TEACHING IN THE AGE OF AI: MAPPING PRE-SERVICE SPECIAL EDUCATION TEACHERS' ORIENTATIONS BETWEEN RESISTANCE AND FASCINATION

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ABSTRACT
This study examines attitudes toward artificial intelligence in teaching and learning among 616 participants enrolled in a specialization program for special education support teaching. Survey results show that AI acceptance is associated with professional motivation, perceived competence, concerns about students' learning experiences, and the educational meaning attributed to technology. The research highlights the need for teacher education programs that support a critical and pedagogically grounded use of AI in inclusive contexts.

KEYWORDS
Teacher education; artificial intelligence in education; special education teachers;

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1. Introduction

The progressive diffusion of artificial intelligence (AI) is introducing significant changes in the processes by which knowledge is constructed, organized, and shared, influencing how information is selected, processed, and made available in educational contexts. In this scenario, schools are called upon to engage with tools capable of generating content, adapting teaching materials to students' needs, facilitating access to digital resources, and supporting the development of more flexible and inclusive learning environments (Holmes et al., 2019). However, the introduction of these systems does not merely represent a technological innovation; rather, it calls for broader reflection on the role of didactic mediation, on the modes of educational design, and on the conditions that enable each student to participate actively in learning processes, access knowledge, and experience meaningful educational pathways.

The potential of AI systems is particularly evident in their ability to design more personalized learning pathways, differentiate teaching materials, and provide more accessible resources that respond to the plurality of educational needs characterizing today's classrooms (Holmes & Tuomi, 2022; Toci et al., 2025). From this perspective, such tools may represent significant support for the construction of more flexible and inclusive learning contexts, capable of promoting the active participation of all students and enhancing their potential (Bruni & Murgia, 2025; Lamacchia et al., 2025; Pellegrini & Sebastiani, 2024). Their educational contribution, however, does not lie exclusively in their technological features, but in their capacity to be integrated into intentional, reflective instructional design aimed at valuing differences. In this sense, AI acquires genuine formative value only when it is mediated by teachers' professional competence and embedded within an educational relationship that guides its use critically and consciously (Nirchi et al., 2025).

From this perspective, the way teachers view artificial intelligence assumes central importance (Fiorucci & Bevilacqua, 2026). Indeed, Gordo-Vidal e Gordo-Herrera (2025) e Pelau et al. (2021) highlight how reactions to AI tools can involve both fascination and resistance, characterized on the one hand by curiosity, positive feelings, and satisfaction associated with interacting with intelligent technologies - which are intertwined with positive motivation toward such tools and a positive perception of AI - while resistance encompasses anxiety, distrust, a perceived loss of control, and concerns about their future implications, which can fuel professional anxieties and technoparanoia. This interplay is particularly relevant in the field of education, where the potential for innovation depends not only on access to advanced technologies but also on how teachers understand, evaluate, and integrate them into their professional practice (Belghouar, 2026). Indeed, the mere availability of technologically advanced tools is not, in itself, sufficient to generate innovation or improve the quality of teaching. What proves decisive is the meaning teachers attribute to such tools in light of their professional experiences, the beliefs constructed through educational practice, their perceived competence, and the conception that shapes the relationship between teaching, learning, and inclusion. For this reason, the acceptance of AI systems cannot be interpreted solely in terms of technical skills or access opportunities, but must also be considered in light of perceived usefulness, ease of use, and coherence with the educational aims being pursued (Ofem et al., 2025).

Among the theoretical models most widely used to understand technology adoption processes, the Technology Acceptance Model (TAM; Venkatesh & Davis, 2000) represents one of the most established frameworks. According to this approach, the propensity to use a technology mainly depends on two factors: Perceived Usefulness (PU), that is, the belief that the technology can contribute to improving one’s professional activity, and Perceived Ease of Use

(PEOU), which refers to the perceived simplicity with which it can be learned and used. These dimensions are associated with Behavioral Intention (BI), considered an important indicator of future adoption of the tool.

In educational contexts, however, these categories take on a broader meaning than a strictly functional reading would suggest. Perceived usefulness does not concern only operational efficiency but also the possibility of supporting meaningful learning, fostering the participation of all students, expanding accessibility, and improving the quality of instructional design. Similarly, ease of use does not simply coincide with the technical simplicity of the tool, but with its effective integration into everyday educational practice, without compromising teachers' decision-making role and professional responsibility. From this perspective, teachers tend to show greater willingness toward technologies perceived as useful, accessible, and coherent with their educational aims, especially when these technologies are regarded as tools supporting didactic mediation rather than as elements replacing professional action (Lamacchia et al., 2025; Ofem et al., 2025).

Alongside these aspects, some socio-demographic variables, including age, may also contribute to explaining differences in AI acceptance processes in school settings. The available evidence, however, remains limited: few studies have compared teachers belonging to different generational groups (Dumagay et al., 2025), while numerous investigations have focused mainly on the university context (Funa & Gabay, 2026; Yang & Li, 2026). In the Italian context, this gap appears particularly evident, especially with reference to inclusive teaching and special education support (Fiorucci & Bevilacqua, 2026). In any case, age cannot be interpreted as a direct indicator of openness or resistance to innovation; rather, it should be understood in light of professional experience, training opportunities, and the organizational cultures within which each teacher has developed their relationship with technology.

AI acceptance, moreover, does not depend solely on rational evaluation. The

complexity of these systems, their growing operational capacity, and the forms of interaction they make possible often generate articulated experiences in which interest and caution, trust and mistrust, the desire to experiment, and the need for control coexist and intertwine with teachers' professional identity. Attitudes toward AI are therefore shaped through a process in which the assessment of the tool's potential is confronted with the meaning attributed to the teaching role, educational responsibility, and representations of the relationship between the human and technological dimensions (Hazzan-Bishara, Kol & Levy, 2025; Sanusi et al., 2024). The decision to integrate or not integrate such systems into teaching practice thus appears to result from a complex interaction among cognitive, emotional, ethical, and professional factors (Farooq, 2025; Sultan et al., 2025; Wang et al., 2025). Resistance to AI can be interpreted as the expression of a relationship between technological innovation and teacher professionalism that is still being developed. Difficulty in understanding how algorithms work, fear of possible professional replacement, uncertainty about the autonomy of intelligent systems, and the perception of a progressive loss of control may foster attitudes of caution or mistrust (Tekin, 2024). In these cases, the issue does not concern the technology itself alone, but the way it is perceived in relation to the educational function, professional competence, and the responsibility to guide students toward a critical and conscious use of digital tools.

The rapid evolution of AI-based technologies may also generate feelings of inadequacy among teachers and the perception of a constant need for professional updating, especially when innovation processes are not accompanied by appropriate training pathways. The risk does not lie only in the non-use of such tools, but in the development of a defensive attitude toward technology, experienced as an element capable of challenging professional knowledge and control over the educational process. Added to this are pedagogical and ethical concerns related to the possibility that the immediacy

of the responses provided by intelligent systems may foster forms of cognitive dependence and poorly conscious delegation among students (Chounta et al., 2022). Unmediated use of AI could indeed limit the development of fundamental competences such as critical thinking, problem solving, and metacognitive reflection, all of which are essential for promoting autonomy, participation, and inclusion. When these fears become consolidated, technology risks being perceived as an element foreign to educational culture, to be avoided rather than critically explored (Qureshi et al., 2026).

This attitude, however, should not be considered immutable. The relationship between teachers and AI is continuously constructed and transformed through the interaction between factors that hinder innovation and conditions that foster its conscious and pedagogically oriented use (Sultan et al., 2025). Among the latter, particular importance is assumed by the possibility of recognizing AI as a resource serving the improvement of educational opportunities and the promotion of the common good (Chai et al., 2020; Lin et al., 2025). When teachers perceive intelligent technologies as having the potential to reduce barriers to learning, expand didactic mediators, and support personalized pathways for students with Special Educational Needs, attention tends to shift from the perception of threat to the appreciation of the opportunities offered. From this perspective, AI adoption assumes an educational and ethical value oriented toward the promotion of equity, participation, and accessibility.

A fundamental role in this process is played by teachers' capacity to exercise an active and reflective stance toward innovation. Welcoming new technologies means being able to interpret them critically, select them according to students' needs, adapt them to contexts, and integrate them within coherent instructional design. In this direction, intrinsic motivation represents an important lever, as it sustains interest in experimentation when it arises from professional curiosity and the search for increasingly effective and inclusive strategies (Yurt & Kaşarcı, 2025). For this willingness to translate into concrete

practice, however, a sense of self-efficacy is essential, understood as confidence in one's ability to pedagogically govern innovation. This belief enables teachers to view automation not as a threat to teacher professionalism but as a resource capable of expanding the possibilities of educational mediation (Tekin, 2024).

In light of these premises, this contribution presents the results of quantitative research aimed at examining the conditions that favor or hinder the pedagogically meaningful integration of AI in educational contexts, taking as its object of analysis the psychological and professional factors associated with its acceptance among teachers enrolled in a specialization program for special education support activities. Specifically, the research investigates the simultaneous contribution of AI-related resistance factors - Learning, Job Replacement, Sociotechnical Blindness, AI Configuration, Technical Proficiency, Job Displacement, Student Experience, and Techno-Paranoia - and positive motivational factors – AI for Social Good, Intrinsic Motivation, and Self-Efficacy - in predicting the three core dimensions of the Technology Acceptance Model: perceived usefulness, perceived ease of use, and behavioral intention to use AI. The research also examines differences among participants belonging to Generation Z (born between 1997 and 2012), Millennials (born between 1981 and 1996), and Generation X (born between 1965 and 1980) (Balon, 2024), with the aim of understanding whether and to what extent different generational cohorts and training pathways affect the way prospective special education teachers interpret AI as a possible resource for didactic mediation, accessibility, and school inclusion.

2. Methods

2.1.1 *Aim and Research Question*

The present study aimed to examine the psychological, motivational and attitudinal factors associated with participants' acceptance of AI in educational

contexts. Specifically, it examined how a positive orientation toward AI, conceptually related to fascination and assessed through Intrinsic Motivation and perceptions of AI for Social Good, and a resistant orientation, reflected in AI-related anxieties, fears, professional concerns, and techno-paranoia, together with AI-related Self-Efficacy, were associated with participants' perceived usefulness, perceived ease of use, and behavioral intention to use AI. Specifically, the study investigated the extent to which AI-related resistance factors–including Learning Anxiety, Job Replacement, Sociotechnical Blindness, AI Configuration, Technical Proficiency, Job Displacement, Student Experience, and Techno-Paranoia–and positive psychological and motivational factors, including perceptions of AI for Social Good, Intrinsic Motivation, and Self-Efficacy, were associated with perceived usefulness, perceived ease of use, and behavioral intention to use AI. In addition, the study explored whether these associations differed across generational cohorts (Gen Z, Millennials, and Gen X) through a structural invariance analysis.

2.2 *Participants*

The research sample consisted of 616 participants enrolled in a specialization program for special education support teaching. Participants' mean age was 37.1 years (*SD* = 9.43), with an age range of 19 to 61 years. The generational composition of the sample was heterogeneous: Millennials represented the largest group, accounting for 50.2% of the sample (n = 309), followed by Gen Z, which accounted for 27.9% (n = 172), and Gen X, which accounted for 21.9% (n = 135). With regard to gender, the sample was predominantly female: women represented 81% of participants (n = 499), men accounted for 18.2% (n = 112), and 0.8% of respondents did not specify their gender (n = 5). In terms of admission qualifications, most participants held a university degree (70.5%, n = 434), followed by those holding a technical-practical teacher diploma (ITP; 20.1%, n = 124), and those with qualifications from an Academy of Fine Arts or

a Music Conservatory (9.4%, n = 58). More than half of the participants were enrolled in the specialization pathway for upper secondary education (55.7%, n = 343), whereas 20.3% (n = 125) attended the pathway for primary school, 15.6% (n = 96) the pathway for lower secondary education, and 8.4% (n = 52) the pathway for pre-primary education. The sample included participants with heterogeneous professional backgrounds and different levels of teaching experience. At the time of data collection, 390 participants (63.3%) did not hold a teaching contract, 34 (5.5%) held a fixed-term teaching appointment, 91 (14.8%) held a teaching appointment in a curricular subject or general education post, and 101 (16.4%) held a special education support teaching appointment. Regarding teaching experience, 311 participants (50.5%) reported no previous years of service, 227 (36.9%) reported between 1 and 5 years, 54 (8.8%) between 6 and 10 years, and 24 (3.9%) more than 11 years of service. Thus, the sample comprised both individuals without previous teaching experience and in-service teachers.

2.3 ***Procedure and instruments***

Prior to data collection, the full research protocol was submitted to and approved by the Research Ethics Committee of "Kore University of Enna". The research was conducted in accordance with the ethical principles for research involving human participants and with the Declaration of Helsinki (2013). Participation was voluntary and anonymous. Electronic informed consent was obtained before completion of the questionnaire, after participants had been informed about the aims and procedures of the study, the handling of their data, and their right to withdraw at any time before submitting their responses. Data were collected via Google Forms over a two-month period and analyzed exclusively in aggregate form. Because all questionnaire items were mandatory, submitted questionnaires contained no item-level missing data.

The first section of the questionnaire collected sociodemographic information concerning age, gender, years of service, the specialization pathway attended, and the admission qualification required for enrolment in the course. All instruments were administered in Italian. The questionnaire developed by Lamacchia et al. (2025) was already available in Italian. Following Duffy (2006), measures for which no validated Italian version was available were translated into Italian and independently back-translated into the source language by a bilingual translator who did not have access to the original items. Discrepancies between the original and back-translated versions were resolved by consensus to ensure semantic and conceptual equivalence.

The Technology Acceptance Model (TAM) was adopted as the theoretical framework for examining participants' orientations toward AI in teaching and learning processes. Its three core dimensions were assessed using the questionnaire developed by Lamacchia et al. (2025), which was structured on the basis of the TAM. The questionnaire consists of 30 items rated on a 4-point Likert scale, ranging from 1 = strongly disagree to 4 = strongly agree. It includes three dimensions: *Perceived Usefulness* (PU; 10 items), which assessed the perceived usefulness of AI in supporting and improving instructional practice; *Perceived Ease of Use* (PEOU; 10 items), which examined the perceived ease of integrating AI tools into classroom management and lesson planning; and *Behavioral Intention* (BI; 10 items), which captured teachers' willingness to adopt AI in their professional practice. Subscale scores were computed as the mean of the corresponding items, with higher scores reflecting greater Perceived Usefulness, Perceived Ease of Use, and Behavioral Intention, respectively. No items required reverse scoring. In the present study, internal consistency coefficients were excellent for all dimensions: PU: $\alpha = .94$; PEOU: $\alpha = .93$; BI: $\alpha = .95$.

The *Artificial Intelligence Anxiety Scale* (AIA; Wang & Wang, 2022) was used to assess perceived discomfort and apprehension toward AI-based technologies

and products regarded as potentially beyond human control. The scale was adapted into Italian through the back-translation procedure. The 21-item scale is rated on a 7-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree, and comprises four dimensions: *Learning* (eight items), referring to the fear of not understanding how AI works; *Job Replacement* (six items), concerning fear of possible professional replacement; *Sociotechnical Blindness* (four items), referring to distorted perceptions of technological development and uncertainty about the autonomy of intelligent systems; and *AI Configuration* (three items), concerning fear that AI systems may escape human control. A mean score was calculated separately for each subscale, with higher scores indicating greater anxiety in the corresponding domain. No items required reverse scoring. In the present study, the subscales showed excellent internal consistency: Learning: $\alpha = .97$; Job Replacement: $\alpha = .93$; Sociotechnical Blindness: $\alpha = .91$; AI Configuration: $\alpha = .94$.

The *Teacher Artificial Intelligence Anxiety Scale* (TAIA; Liu & Liu, 2025) was employed to examine AI-related anxiety in relation to teachers' professional roles. The original instrument comprises 21 items organized into five distinct dimensions. In the present study, 14 items corresponding to three complete subscales were administered: *Technical Proficiency* (four items), which assessed anxiety related to mastering and adapting to new AI tools; *Job Displacement* (six items), referring to insecurity associated with the possible redefinition or replacement of the professional role; and *Student Experience* (four items), concerning worries about students' excessive dependence on AI and the consequent weakening of critical thinking skills. The Technological Support and Research Development subscales were not administered because they assess institutional support for AI use and AI-related research activities, respectively, which fell outside the scope of the present study. The analysis focused specifically on individual psychological and professional factors associated with AI acceptance in teaching and learning contexts. All items were

rated on a 7-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. A mean score was calculated separately for each subscale, with higher scores indicating greater anxiety in the corresponding domain. No items required reverse scoring. In the present study, reliability analysis indicated good to excellent internal consistency: Technical Proficiency: α = .86; Job Displacement: α = .90; Student Experience: α = .94.

The *Techno-Paranoia* subscale of the *Technophobia Scale* (Khasawneh, 2018) was used to assess suspicion, mistrust, and unjustified fears toward technology. The subscale consisted of five items rated on a 5-point Likert scale, ranging from 1 = disagree to 5 = agree, and examines the extent to which such apprehensions may contribute to technology-avoidance behaviors. A mean score was calculated, with higher scores indicating greater techno-paranoia. No items required reverse scoring. In the present study, the subscale showed good internal consistency: α = .87.

The *AI for Social Good* (SG) subscale (Sanusi et al., 2024) was used to examine the extent to which AI systems are perceived as tools oriented toward societal improvement. It consisted of four items rated on a 6-point Likert scale, ranging from 1 = strongly disagree to 6 = strongly agree. A mean score was calculated, with higher scores indicating a stronger perception of AI as contributing to social good. No items required reverse scoring. In the present study, the scale showed excellent internal consistency: α = .90.

Finally, intrinsic motivation and self-efficacy regarding AI in education were assessed through two subscales developed by Hazzan-Bishara, Kol & Levy (2025), both rated on a 7-point Likert scale, ranging from 1 = strongly disagree to 7 = strongly agree. The Intrinsic Motivation subscale (five items) examined the internal drive that supported teachers' exploration of AI tools, linked to personal satisfaction and professional alignment; the Self-Efficacy subscale (four items) assessed teachers' confidence in their ability to understand, use, and master these tools. A mean score was calculated separately for each

subscale, with higher scores indicating greater intrinsic motivation and AI-related self-efficacy, respectively. No items required reverse scoring. In the present study, both subscales showed excellent internal consistency: Intrinsic Motivation: $\alpha = .94$; Self-Efficacy: $\alpha = .92$.

2.4. Data Analysis

Statistical analyses were conducted using *Jamovi*, version 2.4. Descriptive statistics and distributional indices were computed for the study variables separately for Gen Z, Millennials, and Gen X. Before estimating the path model, potentially influential observations were assessed separately for each outcome equation using Cook's distance, with values greater than 1 considered potentially influential (Cook, 1977). Multicollinearity was evaluated using variance inflation factor (VIFs) and tolerance statistics, both in the overall sample and separately within each generational cohort. VIF values below 5 (Kim, 2019) and tolerance values above .20 (Kutner et al., 2005) were adopted as reference criteria. Bivariate associations among the variables were analyzed using Pearson correlation coefficients. A multi-group path analysis was conducted using the SEMLj module for jamovi, with generational cohort (Gen Z, Millenials, and Gen X) specified as the grouping variable. All variables included in the model were treated as observed composite scores, calculated as the mean of the items comprising the corresponding scale or subscale. The 11 AI-related resistance, psychological, and motivational factors were entered simultaneously as predictors of perceived usefulness, perceived ease of use, and behavioral intention to use AI, resulting in 33 structural regression paths. Model parameters were estimated using maximum likelihood (ML) estimation with the NLMINB optimization algorithm. Ninety-nine percent bias-corrected bootstrap confidence intervals were obtained using 10,000 bootstrap resamples. The statistical significance of individual structural coefficients was evaluated at $\alpha = .01$. Potential differences across generational groups were

examined by comparing an unconstrained model, in which all 33 regression coefficients and the three residual covariances among the outcome variables were freely estimated in each group, with a structurally constrained model, in which these parameters were constrained to equality across groups. The unconstrained model was saturated and therefore had zero degrees of freedom. Imposing equality constraints on the 33 regression coefficients and three residual covariances resulted in 72 degrees of freedom in the constrained model. Model fit was evaluated using the chi-square statistic (χ^2), the Comparative Fit Index (CFI), the Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR). Structural invariance was evaluated through likelihood-ratio chi-square difference tests and changes in the CFI (ΔCFI). A decrease in CFI of .010 or greater was considered indicative of a potential deterioration in model fit.

3. Results

3.1 *Descriptive statistics and path analyses*

Univariate descriptive statistics for Gen Z (n = 172), Millennials (n = 309), and Gen X (n = 135) are reported in Table 1. Skewness and kurtosis values were overall adequate, indicating that the distribution of the variables was suitable for the subsequent analyses. Cook's distance ranged from approximately zero to .032 for PU,.036 for PEOU, and.089 for BI. Thus, no observation exceeded the prespecified threshold of 1. In the overall sample, VIF values ranged from 1.72 to 4.54 and tolerance values ranged from .220 to .581. Across the cohort-specific analyses, VIF values ranged from 1.59 to 4.88 and tolerance values from .205 to .629. These findings indicated that neither influential observations nor problematic multicollinearity were evident according to the prespecified criteria (Kim, 2019; Kutner, 2005). Nevertheless, the VIF values at the upper end of the observed range indicated non-negligible shared variance among

some predictors. Accordingly, the unique effects of individual predictors coefficients in the multivariate models were interpreted cautiously.

Table 1: Descriptive Statistics Across Generational Cohorts

Variable and Cohort	***N***	***M (SD)***	**[Min, Max]**	**Skewness (SE)**	**Kurtosis (SE)**
Perceived Usefulness					
Gen Z	172	3.11 (0.55)	[1.70, 4.00]	0.05 (0.19)	-0.35 (0.37)
Millennials	309	3.04 (0.61)	[1.00, 4.00]	-0.40 (0.14)	0.43 (0.28)
Gen X	135	2.99 (0.56)	[1.30, 4.00]	0.16 (0.21)	0.17 (0.41)
Perceived Ease of Use					
Gen Z	172	2.90 (0.54)	[1.20, 4.00]	0.12 (0.19)	0.54 (0.37)
Millennials	309	2.79 (0.59)	[1.00, 4.00]	-0.01 (0.14)	0.15 (0.28)
Gen X	135	2.76 (0.57)	[1.40, 4.00]	0.41 (0.21)	0.11 (0.41)
Behavioral Intention					
Gen Z	172	3.18 (0.54)	[1.11, 4.00]	-0.35 (0.19)	0.65 (0.37)
Millennials	309	3.07 (0.64)	[1.00, 4.00]	-0.57 (0.14)	0.47 (0.28)
Gen X	135	3.05 (0.55)	[1.00, 4.00]	-0.22 (0.21)	1.04 (0.41)
Learning					
Gen Z	172	2.86 (1.45)	[1.00, 7.00]	0.74 (0.19)	0.02 (0.37)
Millennials	309	2.84 (1.53)	[1.00, 7.00]	0.61 (0.14)	-0.38 (0.28)
Gen X	135	3.19 (1.58)	[1.00, 7.00]	0.35 (0.21)	-0.66 (0.41)
Job Replacement					
Gen Z	172	4.60 (1.57)	[1.00, 7.00]	-0.43 (0.19)	-0.59 (0.37)
Millennials	309	4.80 (1.62)	[1.00, 7.00]	-0.63 (0.14)	-0.33 (0.28)
Gen X	135	4.58 (1.63)	[1.00, 7.00]	-0.53 (0.21)	-0.48 (0.41)
Socio-Technical Blindness					
Gen Z	172	4.72 (1.58)	[1.00, 7.00]	-0.35 (0.19)	-0.64 (0.37)
Millennials	309	5.03 (1.62)	[1.00, 7.00]	-0.74 (0.14)	-0.11 (0.28)
Gen X	135	5.02 (1.58)	[1.00, 7.00]	-0.91 (0.21)	0.29 (0.41)
AI Configuration					
Gen Z	172	3.72 (1.80)	[1.00, 7.00]	0.09 (0.19)	-1.04 (0.37)
Millennials	309	3.87 (1.80)	[1.00, 7.00]	0.03 (0.14)	-0.90 (0.28)
Gen X	135	4.00 (1.82)	[1.00, 7.00]	-0.07 (0.21)	-1.08 (0.41)
Technical Proficiency					
Gen Z	172	3.09 (1.41)	[1.00, 7.00]	0.49 (0.19)	-0.37 (0.37)
Millennials	309	3.07 (1.46)	[1.00, 7.00]	0.51 (0.14)	-0.22 (0.28)
Gen X	135	3.51 (1.47)	[1.00, 7.00]	0.17 (0.21)	-0.47 (0.41)
Job Displacement					
Gen Z	172	3.40 (1.43)	[1.00, 7.00]	0.25 (0.19)	-0.62 (0.37)

Millennials	309	3.44 (1.44)	[1.00, 7.00]	0.25 (0.14)	-0.35 (0.28)
Gen X	135	3.41 (1.54)	[1.00, 7.00]	0.39 (0.21)	-0.54 (0.41)
Student Experience					
Gen Z	172	4.66 (1.66)	[1.00, 7.00]	-0.38 (0.19)	-0.74 (0.37)
Millennials	309	5.14 (1.72)	[1.00, 7.00]	-0.80 (0.14)	-0.19 (0.28)
Gen X	135	5.00 (1.70)	[1.00, 7.00]	-0.86 (0.21)	-0.11 (0.41)
Techno-Paranoia					
Gen Z	172	3.10 (1.06)	[1.00, 5.00]	-0.20 (0.19)	-0.58 (0.37)
Millennials	309	3.26 (1.10)	[1.00, 5.00]	-0.26 (0.14)	-0.64 (0.28)
Gen X	135	3.19 (1.10)	[1.00, 5.00]	-0.23 (0.21)	-0.78 (0.41)
AI for Social Good					
Gen Z	172	4.40 (1.09)	[1.25, 6.00]	-0.43 (0.19)	-0.41 (0.37)
Millennials	309	4.53 (1.13)	[1.00, 6.00]	-0.72 (0.14)	0.10 (0.28)
Gen X	135	4.68 (1.08)	[1.00, 6.00]	-1.06 (0.21)	1.23 (0.41)
Intrinsic Motivation					
Gen Z	172	5.15 (1.34)	[1.20, 7.00]	-0.36 (0.19)	-0.62 (0.37)
Millennials	309	5.22 (1.43)	[1.00, 7.00]	-0.69 (0.14)	0.08 (0.28)
Gen X	135	5.27 (1.26)	[1.00, 7.00]	-0.53 (0.21)	-0.08 (0.41)
Self-Efficacy					
Gen Z	172	5.26 (1.18)	[2.00, 7.00]	-0.32 (0.19)	-0.66 (0.37)
Millennials	309	5.17 (1.38)	[1.00, 7.00]	-0.52 (0.14)	-0.34 (0.28)
Gen X	135	5.04 (1.33)	[1.00, 7.00]	-0.45 (0.21)	-0.19 (0.41)

Note. *N = sample size; M = mean; SD = standard deviation; Min = minimum; Max = maximum; SE= standard error.*

The bivariate correlation analysis (Table 2) showed a coherent pattern of associations among the study dimensions. The three components of the TAM–PU, PEOU, and BI– were positively and significantly associated with one another. Specifically, PU was strongly related with both PEOU ($r = .623$, $p < .01$) and BI ($r = .795$, $p < .01$), and PEOU was also positively associated with BI ($r = .568$, $p < .01$). These findings showed that participants' willingness to integrate AI into their instructional practice was closely linked to their perceptions of its usefulness and operational accessibility. The TAM dimensions were also positively associated with Intrinsic motivation, self-efficacy, and AI for Social Good. This pattern may suggest that participants' openness to using AI was related not only to their functional evaluation of these tools but also to their perceived as consistent with professional practice and broader educational aims. Conversely, variables related to resistance toward AI were negatively associated with the TAM dimensions. In particular, lower PEOU was associated with greater concerns about technical mastery, professional replacement, and difficulties in understanding how AI works. PU and BI were also negatively associated with some resistance dimensions. Participants reporting greater

technological anxiety and professional concerns tended to report lower perceived usefulness and behavioral intention, whereas concerns about students' experience were specifically associated with lower perceived usefulness. The resistance dimensions were also strongly interconnected, with the strongest associations concerning fears of professional replacement, distorted representations of technological development, perceived loss of control, and concerns about the impact of AI on students' experience. Finally, age showed a positive, although modest, correlation with Technical Proficiency ($r = .115$, $p < .01$).

Table 2: *Bivariate Pearson Correlation Matrix (N=616)*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. PU	—													
2. PEOU	.623*	—												
3. BI	.795*	.568*	—											
4. Learning	-.067	-.145*	-.119*	—										
5. Job replacement	-.098	-.117*	-.067	.336*	—									
6. Sociotechnical Blindness	-.076	-.147*	-.031	.295*	.851*	—								
7. AI Configuration	-.050	-.095	-.060	.478*	.611*	.642*	—							
8. Technical Proficiency	-.134*	-.218*	-.125*	.673*	.398*	.411*	.511*	—						
9. Job Displacement	-.125*	-.156*	-.126*	.584*	.547*	.519*	.585*	.720*	—					
10. Student Experience	-.133*	-.140*	-.068	.201*	.681*	.704*	.427*	.393*	.513*	—				
11. Techno-Paranoia	-.083	-.085	-.088	.362*	.617*	.589*	.577*	.443*	.644*	.516*	—			
12. AI for Social Good	.433*	.259*	.475*	-.043	-.010	.018	-.049	-.051	-.043	.074	.021	—		
13. Intrinsic Motivation	.537*	.376*	.629*	-.121*	-.031	-.003	-.107	-.130*	-.124*	.041	-.016	.642*	—	
14. Self-Efficacy	.484*	.507*	.562*	-.208*	-.061	-.029	-.110	-.245*	-.177*	-.003	-.037	.530*	.793*	
15. Age	-.036	-.074	-.063	.094	-.037	.044	.067	.115*	.017	.066	.032	.092	.044	-.047

Note. *PU = Perceived Usefulness; PEOU = Perceived Ease of Use; BI = Behavioral Intention. * p <.01*

To examine whether the relationships among the variables differed across generational cohorts, the structural invariance of the model was tested across

Gen Z, Millennials, and Gen X. In the unconstrained model, the 33 regression coefficients and the three residual covariances among BI, PU, and PEOU were freely estimated in each group. This model was saturated [χ^2 (0) = 0.00, CFI = 1.000, RMSEA = .000, and SRMR = .000]. In the structurally constrained model, the same parameters were constrained to equality across the three groups. The constrained model showed good fit [χ^2 (72) = 84.72, p = .145, CFI = .991, RMSEA = .030, SRMR = .029]. The likelihood-ratio chi-square difference test was not statistically significant [$\Delta\chi^2$ (72) = 84.72, p = .145], and the decrease in CFI remained below the adopted threshold (ΔCFI = .009). Thus, imposing equality constraints did not produce a statistically significant deterioration in model fit, supporting structural invariance across the three groups. However, because ΔCFI was close to .010, this finding should be interpreted cautiously. The coefficients reported in Table 3 were obtained from the structurally constrained model. Because equality constraints were imposed on the unstandardized regression coefficients, the unstandardized estimates (B), z statistics, and p values were common across the three generational cohorts. Group-specific standardized coefficients (β) were also reported for Gen Z, Millennials, and Gen X. These standardized coefficients could differ across groups because they were calculated using the group-specific variances of the predictors and outcome.

Given that the model comparison did not provide evidence of structural differences across the three cohorts, the common unstandardized regression coefficients from the structurally constrained model were interpreted. With regard to BI, Intrinsic Motivation was positively associated with it (B = .114, SE = .018, p < .001). None of the AI-related resistance dimensions was significantly associated with BI. With regard to PU, significant associations emerged both with positive motivational factors and with some concerns related to students' use of AI. Intrinsic Motivation (B = .161, SE = .022, p < .001), AI for Social Good (B = .080, SE = .019, p < .001) and self-efficacy (B = .063, SE = .022, p = .004)

were positively associated with PU. Conversely, concerns related to Student Experience – particularly excessive dependence on AI and the possible weakening of critical thinking – were negatively associated with PU (B = −.046, SE = .014, p = .001). Regarding PEOU, Self-Efficacy showed a significant positive association (B = .229, SE = .025, p < .001). Thus, greater confidence in one's ability to understand and use AI tools was associated with greater perception of their operational accessibility. Conversely, Sociotechnical Blindness was negatively associated with PEOU (B = −.068, SE = .026, p = .009), indicating that unclear or distorted representations of AI functioning and technological development were associated with lower perceived ease of use.

Table 3: Multi-Group Path Estimates from the Structurally Constrained Model Across Generational Cohorts (N = 616).

Outcome	Predictor	B[99% CI]	SE	z	p	β (Gen Z)	β (Millennials)	β (Gen X)
BI	Learning	-0.029[-.060, .003]	0.012	-2.390	.017	-0.070	-0.074	-0.081
	Job Replacement	-0.012 [-.057, .032]	0.017	-0.695	.487	-0.030	-0.031	-0.033
	Sociotechnical Blindness	0.033 [-.012, .085]	0.017	1.892	.058	0.086	0.088	0.092
	AI Configuration	0.004 [-.025, .036]	0.011	0.403	.687	0.013	0.013	0.014
	Technical Proficiency	0.025 [-.015, .064]	0.015	1.679	.093	0.058	0.060	0.065
	Job Displacement	0.001 [-.040, .044]	0.016	0.088	.930	0.003	0.003	0.004
	Student Experience	-0.002 [-.034, .028]	0.012	-0.129	.897	-0.004	-0.004	-0.005
	Techno-Paranoia	-0.035 [-.079, .010]	0.017	-2.024	.043	-0.062	-0.064	-0.069
	AI for Social Good	0.020 [-.021, .063]	0.016	1.316	.188	0.037	0.038	0.039
	Intrinsic Motivation	**0.114** [.069, .161]	**0.018**	**6.237**	**<.001**	**0.252**	**0.268**	**0.253**
	Self-Efficacy	0.001 [-.045, .048]	0.018	0.045	.965	0.002	0.002	0.002
PU	Learning	0.015 [-.025, .054]	0.015	1.011	.312	0.039	0.038	0.044
	Job Replacement	-0.025 [-.078, .027]	0.020	-1.242	.214	-0.070	-0.068	-0.076
	Sociotechnical Blindness	0.047 [-.007, .101]	0.021	2.198	.028	0.130	0.124	0.136
	AI Configuration	0.021 [-.012, .054]	0.013	1.536	.125	0.065	0.061	0.069
	Technical Proficiency	-0.001 [-.050, .048]	0.019	-0.032	.974	-0.001	-0.001	-0.002
	Job Displacement	-0.002 [-.054, .048]	0.020	-0.108	.914	-0.005	-0.005	-0.006
	Student Experience	**-0.046** [-.084, -.012]	**0.014**	**-3.235**	**.001**	**-0.136**	**-0.131**	**-0.145**
	Techno-Paranoia	-0.024 [-.082, .034]	0.022	-1.105	.269	-0.044	-0.043	-0.048
	AI for Social Good	**0.080** [.031, .129]	**0.019**	**4.298**	**<.001**	**0.154**	**0.150**	**0.160**
	Intrinsic Motivation	**0.161** [.104, .219]	**0.022**	**7.508**	**<.001**	**0.380**	**0.379**	**0.375**
	Self-Efficacy	**0.063** [.006, .120]	**0.022**	**2.875**	**.004**	**0.132**	**0.144**	**0.155**
PEOU	Learning	-0.006 [-.053, .041]	0.018	-0.301	.764	-0.014	-0.015	-0.016
	Job Replacement	0.036 [-.028, .101]	0.025	1.438	.150	0.097	0.100	0.105
	Sociotechnical Blindness	**-0.068** [-.135, -.001]	**0.026**	**-2.608**	**.009**	**-0.184**	**-0.188**	**-0.191**
	AI Configuration	0.028 [-.013, .069]	0.016	1.706	.088	0.086	0.086	0.091
	Technical Proficiency	-0.035 [-.092, .023]	0.022	-1.577	.115	-0.086	-0.089	-0.093
	Job Displacement	0.018 [-.044, .082]	0.024	0.765	.444	0.045	0.045	0.051
	Student Experience	-0.029 [-.075, .018]	0.018	-1.673	.094	-0.084	-0.087	-0.090
	Techno-Paranoia	-.001 [-.068, .066]	0.026	-0.033	.974	-0.002	-0.002	-0.002
	AI for Social Good	0.016 [-043, .075]	0.023	0.704	.482	0.030	0.032	0.031
	Intrinsic Motivation	-0.019 [-.087, .049]	0.026	-0.731	.465	-0.044	-0.047	-0.043
	Self-Efficacy	**0.229** [.165, .294]	**0.025**	**9.044**	**<.001**	**0.465**	**0.544**	**0.546**

Note. *B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient; BI = behavioral intention; PU = perceived usefulness; PEOU = perceived ease of use. Unstandardized regression coefficients were constrained to equality across Gen Z, Millennials, and Gen X; consequently, B, SE, z, and p-*

value are common across groups. Standardized coefficients were calculated using group-specific variances and may therefore differ across cohorts. Statistical significance was evaluated at α=.01. Significant effects are shown in bold. 99% bias-corrected bootstrap confidence intervals were based on 10,000 resamples.

4. Discussion

The research examined the orientations toward the integration of AI into teaching and learning processes among participants enrolled in a specialization program for special education support teaching, outlining a picture in which openness to these tools cannot be reduced to a single dimension. Rather, in the present study, AI acceptance was associated with professional motivation, perceived competence, representations of technology, and attention to its possible educational implications. The issue, therefore, may not simply concern the acceptance of innovative applications, but also the meaning that course participants attribute to AI systems within instructional design, educational mediation, and the construction of genuinely inclusive learning environments.

In this direction, a first relevant finding concerns the absence of detectable structural differences among Gen Z, Millennials, and Gen X in the relationships between motivational factors, resistance factors, and orientations toward AI. Although this finding suggests that the associations examined were broadly similar across the three groups in the present study, it should not be interpreted as evidence of general equivalence among generations. The findings, however, may suggest that moving beyond an interpretation of innovation based primarily on age, according to which greater or lesser openness to digital technologies would depend almost automatically on generational membership. In the sample examined, the orientations toward AI appeared instead to cut across different generational cohorts and to be associated with more specifically professional and psychological factors, such as perceived competence, the value attributed to technological tools, concerns regarding students, and the ability to integrate these tools into a thoughtful and controlled teaching practice consistent with educational aims.

Within this framework, intrinsic motivation assumes particular significance. Intrinsic motivation emerged as the only variable positively associated with behavioral intention. More specifically, course participants' intention to integrate AI systems was associated with a personal and professional disposition toward exploring, experimenting with, and learning to use new tools. Interest in AI, therefore, may not be limited to a technical evaluation but may also be related to the possibility of recognizing these systems as a form of support consistent with one's view of teaching and the aims of inclusive education (Bruni & Murgia, 2025; Lamacchia et al., 2025). Course participants might therefore be more inclined to approach AI when it is perceived neither as a tool external to the teaching profession nor as a demand imposed by technological innovation, but as a resource that could become part of the teacher's professional repertoire, provided that it is understood, selected, and pedagogically mediated (Chounta et al., 2022; Hazzan-Bishara, Kol & Levy, 2025). However, this openness does preclude the presence of fears and resistance (Gallese, Moriggi & Rivoltella, 2025), which may continue to characterize the relationships with technologies perceived as complex, rapidly evolving, and not always fully transparent. Concerns about understanding how AI systems work, technical mastery, the possible redefinition of the teaching role, or professional replacement may express a form of caution that cannot be dismissed as a simple rejection of innovation (Qureshi et al., 2026; Wang et al., 2025). Rather, they point to the potential need to accompany engagement with AI through training pathways capable of making these tools understandable and pedagogically manageable (Pellegrini & Sebastiani, 2024). In the present model, however, these resistance dimensions were not significantly associated with participants' willingness to use AI. Instead, this willingness was more closely associated with the recognition of AI's educational and professional value. Perceived usefulness can also be situated within this perspective. Perceived usefulness was positively associated with intrinsic motivation, self-

efficacy, and perceptions of AI as contributing to social good. These findings may suggest that participants who expressed greater interest in AI, greater confidence in their ability to use it, and stronger perceptions of its potential social value also may tend to regard it as more useful for educational practice. In particular, the association with perceptions of AI as a tool oriented toward social good may indicate that its perceived usefulness was related not only to operational effectiveness and opportunities of explore and experiment with new tools, but also to broader educational and social purposes, such as accessibility, the diversification of didactic mediators (Galli, 2025), and student participation. In this sense, the usefulness of AI may not be understood as an intrinsic quality of the tool, but as a possibility that takes shape when technology is embedded within intentional instructional design, capable of orienting its use toward inclusion and the quality of the educational experience (Toci et al., 2025; Yurt & Kaşarcı, 2025). Alongside this openness, however, concerns also emerged regarding the implications of AI use for students' experiences. In the present study, concerns about students' experiences were negatively associated with perceived usefulness; meaning that participants who expressed greater concern about students' excessive reliance on AI and the potential weakening of critical thinking tended to report lower perceived usefulness. This association may reflect concerns that inadequately mediated AI use could be related with forms of dependence, weakened critical thinking, or reduced metacognitive autonomy, calling for a clear distinction between support and substitution. From a pedagogical perspective, these findings underscore the importance of distinguishing between uses of AI that support students' participation and autonomy and uses that might encourage excessive delegation (Holmes et al., 2019; Holmes & Tuomi, 2022). Indeed, making content, materials, and learning pathways more accessible does not mean depriving pupils of opportunities for personal elaboration, choice, and reflection, but rather creating conditions that enable them to participate more

consciously and actively in the learning experience. AI could therefore represent a resource for inclusive education when it uses is associated with supports for cognitive and metacognitive processes without impoverishing them, expanded access without reducing the formative complexity of the task, and accompanied autonomy without producing new forms of delegation (Liu et al., 2025; Nirchi et al., 2025; Ofem et al., 2025). The finding concerning self-efficacy introduces a further element for reflection. In this study, participants' confidence in their ability to understand and use these tools was associated with both perceived ease of use and perceived usefulness. This pattern suggests that a sense of competence may represent an important factor in approaching complex technologies, perceiving them as manageable in teaching practice, and recognizing their usefulness. This finding is consistent with the conceptualization of AI-related self-efficacy as confidence in one's capacity to understand, use, and master AI tools (Hazzan-Bishara, Kol & Levy, 2025). Course participants who perceived greater mastery of these tools also tended to regard them as more accessible and manageable, and to recognize their relevance to educational aims, pupils' needs, and the quality of instructional design. Feeling able to use AI may therefore be associated not only with recognizing its importance and attributing educational value to it, but also with the ability to understand it, orient its use, and integrate it into intentional didactic mediation (Sanusi et al., 2024; Sultan et al., 2025; Tekin, 2024; Wang et al., 2025). From this perspective, the teacher's role remains decisive, not as a mere user of applications, but as a professional called upon to interpret these tools, regulate their use, and evaluate their actual impact on the quality of the educational experience (Yurt & Kaşarcı, 2025). Finally, perceived ease of use may be closely connected to the clarity with which course participants understand how AI systems work. In this study, sociotechnical blindness was negatively associated with perceived ease of use. This finding suggests that when representations of intelligent technologies are partial, confused, or

distorted, these tools tend to be perceived as less accessible and more difficult to integrate into everyday practice. The opacity of the processes through which responses are generated, uncertainty about the data used, and limited understanding of reliability margins may contribute to perceptions of AI as a complex and difficult to control tool characterized by operational boundaries that are not always clearly defined (Qureshi et al., 2026). Understanding how AI systems works may therefore represent not only a technical objective but also a pedagogically relevant condition associated with more informed evaluation and pedagogical mediation of these technologies (Perla & Fabris, 2025), enabling users to exercise critical control over the tools and to integrate them more consciously into educational design and classroom activities.

5. Conclusions, limitations and future research directions

The findings of this research suggest that AI should not be placed merely within the framework of instrumental innovation, but rather within the more complex domain of didactic mediation, where any technology acquires value only insofar as it is questioned, selected, and oriented by conscious educational intentionality. For participants enrolled in the specialization program for special education support teaching, willingness to integrate these systems did not appear to be associated solely with operational familiarity, but was also be linked to variables such as professional motivation, perceived competence, representations of technology, and attention to AI's possible implications for pupils' educational experiences.

From this perspective, teacher education cannot be limited to introducing course participants to the use of applications, as if technical mastery alone were sufficient to guarantee educational innovation. Rather, the findings of this study call for a reconsideration of the instructional design of teacher education programs, particularly of Information and Communication Technologies (ICT)-related modules, which should not be confined to the development of

instrumental and operational skills, although such skills remain necessary for developing familiarity with digital environments and artificial intelligence systems. These modules should more explicitly incorporate a reflective (Raimondo & Muscarà, 2025), critical, and pedagogically grounded dimension, enabling teachers to understand not only how to use AI, but also when, why, and under what conditions it should be integrated into teaching and learning processes. In this sense, pedagogical reflection may help address forms of concern, resistance, or perceived threats to professional identity, contributing to a shift in the perception of AI from an object of fascination or defensive rejection to a tool to be critically examined, deliberately selected, and intentionally oriented. Digital competence acquires educational value when it is intertwined with the ability to understand students' needs, provide accessible mediators, support participation, and safeguard learners' autonomy in educational processes (Ranieri, 2022).

The research, however, presents some limitations that point to possible future developments. The cross-sectional nature of the data does not allow the evolution over time of attitudes, motivations, and resistance toward AI to be reconstructed, nor does it allow causal relationships among the variables considered to be established. Future research could therefore adopt longitudinal designs that follow participants throughout the specialization program and during their subsequent professional practice. Such designs would make it possible to observe how orientations toward AI changes in relation to the concrete responsibilities of the teaching profession.

A second limitation concerns the use of self-report instruments, which capture participants' declared perceptions and may be affected by social desirability bias. To deepen the understanding of the phenomenon, it would be appropriate to complement questionnaires with qualitative approaches, such as focus groups, interviews, or observations of teaching practices, capable of bringing to light not only what teachers enrolled in a specialization program for

special education support report about AI, but also how they understand its functioning, interpret its possibilities, and envisage its use in educational design.

A further limitation concerns the comparison among Gen Z, Millennials, and Gen X. The absence of detectable structural differences in the present study does not demonstrate that the cohorts are equivalent in the broader population or support general conclusions about generations. This result should be interpreted with particular caution because the three groups differed in size and the decrease in CFI was close to the prespecified threshold. Furthermore, generational membership may overlap with age, teaching experience, professional status, and previous exposure to digital technologies. Future studies should replicate this comparison in larger, independent, and more balanced samples and examine the distinct contributions of these variables.

Finally, further investigations should pay greater attention to the institutional and organizational conditions in which innovation takes shape: the support provided by schools, the availability of digital infrastructure, the quality of in-service training, and the professional cultures of educational communities. These elements, together with teachers' individual dispositions, may be relevant to understanding the transition from the intention to use AI to teaching practices that are genuinely sustainable, informed, and oriented toward inclusion.

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