as the perfect workaround. If typing two lines is enough to get a well-written essay or a problem solved in three seconds, what will motivate them to engage in cognitive effort, synthesize information, and undergo the labor of independent thought? There is a concrete risk of inducing cognitive laziness.
Algorithmic Inequity and Bias
Artificial intelligence software is programmed with neurotypical students in mind. But what happens when the algorithm is tasked with assessing or supporting a student with a cognitive disability or a neurodivergence? The risk of labelling or penalizing them is extremely high. The machine applies rigid rules.

Table 2. Representative interview excerpts by thematic node (n=8).

The qualitative thematic analysis revealed consistent thematic occurrence: all 8 interviewees (100%) identified the themes of dehumanization, erosion of empathy, and algorithmic bias, while 7 out of 8 teachers (87.50%) highlight the risk of cognitive passivity (Fig. 1).

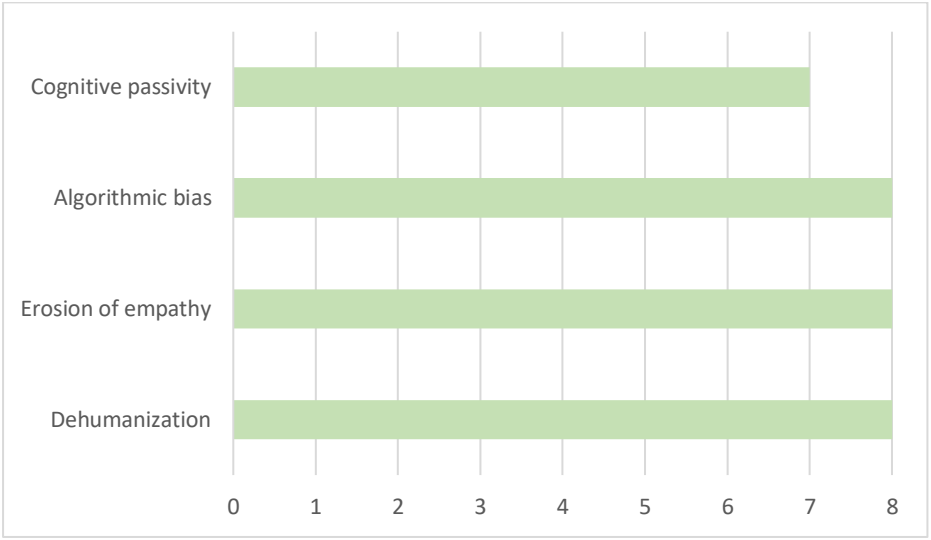


Figure 1. Thematic salience emerging from qualitative analysis (n=8).

As formalized in Figure 2, data triangulation is presented as a joint display combining quantitative percentage distributions with qualitative narrative themes. Quantitative distributions indicate a contrast between administrative acceptance (67.2% agreement) and operational hesitation in classroom routines (50.8% regular use; 27.4% student self-assessment). Concurrently, the qualitative findings provide explanatory context regarding affective concerns—such as the risk of contextual dehumanization, erosion of empathy, and algorithmic biases—explaining why teacher adoption remains largely restricted to logistical tasks (Holmes et al., 2019).

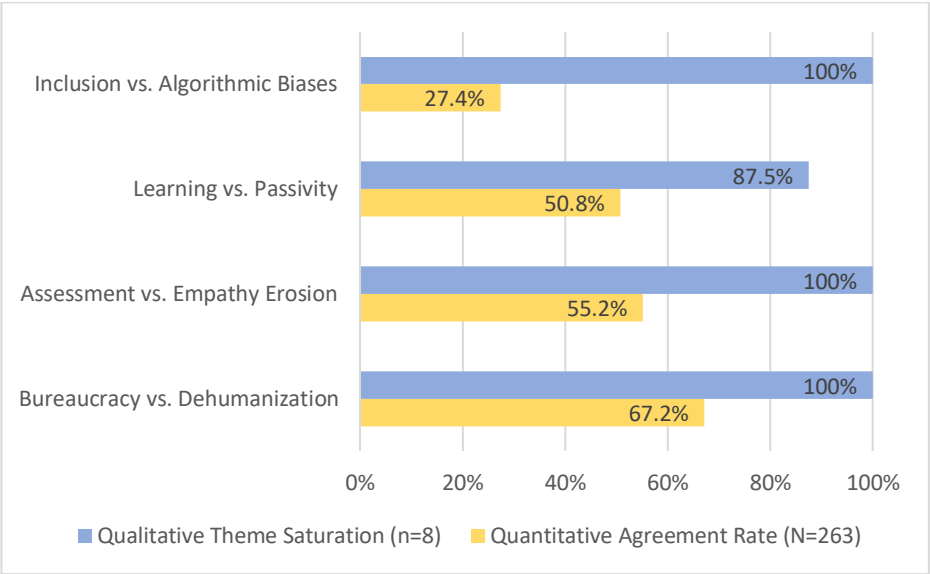


Figure 2. Data Triangulation: Technical/Practical Utility vs. Ethical and Affective Anxieties.

5. Discussion

5.1 Interpretation of the Discrepancy considering the Literature

The descriptive percentage distributions reveal a divergence within teacher response profiles: theoretical familiarity coexists with operational hesitation. On an exploratory-descriptive level, this trend aligns with the hypotheses. Rather than indicating a statistically verified structural gap, these distributions suggest that conceptual awareness does not automatically translate into pedagogical design mastery (Ranieri et al., 2024; Veldhuis et al., 2025).

The observed gap mirrors the results of recent investigations showing that the pervasive introduction of AI in educational contexts generates a similar asymmetry between perceived self-efficacy and actual docimological mastery

(Veldhuis et al., 2025). Pre-service teachers, characterized by chronological maturity but limited field experience, exhibit a fragmented adoption of the technology. AI is experienced as an effective device for logistical optimization and timesaving, but it is not integrated as a catalyst for reflective processes. This is demonstrated by the widespread scepticism regarding the use of AI for student self-assessment and the monitoring of learning processes.

From this perspective, the affective resistance reflected in both the percentage distributions and the qualitative themes recurring across interviewees aligns with the existing literature. Related research (Celik, 2023; Wang & Siau, 2022) confirms that ethical-relational concerns and fears tied to the impoverishment of the educational experience act as stable structural barriers, generating a form of passive resistance to innovation. This defensive posture—which prompts teachers to limit AI use strictly to cases of absolute necessity—is not an isolated phenomenon within this sample. Instead, it aligns with models of educational governance in which teacher hesitation represents a value-driven effort to preserve the centrality of intersubjective relationships and embodied dialogue in the face of pressures toward cold automation (Fullan et al., 2024).

5.2 The Teacher as a Pedagogical Director

The synthesis of percentage distributions and narrative findings confirms that technical ease of use alone is insufficient to ensure structured integration. Addressing teacher hesitation requires shifting training pathways toward a framework centered on the *Human-in-Command* paradigm (European Commission, 2019; Floridi, 2022).

In this paradigm, the educator does not passively accept probabilistic results and algorithmic biases but rather assumes the critical role of a pedagogical director. The teacher becomes a pedagogical director of care (Pellerey, 2024)—

an indispensable mediator capable of converting computational efficiency into emancipatory learning value (Floridi, 2022). As highlighted by the qualitative data regarding inclusion, AI can perform rapid and scalable content differentiation, yet it risks translating into cold instructional isolation or epistemic violence if stripped of human sensitivity.

The Human-in-Command principle dictates that the final evaluative judgment, the interpretation of errors, and the ethical validation of outputs must remain exclusive prerogatives of the human mind. Consequently, the teacher ceases to be a mere dispenser of standardized content, redefining their professional identity around instructional design skills, the evaluation of metacognitive processes, and education in the critical use of technological tools.

6. Conclusions

To address teacher resistance driven by ethical concerns over AI, this study proposes integrating a Digital Affective Literacy Model into ICT training for special education, fostering a balanced integration of technical, pedagogical, critical, and ethical-affective competencies. This approach articulates these integrated domains across three main axes:

- Algorithmic Ethics: Using prompt reverse engineering to critically analyze LLM outputs and identify systemic biases regarding neurodivergent students;
- Human-in-Command Design: Utilizing generative AI as an adaptive scaffolding tool for Individualized Education Plan (IEP) design, tailoring

content through special pedagogy mediators like alternative communication;

- Digital Empathy: Utilizing role-playing and case studies to counteract technological isolation, preserving pedagogical care and clinical listening.

Ultimately, this research contributes to the global debate on ethical AI adoption, demonstrating that effective educational governance relies on the harmonious synergy between technical fluency, pedagogical design, and socio-emotional and critical skills.

Although limited by an exploratory design and a non-probability sample from a single university, these boundaries outline future research opportunities. Longitudinal and experimental investigations are needed to evaluate the classroom effectiveness of this literacy model, tracking its direct impact on inclusion and the academic success of vulnerable students.

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