POST-CRITICAL MEDIA LITERACIES IN TEACHERS: IDENTIFY ABLEISM IN GENERATIVE AI AND EDUCATIONAL PRACTICES

COMPETENZE DI POST-CRITICAL MEDIA LITERACIES NEI DOCENTI: RICONOSCERE L'ABILISMO NELL'IA GENERATIVA E NELLE PRATICHE EDUCATIVE

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ABSTRACT
This study investigates how 163 support teachers engaged with generative AI to represent inclusive classrooms (Shew, 2023; Meyer et al., 2014). Through a mixed-method design, it analyzes their abilities to detect bias (decoding) and to guide AI outputs via prompts (encoding). Results highlight limited awareness of ableist patterns and the potential of "Post"-Critical Media Literacy (Kellner & Share, 2007) to foster inclusive, reflective AI use in education.

Lo studio analizza come 163 insegnanti di sostegno hanno utilizzato l'IA generativa per rappresentare una classe inclusiva (Shew, 2023; Meyer et al., 2014). Attraverso un disegno di ricerca mixed-method, sono state indagate le competenze di rilevare bias (decoding) e guidare l'output dell'IA (encoding). I risultati mostrano una limitata consapevolezza dell'abileismo e il potenziale della Post-Critical Media Literacy (Kellner & Share, 2007) per un uso inclusivo e critico dell'IA.

KEYWORDS
PCML; techno-ableism; teachers' competencies; AI literacy
PCML; techno-ableismo; competenze degli insegnanti; AI literacy

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Introduction

The advent of generative Artificial Intelligence in the classroom is not merely a technical upgrade; it inaugurates a new ecology of knowledge—a true “epistemic shift” that calls into question the very posture of teacher and learner alike. For years, schooling has operated—often unwittingly—under what we might term the dictatorship of the question: education has been gauged by the ability to retrieve the “right” piece of information, to craft the perfect search query, and more recently, to consult a virtual assistant. Yet in the post-digital age, “what matters is no longer *what* we ask the machine, but *what* we build *with* it” (Panciroli & Rivoltella, 2023a). This is precisely where Post-Critical Media Literacy (PCML) proves indispensable. Whereas “classical” critical media literacy focused on unmasking the power logics embedded in media texts, the post-critical perspective shifts the centre of gravity: from decoding pre-packaged messages to *designing* new responses through prompts that function as genuine acts of co-authorship. In other words, it is no longer enough to decipher AI-generated images or texts; we must master the art of questioning the machine generatively so that its output embodies inclusive and plural educational aims. Framed by this perspective, the present study poses two research questions: (1) To what extent do support teachers possess the competence to read AI-generated representations critically? (2) How effectively can they craft prompts that steer the algorithm toward inclusive instructional scenarios? To answer these questions, we developed a mixed questionnaire comprising a decoding section (image analysis) and an encoding section (prompt writing and refinement), which was administered to 163 teachers and educators. After outlining the theoretical background (Section 1-2) and the methodological design (Section 3-4), we present our findings (Section 5) and discuss their implications for a “pedagogy of the response,” capable of transforming AI from a mere content provider into a genuine cognitive partner in learning.

1. From Media literacy to Post-Critical Media Literacy

Media literacy has emerged from the broader field of Media Education, which refers to the educational process aimed at preparing citizens for a critical and competent use of media. Rooted in the second half of the 20th century, in response to the increasing pervasiveness of mass media in society, media education originally aimed to cultivate critical awareness of media texts, often emphasizing protectionist approaches focused on shielding young audiences from potentially harmful content (Buckingham, 2003; Masterman, 1985). By the 1990s, and the rise of digital media later in the early 21st century, the increasing democratization of media production and the diversification of media platforms brough the term *media literacy* to describe a broader set of competencies necessary for engaging with media in everyday life, such as accessing, analyzing, evaluating, creating, and acting media contents (Hobbs, 2010). This evolution marked a departure from passive consumption toward active and participatory engagement (Aufderheide & Firestone, 1993). A comprehensive and commonly shared definition was given by UNESCO (Grizzle et al., 2011), which summarizes media literacy as "the ability to read, analyze, evaluate and produce communication in a variety of media forms (e.g. television, print, radio, computers etc.)" (p. 188), although it is seen as a part of the wider framework of Media and Information Literacy.

While some authors focused on conceptually expanding the term with the new literacies specifically related to the use of digital technologies, online information management, cybersecurity, and participation in digital environments (Eshet, 2004; Martin & Grudziecki, 2006), others emphasized that media literacy is not only a set of technical skills, but a crucial cultural and social competence that allows people to actively engage in the public discourse (Kellner & Share, 2007, 2009; Livingstone, 2004). Kellner & Share (2007, 2009) proposed the Critical Media Education framework, which adds a further layer of complexity by emphasizing the necessity of questioning media content through the lens of power dynamics. They argue that critical media literacy needs to include the ability to reveal ideological, economic, and cultural structures that influence media production and representation. In this light, the skill of decoding becomes crucial: it implies the ability to detect and deconstruct biases related to gender, race, culture, social class, and disability, and to understand how media may reinforce stereotypes and systemic discrimination (Buolamwini & Gebru, 2018; Kellner & Share, 2007).

Today's context is increasingly described as "post-digital" (Cramer, 2014; Jandrić et al., 2018), a condition where digital technologies, artificial intelligence and smart objects are so deeply embedded in everyday life that distinctions between physical and digital activities become blurred, reshaping the ways we access, produce, and disseminate information. In this new landscape, Critical Media Literacy evolves into Post-Critical Media Literacy. While preserving the deconstructivity of the decoding component, PCML emphasizes encoding skills, the ability to consciously and ethically produce media content. Given the participatory nature of contemporary media environments, every individual is a potential media producer; it is therefore essential to recognize one's own biases in media creation, assess the social and cultural implications of media production, and engage responsibly with generative AI and other digital tools. In fact, as generative AI systems such as ChatGPT, DALL·E, and Midjourney become increasingly integrated into educational and communicative contexts, the need for AI literacy has grown significantly, particularly in the field of education (Panciroli & Rivoltella, 2023b). AI literacy refers to the ability to understand how AI works, critically interpret its outputs, and ethically engage with AI tools (Long & Magerko, 2020; Ng et al., 2021). Recent literature stresses that AI literacy must go beyond functional skills to include critical awareness of the socio-technical contexts in which AI systems operate: this includes recognizing algorithmic bias, questioning the neutrality of machine-generated content, and understanding the implications of surveillance and datafication inherent in many AI technologies (Veldhuis et al., 2025). In the context of Post-Critical Media Literacy, AI literacy becomes an essential dimension: users must be equipped not only to decode AI-generated media, but also to encode ethically responsible content using AI, both applying the lens of equality, diversity, inclusion and accessibility. This dual competency is crucial in light of the increasing accessibility of generative tools that allow individuals to contribute to the media landscape at scale. AI literacy, therefore, forms a foundational pillar for civic education, democratic participation, and digital justice in a society shaped by intelligent technologies.

1.1 Teachers' decoding and encoding competencies

The rise of generative AI in 2022–2023 led many teachers to experiment with these tools. In fact, the OECD report in 2023 found that most K-12 teachers had already used ChatGPT for their work: 40% use it weekly and 10% almost daily, and over 88% of them reported it had a positive impact on their teaching (OECD, 2023). However, formal policies and teacher training often lack on specific workshops on digital/AI skills. As the report continues, none of the 18 OECD countries surveyed had an official regulation on AI in education, and only half had issued even clear but non-binding frameworks on its use (OECD, 2023). The gap is evident: teachers are eager to use AI, but often feel unprepared and unsupported, especially on how to use the tools in classrooms (training, support, academic integrity and pedagogical control), and ethical issues (privacy, bias, teacher's role), as also confirmed by Sperling et al.

(2024). In this landscape, how can we define teachers' AI-literacy?
As we mentioned earlier, AI literacy requires specific technical, pedagogical and content knowledge to be applied and defined by a set of different skills (Ng et al., 2021). However, to draw an analogy to traditional literacy, teachers (and students) must be able to read and understand AI-generated media (decoding skills) and write or express ideas with AI (encoding skills). Decoding refers to a teacher's ability to critically understand and evaluate AI's outputs and workings. Decoding skills are strongly related to *data literacy*, the ability to interpret and draw insight from data, as well as understanding how AI works (including machine learning, neural networks and LLMs) (Sattelmaier & Pawlowski, 2023). On the other side, encoding competencies involve a teacher's ability to communicate with the AI or to create content in collaboration with it, through a prompt. According to Sattelmaier & Pawlowski (2023), encoding skills connect with basic programming or scripting abilities, or what is known as computational thinking in education: understanding how to break tasks into steps and give instructions to a computer. In sum, in a PCML perspective, decoding skills enable teachers to be critical consumers of AI, while encoding let them be active producers in ways that enhance learning, taking full advantage of the AI as complementary tool, and not replacing of the roles of teachers, as UNESCO's framework emphasizes (Miao & Cukurova, 2024). For this reason, decoding and encoding competencies are not just technical skills; they have deep pedagogical relevance. A teacher who can decode AI outputs will model critical thinking for students, but for teachers to impart that, they themselves must be able to dissect AI outputs and discuss their flaws or merits.

2. Beyond AI Neutrality: Algorithms, Ableist Representations, and new media Literacies.

The introduction of Artificial Intelligence (AI) into inclusive educational contexts offers innovative potential but simultaneously raises critical concerns regarding the cultural biases embedded within these systems. Although the prompts employed may appear neutral, AI algorithms tend to mirror the dominant data and narratives present in society, including those related to students with *Special educational needs* (SEN). As Noble (2018) highlights, algorithms are far from neutral and often perpetuate existing prejudices and inequalities. In other words, AI ends up privileging dominant perspectives (such as "normative" representations of ability) and marginalizing differences: an output generated for a generic educational case may disregard the presence of students with disabilities or portray them in stereotypical ways unless such characteristics are explicitly stated. For instance, a large-scale language model asked to describe “an ideal student in the classroom” might portray only a learner without disabilities, reflecting the implicit assumption that normalcy equates to the absence of SEN. Similarly, asking an AI to narrate the story of a student with autism might result in narratives that reproduce widespread clichés (the “isolated genius” or the “eternally problematic child”), a sign that simplified cultural representations of neurodiversity have been internalized by the model.

These phenomena illustrate how even seemingly neutral requests can lead to outcomes laden with implicit bias. Contemporary research on so-called algorithmic bias and algorithmic oppression has shown that automated systems often amplify stereotypes about marginalized groups (Noble, 2018; Benjamin, 2019). Benjamin (2019) warns that “technical fixes” can paradoxically reinforce the status quo rather than correct injustices: what the author terms the *New Jim Code* refers to the use of new technologies that mirror and reproduce existing inequities, even while being framed as more “objective” or “progressive” compared to past discriminatory practices (Benjamin, 2019; 2024). For AI to truly become a tool for inclusion—rather than an amplifier of prejudice—teachers must develop advanced competences in *Post-Critical Media Literacy*. This notion expands the concept of critical media literacy by emphasizing not only the critical decoding of AI-generated messages, but also the capacity for encoding—that is, the ability to actively intervene in content generation to enhance the representation of marginalized groups. Indeed, the term *post-critical* underscores a shift from analysis to design: it is no longer sufficient to merely deconstruct media messages; one must be able to construct new ones—more equitable and inclusive—by actively shaping the production of meaning.

As Kellner and Share (2007) emphasize, robust media literacy entails both the critical reading of media forms and the conscious production of new texts: it requires the ability to analyze codes, conventions, and stereotypes in media, as well as the competence to construct alternative narratives that challenge dominant ones. This dual dimension—decoding and encoding—aims to empower students and citizens, enabling them to actively participate in media culture rather than passively consume it. Applied to today’s generative AI context, this means that the teacher must act as both a critical filter and a co-creator of AI-mediated content. In this approach, critical vigilance is central: as Benjamin (2019) cautions, the mere absence of malicious intent is not a sufficient excuse when technological systems end up perpetuating inequalities. The teacher must therefore not assume that AI is "objective" or inherently fair: it is their responsibility to actively interrogate algorithmic results and to filter or correct outputs that are inappropriate in inclusive settings.

First, the critical decoding of AI-generated representations requires the teacher to scrutinize the material produced by algorithms with a keen eye. They must be able to detect distortions, omissions, or ableist biases in texts, images, or any output generated by AI. For instance, if an AI system proposes an educational case study in which all represented students are neurotypical and non-disabled, the critically literate teacher will recognize the unidimensionality of the scenario and problematize it. Similarly, when confronted with an automatically generated historical summary that ignores the contributions of individuals with disabilities, the teacher will be able to identify this omission and provide contextualization—either by supplementing the missing information themselves or by prompting the AI to revise the output. This phase of critical decoding draws on textual analysis and the recognition of ideological frames—well-established skills within traditional media literacy—yet applies them to the new artefacts produced by algorithms.

Second, the strategy of encoding implies that the teacher adopts proactive measures to guide AI production toward more equitable representation. This may include the careful crafting of prompts: by formulating detailed requests that anticipate inclusivity, teachers can steer AI to generate content that is more respectful of diversity. A conscious educator, rather than generically asking a system to create an exercise or example, may specify in the prompt the presence of students with SEN in positive and active roles, or explicitly request non-stigmatizing language. This pedagogical encoding practice leverages the malleability of generative models: for example, one could instruct a virtual assistant to explain a scientific concept using different learning modalities, offering visual descriptions and text alternatives for those with visual impairments, or using simple yet non-infantilizing language for students with cognitive disorders. In doing so, the teacher becomes a co-author of the material alongside the AI, directing it toward more inclusive outcomes. Indeed, literature highlights how the alternative production of representations can actively challenge narratives that would otherwise appear "natural" and unquestioned—a principle that, in this context, translates into reviewing and reformulating AI outputs to make them less tacitly ableist and more representative of the real heterogeneity found in classrooms.

These *post-critical literacy* competences among teachers also play a key role in transferring such sensibilities to students. A teacher trained in this regard will not only be able to correct biases in digital tools but also to engage students in critical dialogue around AI outputs, fostering their critical thinking. A poorly diversified output—for instance, a list of historical figures generated by AI that includes only Western men and no women or persons with disabilities—can become an opportunity for reflection: the teacher may encourage the class to question such absences and to fill the gaps, introducing female figures and protagonists with disabilities (e.g., scientists like Marie Curie or scientists with disabilities like Stephen Hawking) to enrich the narrative. For example, the class might discuss why a certain AI-generated story about a "special student" appears stereotypical, helping students to deconstruct such stereotypes and to imagine alternative, more respectful narratives.

In this way, AI becomes an object of analysis, not merely a source of information: the class learns to read algorithmic outputs consciously—an essential step to avoid uncritically delegating the construction of social imagery to AI. As Kellner and Share (2007) advocate, integrating critical media literacy—updated to reflect current technological contexts—into the school curriculum can foster greater democratization of knowledge and access, shaping teachers and learners who are capable of engaging with digital media (including AI) in a reflective and inclusion-oriented manner. It must also be noted that formal education has often failed to keep pace with media transformations: as a result, many teachers today may still lack competences in media literacy as applied to AI. A specific training—both pre-service and in-service—is thus necessary to develop critical digital literacy geared toward inclusion. Only by investing in teachers' preparation in this sense will it be possible to harness AI in education as a tool for empowerment and accessibility, while simultaneously avoiding the unintentional perpetuation of existing ableist biases.

2.1 Ableism, Compensation, and Equity

The use of educational technologies for students with special needs has traditionally followed a compensatory rather than an equitable logic. Digital tools are often employed to help individual students with disabilities approximate a normative performance standard, rather than transforming educational environments to be accessible from the outset. This approach, rooted in a medicalized framework, reinforces ableist assumptions by implying that the “problem” lies within the student rather than the system that fails to adapt. As Shew (2023) argues, this reflects *techno-ableism*: the misguided belief that technology can or should “fix” disability, rather than addressing the structural barriers that create exclusion in the first place.

A key risk of this approach is the implicit transfer of ableist expectations onto technologies themselves. When digital tools are designed merely to “compensate” for functional differences without questioning normative standards, they reproduce exclusion under the guise of innovation. This not only distorts the educational purpose of technology—reducing it to mere performance enhancement—but also undermines inclusive design principles such as those of the *International Classification of Functioning, Disability and Health* (ICF), which emphasize removing environmental barriers to enable meaningful participation (WHO, 2001).

Moreover, even when technologies aim to be inclusive, they often embed the perspectives and biases of their designers. Many “assistive” tools are created without the involvement of disabled people, resulting in products that fail to meet real needs. As Shew notes, people with disabilities are the true experts in the technologies that affect them, yet they are rarely included in design processes. This leads to devices that reflect normative imaginaries—aiming to normalize rather than accommodate—and to platforms that impose rigid models of learning, poorly suited to neurodiverse students.

This dynamic creates a double layer of *techno-ableism*: first, by assigning the burden of adaptation to the individual through technological compensation; second, by embedding ableist design assumptions into the tools themselves. As Benjamin (2019) warns with her concept of the *New Jim Code*, technological innovation often replicates existing inequalities while being framed as objective or progressive. Similarly, *techno-ableism* risks perpetuating exclusion in subtler forms under a “hi-tech” veneer.

To break this cycle, the focus must shift from correcting the individual to transforming learning environments. Inclusive education should adopt principles like *Universal Design for Learning* (Meyer et al., 2014), which view learner variability as the norm. Technologies that provide flexible, customizable interfaces—accessible texts, captions, audio descriptions—benefit all students without labeling some as “needy.” In this vision, AI becomes part of a genuinely inclusive educational ecosystem, not a compensatory add-on, but a tool to support multiple ways of learning and expressing potential.

3. Research and methods

This exploratory study investigates the AI literacy of K-12 support teachers and educators by analysing how they work with generative AI to portray classroom settings, detect ableist bias, and articulate criteria for inclusive representation. A convenience sample recruited via snowballing completed a two-part, semi-structured questionnaire.
Section 1 (Decoding) asked participants (a) to decide whether five classroom images were AI-generated or photographic, (b) to justify each decision, and (c) to select and explain which image they deemed most inclusive, thereby gauging their sensitivity to visual markers of ableism. *Section 2 (Encoding)* required them to (a) draft an initial prompt for an “inclusive classroom,” (b) iteratively refine that prompt until the resulting image matched their ideal, and (c) reflect on the choices made—capturing both their prompt-engineering strategies and their underlying inclusion criteria. Quantitative items (e.g., forced-choice recognitions and Likert scales) were processed in SPSS v25 with descriptive statistics, while qualitative, open-ended responses were thematically coded by two independent researchers who resolved discrepancies through discussion to ensure reliability. This mixed-methods design yields an integrated picture of current competencies, recurring challenges, and emergent practices that can shape future training programmes and pedagogical frameworks for AI-supported inclusive education.

3.1 Instrument: Decoding–Encoding Questionnaire

The survey was developed specifically for this study and was structured in two main sections, each targeting a distinct dimension of critical media literacy in relation to AI-generated content: decoding and encoding, starting from the existing frameworks in media literacy education (Hobbs, 2010; Kellner & Share, 2007), as well as recent proposals for AI literacy in teacher professional development (Ng et al., 2021; UNESCO, 2024).

Decoding section

Participants examined five classroom images (Fig. 1). For each image they were asked to: (a) decide whether it was AI-generated or a human photograph and (b) choose the image they considered most inclusive, briefly justifying their choice. These justifications were later recoded against sixteen pre-defined indicators of inclusive representation (e.g., disability visibility, gender balance, racial diversity).

Encoding section

Teachers then used a generative-AI platform (e.g., DALL·E or Midjourney) to create an image of an inclusive classroom. They reported: (a) their initial prompt, (b) the final prompt after any iterative refinements, and (c) a short self-reflection on the co-creation process. This task captured their prompt-design strategies and the extent to which inclusive-design principles were internalised.

Figure 1 - Set of images used for the Decoding section

4. Methods of Analysis

To analyze the open-ended responses, we conducted a thematic content analysis based on a set of pre-identified categories representing common ableist and representational biases frequently found in educational imagery. These categories were developed a priori, drawing on literature concerning visual representations of disability and diversity in educational contexts, as well as preliminary examination of a subset of AI-generated images. The list included 16 potential indicators of bias, such as: 1) Invisibility of disability (absence of individuals with disabilities); 2) Reduction of disability to visible/physical impairments; 3) Stereotypically compassionate or paternalistic portrayals; 4) Lack of representation of invisible disabilities; 5) Absence of assistive tools or technologies; 6) Disability represented only through one gender; 7) Ethnic homogeneity; 8) Unrealistic technological settings; 9) Teacher portrayed as sole source of knowledge; 10) Lack of observable student-teacher or peer interaction; 11) Disability portrayed as passive condition; 12) Absence of collaborative learning dynamics; 13) Lack of representation of ethnic minorities; 14) Non-inclusive classroom layout or spatial design; 15) Exclusive portrayal of female teachers; 16) Unrealistic physical proportions or distortions. Based on these categories, we developed a coding checklist that was used to systematically examine whether and how participants identified these elements in their responses. Each participant's text was coded for the presence or absence of references to the predefined bias indicators. This process allowed us to quantify patterns in the participants' critical reflection and to evaluate the extent to which they were able to detect problematic visual tropes related to inclusion, diversity, and representation in AI-generated educational images.

5. Results

5.1 Participants

The study involved a convenience sample of 163 participants working in K-12 education, mostly ranging from 31 to 50 years old, including in-service (26%) support teachers, in-training support teachers (87%) and in-service educators (13%) enrolled in professional training programs. All participants took part in one-session workshops focused on the use of generative AI in inclusive education. The workshops were held in Rome and Bologna during April 2025, and participation in the study was voluntary. Completion of the survey required approximately 30-40 minutes. Participants had diverse educational backgrounds and professional experience: 71% of teachers were already working, of which 52,5% had less than 5 years of experience in educational contexts. On the other hand, 66.7% of educators have worked in the field for more than 7 years. Informed consent was obtained from all participants, and ethical procedures were followed in accordance with institutional research guidelines. Table 1 below provides a summary of the key demographic and professional characteristics of the participants:

Characteristics	**Variables**	**%**
Job role	In-training support teachers	87.1
	In-service support teachers	26.9
	Educators	12.9
Age	Less than 30 years	18.4
	31-40	28.2
	41-50	38.7
	More than 50 years	14.7
Education	School-leaving certificate	19.6
	University degree	76.7
	PhD	3.7
Years of working	Less than 1 year	9.8
	1 year	2.5
	2-4 years	35.2
	5-7 years	25.4
	More than 7	27.0

Table 1 - Participants descriptives

To explore participants' knowledge of AI tools and their usage in daily life, an initial set of questions were included. Regarding which software they already knew, ChatGPT (43%), Gemini (24%) and Copilot (16%) were the AI tool most known by the participants, while Figure 2 shows how often they use AI for different purposes in everyday life. Teachers seem to be more inclined to use generative AI tools for personal support rather than for direct pedagogical purposes. Tasks such as improving their own writing process (49.7% sometimes; 24.5% often) and summarizing or simplifying texts for personal use (50.3% sometimes) are among the most frequently reported uses. Conversely, activities that involve direct student engagement, such as enhancing students' writing (58.3% never) or simplifying texts for students (42.3% never), are used far less frequently. Particularly underutilized is the application of AI for monitoring classroom learning processes, with 70.6% of respondents stating they never use AI for this purpose. This gap highlights the importance of providing teachers with training on AI in Education: not only to introduce AI tools, but also to help them exploring how these technologies can meaningfully support teaching and learning.

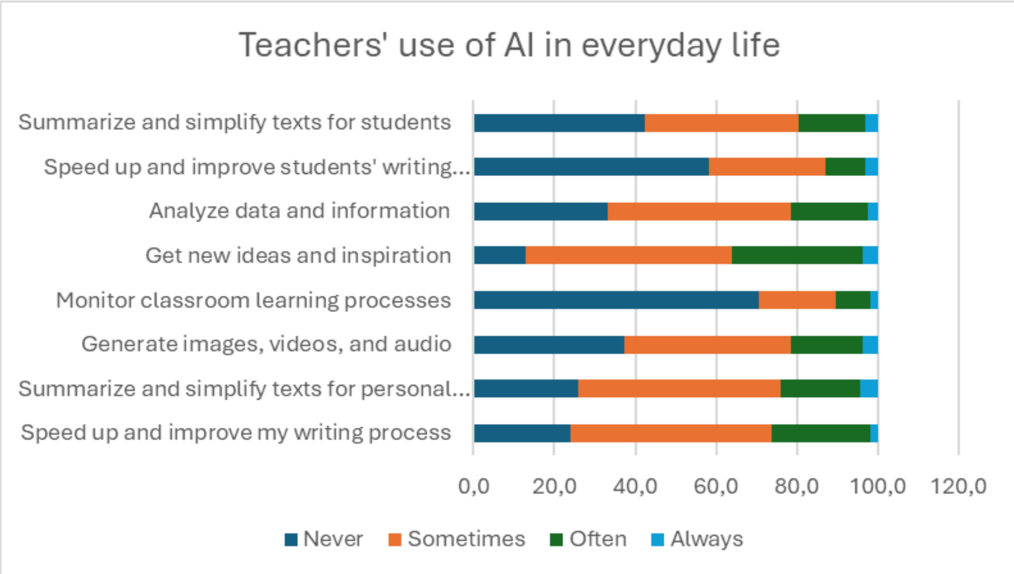

Figure 2 - Teacher's use of AI in everyday life

5.2 Decoding (A): AI or Human-generated?

In this step we asked participants to distinguish between AI and human-generated images, in order to assess an initial, foundational level of media literacy. Subsequently, by inviting participants to explain their choices, we aimed to explore a more advanced dimension: their capacity to *reflect critically* on the features, assumptions, and potential implications embedded in the content.
Regarding the first step, results suggest that certain AI images are, in 3 out 5 cases, easily recognized by *Unrealistic visual representations* (ranging from 81.3% to

93.9%), indicating that most teachers perceived the images as visually implausible or stylistically artificial. Some responses reported that “bodies seemed real, but colors are too vivid”, “the eyes look like plastic”, “strange proportions of hands” and other comments referring to “cartoonish,” “fake,” “surreal,” “plastic faces,” etc. However, Image 2 and Image 4 brought nearly all participants (93.1%) to misidentify them, due to their ambiguous or misleading visual cues. Interesting to note is that Image 2 was AI generated, recognized by 93.1% as photography, while Image 4 was an actual photography misread as AI. Regarding the criteria they used to depict if an image was AI generated or not, categories other than Unrealistic visual representation were mentioned less frequently. Another visual clue that made them question the authenticity of the image was the *Classroom layout or spatial design* (values ranging from 2.8% to 6.5%), with comments like “It looks like an activity actually carried out in class, but the classroom is too tidy”, “The arrangement of the desks isn’t that of a real school”, “The setting resembles a photographic studio” etc. “Disability represented only as physical impairment” was recognized on in Image 1, by 1.3%. The results are shown in Table 2.

	Img 1	***Img 2***	***Img 3***	***Img 4***	***Img 5***
Right	96.3%	6.9%	89.4%	46.9%	96.3%
Wrong	3.7%	93.1%	10.6%	53.1%	3.7%
Category					
Unrealistic visual representation	82,4 %	89,5 %	93,9 %	88,3 %	81,3 %
Non-inclusive classroom layout or spatial design	7,2 %	8,3 %	3,5 %	4,5 %	8,4 %
Absence of collaborative learning dynamics	6,5 %	0 %	0 %	0 %	2,8 %
Unrealistic technological equipment	2,6 %	0 %	0 %	6,3 %	5,6 %
Unrealistic proportions	0 %	2,3 %	2,6 %	0,9 %	1,9 %
Reduction of disability to visible/physical impairments	1,3 %	0 %	0 %	0 %	0 %

Table 2 - Decoding (A)

5.3 Decoding (B): Which image is the most inclusive?

When asked to select the image they perceived as most inclusive and explaining why, 42% preferred Image 1 (see Figure 3), mostly because of the classroom setting that allowed movement, interaction between peers, and the "presence of different solutions for different needs". Another interesting aspect they considered relevant was the personalization of the activity ("students are focused on doing different activities") and the active participation of everyone involved. The presence of the dog for pet-therapy and the teacher as facilitator was mentioned respectively 7 and 4 times. The presence of students with disabilities was mentioned in 6 cases.

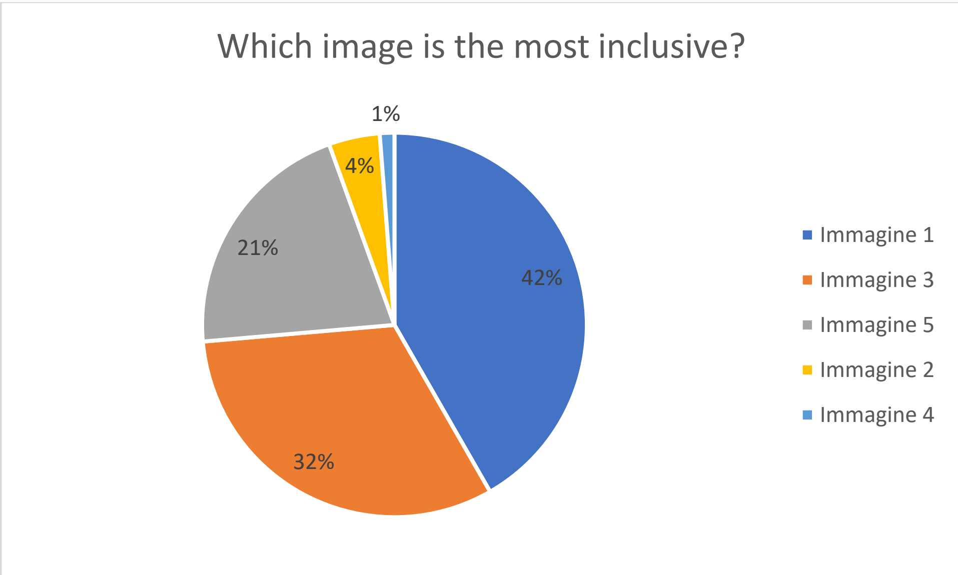

Figure 3 - The most inclusive image

Considering all of the responses, nearly one-third of the respondents (29.4%) identified the observable student-teacher or peer interaction as the main inclusive criteria, highlighting concerns regarding the relational dynamics within an ideal classroom. Similarly, the classroom layout or spatial design (23.9%) and collaborative learning dynamics (20.9%) were frequently cited, suggesting that participants evaluated inclusivity not merely on the basis of representational diversity, but also through the lens of pedagogical and spatial organization. Absence of assistive tools or technologies (17.8%) and Disability representation (17.2%) were also identified at relatively high rates. In contrast, Lack of representation of invisible disabilities (8.6%) further underscore the importance of both visual and cognitive visibility when evaluating inclusiveness. Other categories such as Teacher portrayed as the sole source of knowledge (3.7%), and various identity-based representational critiques (e.g., ethnic homogeneity, gender-specific portrayal of disability) were cited far less frequently. The results are better shown in Table 3.

Category	%
Observable student-teacher or peer interaction	29,40%
Inclusive classroom layout or spatial design	23,90%
Collaborative learning dynamics	20,90%
Assistive tools or technologies	17,80%
Disability (not) portrayed as passive condition	17,20%
Presence of individuals with disabilities)	16,60%
Representation of invisible disabilities	8,60%
Disability (not only as) visible/physical impairments	4,90%
Teacher portrayed as (not) sole source of knowledge	3,70%

Table 3 – Reasons why the image is considered inclusive

5.4 Decoding (C): Which biases did you encounter in the creation of your image?

The last task related to the decoding skill consisted in checking how many times they encountered biases during the iterative process of image creation through prompting (see Figure 4).

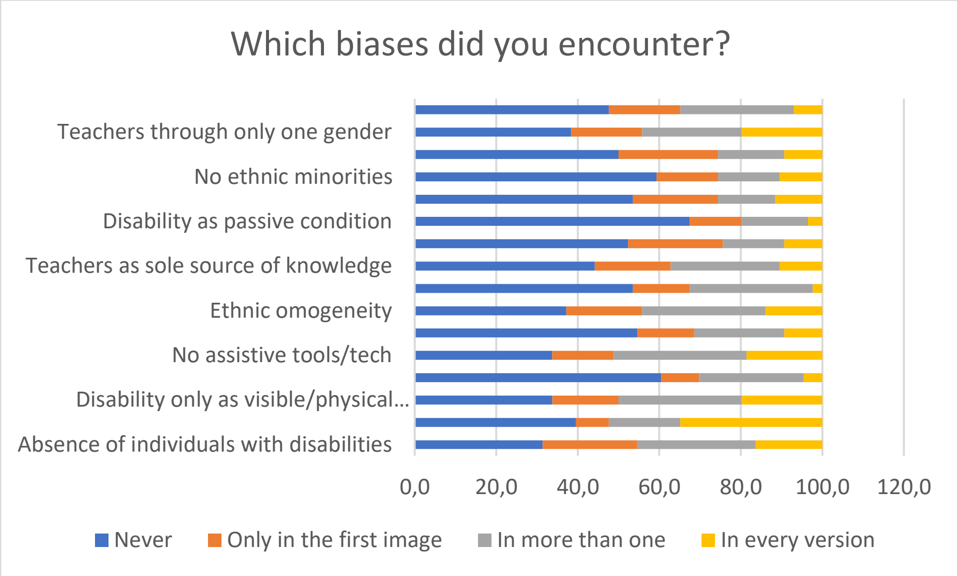

Figure 4 - Which bias did you encounter?

Notably, the *Absence of invisible disabilities* was reported in more than one or every version by a combined 51.2% of respondents, with a general *Absence of individuals with disabilities* similarly persistent, appearing in over 45% of cases. Equally concerning is the recurrent depiction of *Disability only as visible or physical impairments*, noted in 50% of responses across multiple or all versions. The *Lack of assistive tools or technologies* was also a significant theme, with 51.2% of respondents identifying this omission beyond the first image. Biases tied to *Ethnic homogeneity* (30.2% in more than one; 14.0% in every version) and the exclusive portrayal of *Teachers through one gender* (24.4%, and 19.8%) were also prevalent, suggesting limited variability in how the AI model interpreted diversity and roles within the classroom context. Conversely, some biases such as *Compassionate or paternalistic portrayals of disability* (only 9.3% across all non-zero categories) and disability represented through only one gender (8.1% in every version) appeared less frequently, though their presence remains significant in the broader context of inclusive representation.

5.5 Encoding (A): First prompt

The most frequently represented aspect, *Classroom setting* (34.6%), suggests that participants heavily associate inclusivity with the spatial and environmental configuration of the classroom. References to natural light, outdoor learning, flexible furniture arrangements (e.g., round tables, desks in clusters), and the presence of natural elements (e.g., gardens, trees, animals) indicate a preference for open, sensory-rich, and non-traditional learning environments. The second most cited category, *Presence of people with disabilities* (20.5%), demonstrates that participants were attentive to the inclusion of students with various impairments, though the relatively lower percentage compared to setting suggests that physical accessibility may be treated as a visual cue rather than a structural principle. This interpretation is reinforced by the lower percentage of prompts reflecting invisible disabilities (3.8%) or assistive technologies (15.4%), which are essential components of inclusive education but are harder to visualize or represent through AI.

Other categories such as *Ethnic diversity* (14.1%) and *Collaborative learning* (11.5%) appear with moderate frequency, showing some awareness of sociocultural and pedagogical dimensions of inclusion. Still, their underrepresentation compared to more “aesthetic” aspects (like classroom layout) may reflect either the limitations of generative models in capturing complex social dynamics, or users’ own conceptual framing of inclusion as primarily physical or environmental. The results are shown in Table 4.

Aspect	*%*	*Example*
Classroom setting	34.6%	Create an image of a classroom with desks arranged in clusters… Classroom with large windows and a garden outside… Inclusive lesson in a forest circle… Bright classroom with round tables… Class both indoors and outdoors with nature and animals…
Presence of people with disabilities	20.5%	Generate an image with 5 students (sensory disability, SEN, visually impaired…) Class with a student in a wheelchair and a blind girl… Outdoor education with visual/auditory/motor disabilities… Student with diplegia and peer with Charge syndrome… Student with motor disability and classmates using tablets…
Representation of tools/technologies	15.4%	Classroom with IWB and tablets for all… Teacher uses smartboard with AAC… Laptops on desks… Educational robot in the classroom… …
Ethnic diversity	14.1%	Class with multiethnic boys and girls… Strong migratory background… Chinese student and Italian classmates… Girl wearing a veil… …
Collaborative learning	11.5%	Cooperative learning in primary school… PBL in small groups… Group work with desks in clusters… Brainstorming in circle time… …
Gender representation	9.0%	Boys and girls sitting at desks…

Table 4 - Categories and examples of the first prompts

5.6 Encoding (B): Last prompt

While the overall number of responses analyzed was relatively low (n = 69) in comparison to those who submitted the initial prompt, this reduction may itself be meaningful. Several participants commented that they didn't' feel the need to modify their prompt, either because they considered the AI-generated image sufficiently inclusive or because they lacked confidence or strategies to refine it further. Among those who did reformulate, the most frequent pattern was a continued emphasis on *Visible or physical disabilities*, which appeared in 66.7% of final prompts. This reflects a persistent reliance on visually salient markers of inclusion, such as wheelchairs or mobility aids, perhaps because they are more easily imagined or rendered by AI. Surprisingly, *Compassionate or paternalistic portrayals* now appeared in around 22.7% of responses. Other representational tendencies include the explicit portrayal of Female teachers (33.3%), and the recurrence of prompts that presented the teacher as the sole source of knowledge or disability through only one gender, each appearing in 22.2% of prompts. Table 5 shows the results.

Category	%	Example
Reduction to physical impairments	66.7%	Could you generate an image that represents an inclusive learning moment with a boy in a wheelchair... Class with visible disability, such as a wheelchair...
Compassionate/paternalistic portrayals	55.6%	Generate an image in which classmates smile at the student with a disability... Welcoming classroom where others take care of the student...
Only female teachers	33.3%	A female teacher explaining at the blackboard... Female teacher at the interactive whiteboard...
Invisible disabilities	22.8%	Class with student with dyslexia and ADHD...
Disability represented only through one gender	22.7%	Disabled girl at the center of the scene...
Teacher as sole source of knowledge	22.2%	The teacher explains while the others listen...

Table 5 - Categories and examples of the last prompts

Conclusions

This synthesis revisits our research questions through the lens of Post-Critical Media Literacy (PCML), highlighting how teachers can engage with generative AI to challenge—rather than reproduce—ableist assumptions in education. Our findings reveal a notable asymmetry: while over 80% of participants could easily recognize visual cues of AI-generated images (e.g., plastic skin, unnatural lighting), fewer than 2% identified the erasure or stereotyping of disability within those same images. This reflects a well-documented tension in media literacy: surface-level decoding skills are widespread, yet they often fail to address the deeper ideological functions of media (Kellner & Share, 2007).

PCML addresses this gap by linking critical reading with intentional rewriting—or, in the case of AI, with prompting as encoding. Our data show that participants who iterated on their prompts progressively moved toward more inclusive representations: wheelchairs appeared, sensory-friendly layouts replaced rigid desks, and teaching roles became more collaborative. These shifts were not retroactive "fixes" but the result of conscious, proactive prompting. Theoretically, this process challenges what Shew (2023) calls techno-ableism—the belief that better tools will solve disability. Early iterations focused on improving realism, but inclusion emerged only when participants reframed the prompt itself (e.g., "a Deaf student signing with peers"). These choices represent a refusal to let the algorithm's default logic dictate social representation—a move Benjamin (2019) frames as resistance to the New Jim Code. Pedagogically, this shift has two main implications. First, it redefines AI tools not as prosthetics to help "catch up," but as design materials for accessible learning, aligning with Universal Design for Learning (UDL). Second, it positions teachers as co-authors of algorithmic meaning, inviting professional development that treats prompting as an ethical and political practice, not merely a technical one.

Future research should explore whether these practices persist over time, extend across media types, and evolve through co-design with disabled educators and students. Such approaches can push PCML from critique to genuine co-production of inclusive AI cultures.

Author contributions

Although the paper reflects the shared work of all authors, Marika Mascitti was responsible for the formal writing of Sections §1, §1.1, §5.1, §5.2, §5.3, §5.4; Salvatore Messina authored Sections §2, §2.1, §3, §3.1, §4, §5.5 and §5.6; and Chiara Panciroli contributed to §Introduction, §Conclusions and oversaw the final revision of the paper.

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