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AI in education: Evidence from cluster-based profiling of social educators and teachers in Italy

AI in Education: evidenze ed analisi delle pratiche degli operatori socio-educativi e degli insegnanti in Italia

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ABSTRACT The paper examines how professionals working in Italian educational contexts - social educators and teachers - perceive and use Artificial Intelligence (AI) in their professional practice. Conducted within the TEACH-AI project, the study is based on questionnaire data collected from 400 social educators and more than 4,000 curricular and support teachers. The aim is to identify and compare empirically grounded profiles of engagement with AI by analyzing patterns of affordance-in-practice, professional capability, and sentiment. Cluster analyses identified four recurring profiles - Receptive, Adaptive, Oppositional, and Indifferent - showing structurally similar configurations across professional roles. Findings reveal a gap between the predominantly operational use of AI tools and their perceived potential to support reflective, inclusive, and relational educational practices. The paper discusses how cluster-based profiling can inform the design of adaptive and differentiated professional development pathways, moving beyond an understanding of AI integration based solely on levels of adoption.

KEYWORDS Artificial Intelligence; AI Literacy; Education; Social Educators; Teachers; Cluster Analysis.

SOMMARIO Il contributo analizza come i professionisti di contesti educativi italiani - operatori socio-educativi e insegnanti - percepiscono e utilizzano l'Intelligenza Artificiale (IA) nella pratica professionale. Lo studio, realizzato nell'ambito del progetto TEACH-AI, si basa su dati raccolti tramite questionario somministrato a 400 operatori socio-educativi e oltre 4.000 insegnanti curricolari e di sostegno. L'obiettivo è identificare e confrontare profili empiricamente fondati del rapporto con l'IA, considerando pattern di affordance-in-practice, capability professionale e sentiment. Le analisi di cluster hanno individuato quattro profili ricorrenti - Ricettivi, Adattivi, Oppositivi, Indifferenti - strutturalmente simili nei diversi ruoli professionali. I risultati evidenziano un divario tra un uso prevalentemente operativo dell'IA e il suo potenziale percepito nel sostenere pratiche educative riflessive, inclusive e relazionali. Il contributo discute come tali profili possano orientare percorsi di sviluppo professionale adattivi e differenziati.

PAROLE CHIAVE Intelligenza Artificiale; AI Literacy; Educazione; Operatori Socio-Educativi; Insegnanti; Analisi di Cluster.

1. Introduction

Generative Artificial Intelligence (GenAI), which includes tools that are now in common use such as chatbots and search engines, is also spreading rapidly in the socio-educational and school settings thanks to its ease of access, often free of charge, and the opportunities it offers for improvement at the educational, bureaucratic and administrative levels (Giannakos et al., 2025).

In the socio-educational context, machine learning systems make it possible to identify patterns that are not immediately visible to humans, allowing risks to be predicted in critical areas such as child protection, suicide prevention and domestic violence (Hodgson et al., 2022). Furthermore, AI can also serve as a decision-making support tool by reducing the possibility of human error and improving workload management through the automation of repetitive tasks (Reamer, 2023). In the school context, the potential of such systems focuses on the use of AI as a tool to support teaching and learning. From this perspective, intelligent technologies are considered resources for personalising educational processes and enhancing the effectiveness of teaching. In this regard, at European level, the Framework for the Educational Use of Generative AI in European Schools (2025) emphasises the need for guidelines that distinguish between applications aimed at students, teachers and the governance of the education system, calling for a cooperative vision of educational innovation. Despite the potential and proliferation of tool practices, the use of generative AI raises significant concerns related to transparency and the risk of losing the centrality of human intervention. Because algorithms are trained on outdated datasets, they can incorporate and amplify racial, gender or class biases, risking the spread of discriminatory information that further marginalises already vulnerable groups. In addition, the massive collection of sensitive data through, for example, conversations with chatbots, exposes users to risks of privacy violations and unauthorised access (Garkisch & Goldkind, 2025).

Furthermore, socio-educational professions are based on human relationships, and the excessive use of digital technologies could erode empathy and interaction, reducing interpersonal engagement (Hodgson et al., 2023). To counter these risks and enable the

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sustainable integration of these tools, several states and supranational organisations have developed guidelines and regulatory frameworks aimed at developing AI literacy for their citizens.

AI literacy is essential for navigating the use and potential integration of AI systems not only in everyday life but also in professional contexts such as socio-educational and school settings (Adamoli et al., 2025). Building on existing digital and ICT skills, AI literacy aims to bridge the gap between the technological and human dimensions by providing social educators, teachers and students with the skills they need to understand AI systems and their impact on society. In line with its strategic digital priorities, the European Union has developed the "Digital Education Action Plan 2021-2027" (European Commission, 2020), the "European Regulatory Framework on Artificial Intelligence" (European Parliament & Council of the European Union, 2024) and the "General Data Protection Regulation" (European Parliament & Council of the European Union, 2016), emphasising the importance of addressing the influence of AI on human rights and privacy and promoting the informed and critical use of AI. In the field of education, the "Ethical Guidelines on the Use of Artificial Intelligence" (European Commission, Directorate-General for Education, Youth, Sport and Culture, 2022) and "Data in Teaching and Learning for Educators", the "European Framework for the Digital Competence of Citizens, DigComp 3.0" (Cosgrove & Cachia, 2025), and the "European Framework for the Digital Competence of Educators, DigCompEdu" (Redecker, 2017) provide operational and strategic guidance for the protection of students and teachers, highlighting the need for interdisciplinary and inclusive approaches to AI literacy. The OECD, based on the "Recommendation of the Council on Artificial Intelligence" (2024), and the Council of Europe have designed the "AILit Framework" (2025), in which AI literacy is described as a basic skill for democratic participation and proposes a risk-based approach geared towards responsibility and sustainability. UNESCO, starting with the "Beijing Consensus on Artificial Intelligence and Education" (2019), has designed the following documents: "Artificial Intelligence and Education: Guidance for Policymakers" (Miao et al., 2021), "Guidance for the Use of Generative AI in Education and Research" (Miao & Holmes, 2023), "AI Competency Frameworks for Teachers" (Miao & Cukurova, 2024) and "AI Competency Framework for Students" (Miao et al., 2024), all aligned with the United Nations' Sustainable Development Goal 4: "Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all". These frameworks support the integration of AI learning into school curricula and propose a model based on equitable access to AI literacy and the protection of teachers' rights and professionalism, emphasising human-centred interaction, ethical practices and sustainability. In Italy, AI literacy has been incorporated into the "Guidelines for the introduction of artificial intelligence in educational institutions" (Ministero dell'Istruzione e del Merito - MIM, Ministerial Decree No. 166 of 09/08/2025). The proposed model is based on four pillars: reference principles; ethical, technical and regulatory requirements; implementation framework; communication and governance to monitor trials. Digital competence underpins these pillars, with an additional emphasis on preparing students to manage the complex challenges of AI in a rapidly evolving digital landscape.

Starting from this scenario, the CREDDI (Centro Ricerca Educazione Didattica Digitale Innovazione sociale) research group at eCampus University has launched the TEACH-AI project (Transformative Educational Approaches for Civic and Human-centred AI), which aims to analyse how professionals working in the Italian educational context – educators and teachers – perceive and use artificial intelligence (AI) in their professional practices. The data reported

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in this paper were collected using a validated questionnaire administered to a large sample of over 400 educators and more than 4,000 curricular and support teachers (Adamoli et al., 2026a).

This study draws on the ARISE-AI framework (Responsive Integrated Socio-Education–Artificial Intelligence, Adamoli et al., 2026a, 2026b), developed within the TEACH-AI project, as a human-centred framework for AI literacy and the pedagogical orientation of educational practices. Grounded in a co-agency perspective, ARISE-AI integrates three theoretical dimensions: affordance-in-practice, professional capability, and sentiment.

The first dimension adopts the Affordance-In-Practice paradigm (Costa, 2018) to examine the dialectic between the intrinsic properties of technologies and the social dynamics of use. This perspective has made it possible to decode how AI functionalities guide the practices of educators and teachers, starting from the assumption that technological interaction is always mediated by individual agency and situated in the socio-educational context.

Going beyond the concept of mere technical literacy, the dimension of professional capability is based on the contributions of Sen (1985) and Nussbaum (2011). In this context, the effectiveness of AI is not measured by simple access to tools, but by the professional's ability to convert technological resources into meaningful "functions". The investigation therefore shifts towards the actual possibility of use consistent with the values and socio-cultural demands of the reference context.

Finally, the study of sentiment has been borrowed from computational and opinion sciences (Liu, 2012) to pedagogical environments. This dimension posits that participants' emotional responses serve as indicators that can determine positive or negative attitudes towards the adoption or rejection of AI technologies.

Together, these three dimensions have enabled the research group to provide an interpretative framework for designing adaptive and differentiated professional development paths for the various stakeholders involved.

The aim of this study is to identify and compare empirically grounded profiles of social educators' and teachers' relationships with Artificial Intelligence, by analysing patterns of affordance-in-practice, professional capability, and sentiment.

By adopting a cluster-based analytical approach, the study seeks to explore whether stable and comparable profiles emerge across different professional roles, and to examine how such profiles can inform the design of differentiated, human-centred professional development pathways.

2. Materials and methods

2.1. Instrument and data collection procedure

Data collection was carried out using a single questionnaire designed to investigate the relationship between educational professionals and Artificial Intelligence (AI), applied in two closely related versions addressing different professional contexts: socio-educational services and schools. The instrument was conceived as a unified tool, grounded in a common theoretical framework and measurement structure, while allowing for context-specific adaptations to ensure ecological validity and relevance to professional practices.

The questionnaire integrates items addressing knowledge of AI, patterns of use, and related professional practices with the core dimensions of the conceptual framework: affordance-in-practice, capability, deprivation, and sentiment. In both versions, the instrument is organised

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into five sections: the first collects personal and professional background information; the next three sections focus respectively on affordance-in-practice, capability together with the related dimension of deprivation in shaping the relationship with AI, and sentiment toward AI; the final section addresses the cognitive dimension, aimed at assessing familiarity with and basic understanding of AI concepts. The inclusion of capability and deprivation was intended to capture dimensions of AI literacy that cannot be reduced to technical knowledge alone. Accordingly, the dimension of professional capability draws on the capability approach developed by Sen (1985) and Nussbaum (2011). From this perspective, deprivation is understood as a multidimensional condition that emerges when individuals lack the resources, opportunities, competences, social relations, or enabling conditions necessary to develop and realise valued capabilities (Anand et al., 2021).

Within the project, the PAIR questionnaire (Participatory AI for Inclusive Relationships) was originally developed and validated for professionals working in socio-educational contexts (Adamoli et al., 2026b; Rondonotti & Emanuel, in press), with the aim of capturing reflective co-agency in interactions with AI. The development process included an initial expert validation phase (face validity) to assess clarity, relevance, and coherence of items, followed by administration to a national sample of over 400 socio-educational practitioners. The analyses demonstrated good psychometric properties, yielding a stable and interpretable factorial structure and satisfactory reliability indices.

Building on this validated core instrument, an adapted version for the school context was developed in summer 2025, named PAIR-S (Participatory AI for Inclusive Relationships in School, Adamoli et al., 2026a). In particular, the adaptation was guided by the Italian Ministry of Education guidelines for the introduction of AI in educational institutions (Ministero dell'Istruzione e del Merito, 2025), which emphasise the need to tailor AI use to target audiences. Article 4.2 of the guidelines identifies priority areas for schools, including personalisation of teaching materials, development of interactive and innovative tools, production of documentation, organisation of educational visits and extracurricular activities, construction of assessment rubrics, and support for tutoring activities (with and among students and teachers). These areas informed the contextual wording of items related to AI use, while preserving the underlying constructs and measurement logic of the original instrument. The development process included an expert validation phase (face validity) to assess clarity, relevance, and coherence of items, followed by administration to a sample of over 4000 curricular and support teachers. The analyses demonstrated good psychometric properties, yielding a stable and interpretable factorial structure and satisfactory reliability indices.

The internal consistency of the study dimensions was assessed using Cronbach's alpha, calculated separately for social educators and for curricular and support teachers. Overall, the results indicate good to excellent reliability across all scales in both groups. For social educators ($N = 414$), Cronbach's alpha coefficients ranged from .76 to .90, with high levels of internal consistency for Affordance-in-practice ($\alpha = .89$), Capability ($\alpha = .88$), and Deprivation ($\alpha = .90$), and acceptable reliability for Positive Sentiment ($\alpha = .80$) and Negative Sentiment ($\alpha = .76$). Similarly, for curricular and support teachers ($N = 4.224$), the scales showed satisfactory to excellent reliability, with alpha values ranging from .79 to .94. In this group, Affordance-in-practice demonstrated excellent internal consistency ($\alpha = .94$), while Capability ($\alpha = .87$), Positive Sentiment ($\alpha = .90$), Deprivation ($\alpha = .80$), and Negative Sentiment ($\alpha = .79$) all met accepted thresholds for reliability. These findings support the robustness of the instrument across professional roles and confirm the suitability of the scales for subsequent analyses.

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The two questionnaires were administered online via the QuestionPro platform. Participants were informed about the aims of the study, the voluntary nature of participation, and data processing procedures. Informed consent was obtained prior to completion of the questionnaire. No personally identifiable or sensitive data were collected; responses were anonymised and analysed in aggregated form, in accordance with international ethical standards.

2.2. Participants

The study involved two distinct professional groups working in Italian educational and socio-educational contexts (Table 1): practitioners employed in social cooperatives and teachers working in the school system.

Table 1. Sample characteristics by study group.

	Social workers (N = 414)	Teachers (N = 4.224)
Geographical area	61.8% Northern Italy 14.5% Central Italy 23.7% Southern Italy	36.8% Northern Italy 19.6% Central Italy 43.7% Southern Italy
Gender	83.1% Female 16% Male	80% Female 19% Male
Age	M = 41.8 years, SD = 9.99 min = 21; max = 61	M = 36.55 years, SD = 8.78 min = 20; max = 60
Educational qualification	15.9% High school diploma 36.2% Bachelor's degree (29,2% in pedagogy) 34.7% Master's degree (14.8% in pedagogy) 6.8% professional certifications 0.7% Doctoral degree	11.4% High school diploma 2.9% Bachelor's degree 65.2% Master's degree 16.3% Doctoral degree
Professional role	68% educational activities 26% coordination roles 6% administrative positions	42% Curricular teachers: tenured (20.6%), non-tenured (21.6%) 52% Support teachers: tenured (6.7%), non-tenured (45.4%) 6% pre-service teachers
Educational setting / age group served	22.2% early childhood (0-3y) 10.8% pre-school (4-6) 13.7% school-age (7-11) 14.8% pre-adolescents (12-14) 16.2% adolescents (15-19) 7.9% young adults (20-30) 12.2% adults over 30 years 2.2% multiple age groups	3.7% Early childhood 18.1% Primary education 30.7% Lower secondary ed. 4% Upper secondary ed. 0.7% vocational education and training pathways
Teaching experiences (years)	-	M = 7.28, SD = 6.40 min = 0; max = 39

The first group consisted of 414 practitioners employed in 19 social cooperatives operating across Italy. Practitioners worked across a wide range of socio-educational services.

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The second group comprised 4,224 teachers working in Italian schools across all regions of the country. The geographical distribution indicates wide national coverage, with participants employed in all Italian regions.

2.3. Data Analysis

Data were analysed using IBM SPSS Statistics (version 30). In a preliminary step, descriptive statistics - including frequencies, means, and standard deviations - were calculated to provide an overview of the main characteristics of the sample.

To explore recurring patterns in participants' orientations toward Artificial Intelligence, a cluster analysis was conducted using the K-means algorithm (Hartigan & Wong, 1979). This procedure groups cases by iteratively minimizing within-cluster variability while maximizing differences between clusters, allowing the identification of homogeneous participant profiles. Clustering was based on four analytically relevant dimensions derived from the theoretical framework: affordance-in-practice, capability, deprivation, and sentiment. Prior to clustering, all variables were standardized to ensure comparability and to reduce potential distortions due to differing measurement scales. An exploratory diagnostic, a hierarchical cluster analysis using Ward's method and squared Euclidean distance was conducted. The agglomeration schedule and dendrogram were inspected to assess the empirical plausibility of alternative cluster solutions. As an additional robustness check, the K-means algorithm was repeated across multiple random case orderings, and the stability of the resulting cluster structures was examined across runs.

To examine whether the identified clusters differed significantly on the clustering variables and on additional outcome measures, a series of one-way analyses of variance and test t for independent samples were conducted.

3. Results

A k-means cluster analysis was conducted on the standardized scores of Affordance-in-practice, Capability, Deprivation, and Sentiment (positive and negative) to identify homogeneous participant profiles.

The results obtained are presented in accordance with the analytical sequence that was adopted in the study. Firstly, the cluster analysis on the total sample identifies four distinct clusters that reflect different ways of relating to Artificial Intelligence across the dimensions of affordance-in-practice, sentiment, and capability. The four-cluster solution was retained based on theoretical coherence, interpretability, and consistency across professional groups. The solution was further supported by hierarchical clustering diagnostics. Specifically, the agglomeration schedule showed a marked increase in fusion coefficients beyond the four-cluster partition, indicating that this solution represented a reasonable balance between empirical differentiation and substantive interpretability.

In the following section, the results of the cluster analysis are presented in a manner that differentiates between the two primary professional categories, namely educators and teachers. Within the latter category, a further disaggregation is undertaken to distinguish between curricular teachers and support teachers. This approach facilitates the examination of the consistency of the cluster structure across groups, as well as the identification of group-specific distributions and variations.

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In social educators group the optimal four-cluster solution (k = 4) was selected based on theoretical coherence and interpretability. The final model successfully classified the majority of cases.

Figure 1 presents the profile plot of the standardized centroids in social educators. Table 2 presents the final cluster centroids, expressed as mean z-scores, for each variable across the identified clusters.

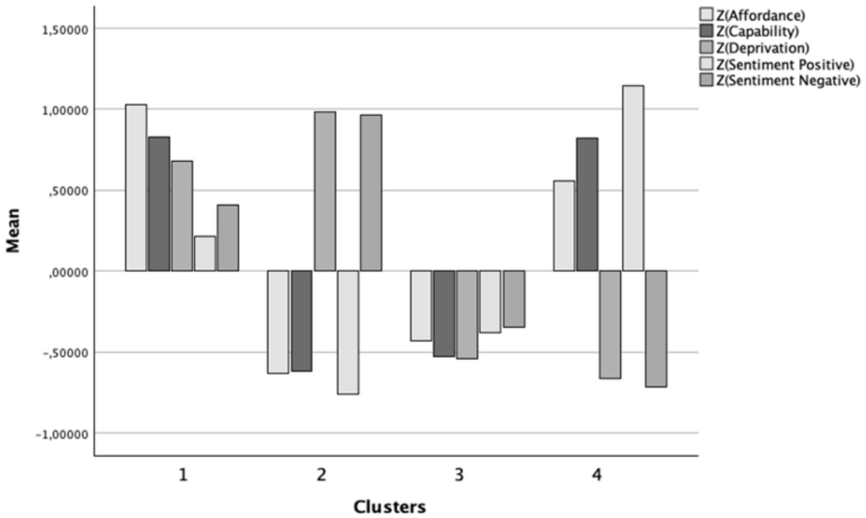

Figure 1. Cluster analysis - profile plot (Social educators).

Table 2. Standardised centroids of the variables (Social educators).

Variable	Cluster 1 (N = 67)	Cluster 2 (N = 100)	Cluster 3 (N = 142)	Cluster 4 (N = 102)
Affordance-in-practice	1.02	-.66	-.43	.59
Capability	.83	-.62	-.53	.82
Deprivation	.68	.98	-.54	-.66
Sentiment positive	.21	-.76	-.38	1.14
Sentiment negative	.41	.96	-.35	-.71

Note: Values are standardized (z-scores). Positive values indicate above-average levels on the respective variable, while negative values indicate below-average levels.

In teachers group cluster analysis was conducted on the entire group and separately on support and curriculum teachers. The same cluster structure (k = 4) emerged as in the group of social educators. Table 3 and 4 presents the final cluster centroids, expressed as mean z-scores, for each variable across the identified clusters. Positive values indicate above-average levels on the respective variable, while negative values indicate below-average levels.

Table 3. Standardised centroids of the variables (Curricular teachers, N = 1.779).

Variable	Cluster 1 (N = 459)	Cluster 2 (N = 362)	Cluster 3 (N = 531)	Cluster 4 (N = 427)
Affordance-in-practice	.37	-.97	-.55	.63
Capability	.48	-.97	-.61	.84
Deprivation	.66	.77	-.67	-.48
Sentiment positive	.26	-1.22	-.34	1.01
Sentiment negative	.57	1.04	-.41	-.83

Table 4. Standardised centroids of the variables (Support teachers, N = 2.194).

Variable	Cluster 1 (N = 627)	Cluster 2 (N = 430)	Cluster 3 (N = 667)	Cluster 4 (N = 470)
Affordance-in-practice	.64	-.78	-.39	.86
Capability	.64	-.83	-.59	.89
Deprivation	.68	.75	-.68	-.74
Sentiment positive	.37	-1.05	-.30	1.03
Sentiment negative	.44	.82	-.41	-.89

Across all the groups, the cluster analyses yielded four structurally similar clusters, indicating consistent patterns in how participants relate to Artificial Intelligence across the dimensions of affordance-in-practice, capability, and sentiment. The clusters can be described as follows.

Cluster 1 is characterised by moderately high levels of affordance-in-practice and capability, combined with elevated deprivation and negative sentiment, alongside residual positive sentiment. This profile reflects participants who engage with AI in a relatively articulated manner while simultaneously experiencing constraints and ambivalent emotional responses.

Cluster 2 displays the most unfavourable profile, marked by very low affordance-in-practice and capability, high levels of deprivation and negative sentiment, and a pronounced reduction in positive sentiment. Participants in this cluster appear to experience substantial limitations and disengagement in their relationship with AI.

Cluster 3 is defined by uniformly low scores across all dimensions, including affordance-in-practice, capability, and both positive and negative sentiment. This profile suggests a predominantly indifferent or minimally engaged stance towards AI.

Cluster 4 represents the most favourable profile, characterised by high affordance-in-practice, strong capability, and elevated positive sentiment, together with low deprivation and negative sentiment. Participants in this cluster demonstrate a proactive and effective engagement with AI.

ANOVA and independent-samples t-tests were used to examine differences across clusters and professional groups on both clustering dimensions and selected outcome variables. Given space constraints, only the most salient trends are reported.

Overall, support teachers tended to display more positively oriented profiles towards Artificial Intelligence than curricular teachers, particularly with respect to affordance-in-practice, capability, and positive sentiment. This tendency is also reflected in participants' expectations regarding the future usefulness of AI in professional tasks. In particular, statistically significant differences emerged among teachers in relation to AI as a support for inclusive and accessible learning, with higher mean scores reported by support teachers (M = 4.43) compared to curricular teachers (M = 4.35), indicating greater sensitivity and attention to this area among the former [$t(3,961) = 2.46$, $p < .05$].

By contrast, socio-educational practitioners showed, on average, a less AI-oriented profile across the considered dimensions. Rather than suggesting resistance, this pattern appears to reflect a more cautious positioning, likely associated with contextual constraints and fewer opportunities for systematic AI integration in socio-educational settings.

Finally, the questionnaire also included a cognitive component aimed at assessing participants' self-reported knowledge of AI, measured on a scale ranging from -5 to +5. The three groups exhibited relatively comparable levels of knowledge, with mean scores of 1.40 for social educators, 1.75 for curricular teachers, and 1.50 for support teachers. An ANOVA conducted on knowledge scores across clusters revealed statistically significant differences ($p < .001$). The cluster 4 showed the highest level of knowledge (M = 1.84), followed by the cluster 2 (M = 1.60) and cluster 3 (M = 1.53), while cluster 1 displayed the lowest average knowledge score (M = 1.38).

4. Discussion

Taken together, the findings suggest that the ARISE–AI framework may offer a useful human-centred lens for interpreting AI literacy and the pedagogical integration of AI, particularly through the interrelated dimensions of affordance-in-practice, professional capability, and sentiment.

Firstly, the findings provide a nuanced picture of the relationship between education professionals and Artificial Intelligence in Italy. The four profiles yielded by the cluster analyses – Adaptives, Oppositionals, Receptives, and Indifferents – proved structurally consistent across the three subgroups examined (social educators, curricular teachers, and support teachers), attesting to the presence of stable and comparable configurations across distinct professional roles.

This convergence indicates that the ways in which professionals relate to AI are not exclusively determined by the specific work context, but may also reflect deeper dispositions rooted in the interplay between competences, perceptions of opportunity and constraint, and emotional-cultural orientations. Starting from this interpretation, and in light of the Technology Readiness model (Parasuraman & Colby, 2015; Mishra et al., 2023), it is possible to argue that the propensity for technology adoption extends beyond mere tool familiarity, involving identity-related and value-laden dimensions of professionalism (Damioli et al., 2021).

A first element for discussion concerns the differences between curricular and support teachers in the use of AI for inclusion. Support teachers exhibited, on average, more positively oriented profiles, particularly with respect to the dimensions of affordance-in-practice, capability, and positive sentiment. The statistically significant differences regarding the perception of AI as a support for inclusive and accessible learning (M = 4.43 vs. 4.35) suggest that sensitivity to the inclusive dimension acts as a catalyst for a more informed appropriation of intelligent technologies.

Consistent with recent literature (Lamacchia et al., 2025; Zawacki-Richter et al., 2019), support teachers recognise in the generative potential of AI – including personalisation, content

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adaptation, and production of accessible resources – a natural extension of their professional mandate. The observed gap also reflects asymmetries in training pathways and professional cultures: curricular teachers appear more oriented toward subject-matter transmission and tend to perceive AI in more instrumental terms, whereas the professional identity of support teachers, built around mediation and differentiation, predisposes them to recognise AI affordances as an extension of differentiated instruction (Conole & Dyke, 2004; Costa, 2018; Hammond, 2010).

A second axis of discussion pertains to the differences among the three professional groups. Although the four-cluster structure emerged with substantial consistency, the distribution of participants within the clusters and the intensity of the dimensions analysed exhibited notable variations. Social educators displayed, on the whole, a less AI-oriented profile – a pattern that should be interpreted not as resistance, but rather as a more cautious positioning, plausibly linked to contextual constraints and fewer opportunities for systematic AI integration within social-educational services.

In socio-educational settings, the adoption of digital technologies tends to be hindered by organisational barriers, service fragmentation, and a professional culture deeply centred on interpersonal relationships (Hodgson et al., 2022). At the same time, the emergence of Receptive profiles among social educators attests that the potential for critical appropriation of AI is not the exclusive preserve of the school context. These findings underscore the need for contextually situated analyses that account for the specific organisational and cultural characteristics of each educational sector.

A third aspect concerns self-reported AI knowledge, which proved to be a cross-cutting yet variable element. Mean scores, ranging from 1.40 to 1.75 on a scale from –5 to +5, indicate an overall modest level of knowledge, albeit with significant differences across clusters. Receptives exhibited the highest knowledge level (M = 1.84), whereas Adaptives, despite displaying moderate levels of affordance and capability, recorded the lowest mean score (M = 1.38).

This dissociation suggests that the operational use of AI can proceed independently of conceptual understanding, thereby giving rise to a risk of uncritical adoption that the literature on AI literacy identifies as one of the foremost challenges facing contemporary educational systems (Long & Magerko, 2020; Ng et al., 2021). The Adaptives profile, in particular, draws attention to the need for professional development pathways that promote not only technical competence but also a critical understanding of AI principles, limitations, and ethical implications (Biagini, 2025; Miao & Cukurova, 2024).

The analysis further reveals a hierarchy of AI use practices. Prevalent applications are concentrated in operational and supportive functions – such as the personalisation of teaching materials, text translation, and content generation – whereas more advanced functionalities, including data analysis, instructional design, and the monitoring of learning processes, remain considerably underutilised.

AI thus appears to be conceived predominantly as an operational facilitator rather than as a cognitive partner – a finding that is consistent with the analyses of Selwyn (2019) and Williamson et al. (2023), who highlight the risk of a performative adoption in which efficiency gains do not translate into a genuine rethinking of pedagogical practices. In parallel, the coexistence of Receptive and Oppositional profiles within the same sample reveals a fundamental tension: negative sentiment cannot be reduced to an individual deficit, but rather reflects systemic tensions between technological innovation, professional identity, and the educational mandate (Al-Zahrani, 2024; Pasquale, 2020). The sentiment dimension, drawn

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from computational opinion analysis (Liu, 2012), is thus confirmed as a crucial analytical lens for understanding the cultural and narrative factors that shape professional practices.

The Indifferents profile warrants specific reflection. The minimal level of engagement it entails suggests that a significant proportion of professionals perceive AI as essentially extraneous to their professional experience. Rather than being a neutral stance, such indifference constitutes a form of silent exclusion that risks widening the digital divide (Carter et al., 2020; Kitsara, 2022). Drawing on Sen's capability approach, this condition can be understood as a failure to convert available technological resources into real freedoms; that is, into substantive opportunities to act and choose within one's professional life (Sen, 1999). Where individuals lack the skills, confidence, or institutional support to engage meaningfully with AI tools, technological agency remains merely formal, and its absence translates into concrete professional deprivation: reduced access to productivity gains, diminished competitiveness, and curtailed participation in an increasingly AI-mediated labour market (Robeyns, 2005; Sen, 1985). This process depends critically on the quality of training and organisational support, which function as the conversion factors, in Sen's terms, that mediate between the availability of a technology and its actual appropriation as a professional capability.

5. Conclusions

The present study offers novel insights into an area that remains comparatively under-explored, particularly within the socio-educational field. Nevertheless, several limitations should be considered when interpreting the findings.

From a methodological standpoint, the use of cluster analysis follows an exploratory rather than confirmatory logic. As widely recognised, cluster solutions are sensitive to analytical decisions such as variable selection and the number of clusters retained (Ketchen & Shook, 1996), while the attribution of substantive meaning to cluster profiles necessarily reflects the researcher's theoretical positioning (Van Mechelen et al., 2023).

Sample-related limitations also apply, given the unequal representation of professional groups and the marked heterogeneity of the socio-educational sample, which reflects the structural fragmentation of these contexts and constrains direct comparability with the teaching population. A further limitation relates to the reliance on self-reported data. Perceptions of AI-related knowledge and use may be influenced by social desirability bias or discrepancies between reported orientations and enacted practices. Future research would benefit from integrating individual-level data with organisational and contextual information in order to capture more accurately how AI is embedded in professional activity.

Despite these constraints, the study highlights the value of a cluster-based reading of professionals' relationships with AI and points to promising directions for both research and practice. The cluster-based study reveals stable profiles, the analysis of which will enable AI literacy experiments and training courses to be implemented in the near future, focusing on the specific characteristics of each profile and moving beyond the classic needs analysis model in a field of research that requires innovation even in the training design phase.

The findings call for a rethinking of professional development along cluster-driven lines: mentoring strategies for Adaptives to consolidate informed integration; ethics- and deontology-focused pathways for Oppositionals; communities of practice for Receptives; and systemic interventions for Indifferents that create enabling and meaningful contexts. This proposal, in line with recent evidence on the personalisation of teacher professional development (Tan et al., 2025; Doss et al., 2025), is grounded in the theoretical framework that interweaves

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affordance-in-practice, capability, and sentiment, thereby contributing to moving beyond uniform conceptions of training in favour of models that acknowledge the complexity and plurality of relationships between education professionals and AI. In this respect, the ARISE–AI framework may be understood as a coherent human-centred reference for interpreting these differentiated profiles and informing context-sensitive approaches to AI literacy and professional development.

6. Authors' contributions

All co-authors contributed to the design and implementation of the research. This contribution represents the result of a collaborative effort by the authors. With regard to the writing of the manuscript, individual contributions may be attributed as follows: Matteo Adamoli authored §1, Federica Emanuel §2, Marco Rondonotti §3, Michele Marangi §4 and Paolo Raviolo §5.

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