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Teachers' self-reported AI literacy across educational levels in Greece: Awareness without conceptual depth?



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Abstract

Artificial intelligence (AI) literacy is increasingly recognized as an essential teacher competence, yet evidence concerning its dimensional structure and variation across educational sectors remains limited. This study investigated self-reported AI literacy among 1,173 in-service teachers in primary, secondary, and higher education in Greece, examining its empirical structure, overall levels, and associations with prior AI-related training and teaching level, while accounting for academic qualifications. Data were collected through a researcher-developed questionnaire and analyzed using exploratory factor analysis, descriptive statistics, and general linear models. Two dimensions emerged: Conceptual–Technical AI Literacy and Critical–Ethical AI Literacy, while Practical AI Use was retained as a separate indicator. Overall self-reported AI literacy was relatively low, with substantially higher scores on critical–ethical indicators than on conceptual–technical indicators, suggesting a profile of perceived awareness without corresponding conceptual depth. Prior AI-related training was positively associated with all AI-literacy outcomes across educational sectors. However, significant teaching-level × training interactions revealed particularly strong associations in higher education, especially for Conceptual–Technical AI Literacy. These findings highlight the multidimensional and context-sensitive nature of teachers' self-reported AI literacy and the importance of distinguishing perceived confidence from demonstrated competence. They underscore the need for differentiated, pedagogically grounded professional development that integrates conceptual understanding, practical AI applications, critical evaluation, and ethical judgment across educational sectors.

Keywords: Artificial Intelligence literacy, teacher professional development, AI-related training; critical and ethical AI literacy, AI literacy assessment

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1. Introduction

Artificial Intelligence (AI) is increasingly embedded in teaching, learning, assessment, and educational infrastructure, contributing to an emerging post-AI educational context in which AI-mediated systems become normalized (Bozkurt et al., 2024; Holmes et al., 2019; Knox, 2019). As learners engage with AI for feedback, scaffolding, and knowledge construction, educators are increasingly expected to mediate these interactions, foster critical engagement, and support metacognitive and ethical awareness (Yi, 2021; Gavriilidou, 2024a).

These expectations highlight the importance of teachers' AI literacy, encompassing conceptual understanding, practical engagement, critical judgment, and ethical awareness (Long & Magerko, 2020; Ng et al., 2021). However, the growing emphasis on AI-driven educational transformation (Fawns, 2019; Author, in press) has not been matched by equally comprehensive evidence concerning teachers' AI literacy across educational sectors. In particular, limited research has examined whether teachers' self-reported competencies develop uniformly or whether familiarity with AI applications and risks coexists with limited understanding of underlying technologies. To the best of our knowledge, no previous study has systematically compared these aspects of teachers' AI literacy across primary, secondary, and higher education in Greece.

Addressing these gaps, the present study examines the empirical structure, overall level, and dimensional profiles of self-reported AI literacy among in-service teachers across primary, secondary, and higher education in Greece. It further investigates associations with prior AI-related education or training and teaching level, accounting for teachers' highest degree attained, with particular attention to whether training-related associations vary across AI-literacy dimensions and educational sectors. The findings aim to inform more targeted, conceptually grounded, and pedagogically meaningful professional development.

2. Literature Review

2.1 AI Literacy: Definitions and Core Competencies

AI literacy is increasingly conceptualized as a multidimensional, context-sensitive competence encompassing the understanding, use, and critical evaluation of AI systems and their societal implications. Long and Magerko (2020) emphasize informed and critical engagement with AI, while Ng et al. (2021) integrate conceptual, practical, and ethical competencies. Extending these perspectives, Yi (2021) and Gavriilidou (2024a, b) foreground metacognition, human agency, and participation in AI-mediated societies, with Gavriilidou characterizing AI literacy as a fourth-generation literacy. Recent frameworks similarly emphasize responsible participation in AI-mediated environments (Mills et al., 2024). Despite differences in emphasis, reviews converge around conceptual–technical, practical–applicational, critical, and ethical domains (Casal-Otero, Catala, & Fernández-Morante, 2023; Almatrafi, Johry, & Lee, 2024). However, conceptual agreement does not necessarily imply that these domains are empirically distinct or develop uniformly.

Differences between conceptual frameworks become particularly apparent in their operationalization. Wang, Rau, and Yuan's (2023) Artificial Intelligence Literacy Scale (AILS) distinguishes awareness, use, evaluation, and ethics, whereas the Scale for the Assessment of Non-Experts' AI Literacy (SNAIL; Laupichler et al., 2023) addresses technical understanding, critical appraisal, and practical application (see also Park, 2026). Although these instruments share broad conceptual concerns, their dimensional structures and item coverage differ. Consequently, similarly named competencies should not automatically be treated as equivalent across measures,

and empirical factor structures may partly reflect instrument design rather than the underlying organization of AI literacy.

Conceptual–technical competence concerns understanding AI concepts, including algorithms, machine learning, model training, and technological limitations. Such knowledge supports informed interpretation of AI outputs without necessarily requiring programming expertise (Ng et al., 2021). Practical–applicational competence involves selecting and using AI tools, evaluating their outputs, and integrating them into educational activities such as lesson planning, differentiation, and feedback (Su & Yang, 2024). The Content and AI-Integrated Learning (CAIIL) framework further situates AI use within disciplinary learning processes (Gavriilidou, 2025). However, frequent tool use does not necessarily indicate pedagogically effective integration, which requires alignment with learning objectives and informed professional judgment (Ng et al., 2021; Wang et al., 2023; Almatrafi et al., 2024).

Ethical competence encompasses awareness of privacy, bias, transparency, academic integrity, and the broader consequences of AI use (Long & Magerko, 2020; Ng et al., 2021; Wang et al., 2023). For teachers, these concerns extend to student protection and responsible educational practice (UNESCO, 2023). Critical competence, although conceptually distinguishable, overlaps with ethical judgment through the evaluation of AI-generated information, recognition of inaccuracies and biases, and verification of outputs (Long & Magerko, 2020). Importantly, awareness of such risks does not necessarily demonstrate the ability to identify them in practice. Nor can individual ethical awareness substitute for institutional guidance and structural support. While, metacognition has also been proposed as a transversal component of AI literacy, supporting recognition of knowledge limitations, reflective decisions about delegating tasks to AI, and the preservation of human agency (Yi, 2021; Gavriilidou, 2024a). Rather than necessarily constituting an independent dimension, it may contribute to the coordination of conceptual, practical, critical, and ethical competencies.

The uneven development of these competencies admits competing explanations. Public and professional discourse may foster familiarity with AI-related risks and ethical issues without providing equivalent opportunities to acquire technical knowledge. Conversely, specialized education may support conceptual understanding beyond everyday tool use. Yet apparent differences may also be methodological, arising from item wording, technical terminology, response formats, or perceived difficulty. Higher self-reported critical or ethical awareness should therefore not be interpreted automatically as stronger demonstrated competence.

Drawing on these perspectives, the present study conceptualizes teachers' AI literacy as a multidimensional, situated professional competence encompassing conceptual–technical understanding, practical engagement with AI tools, and critical–ethical judgment (Long & Magerko, 2020; Ng et al., 2021; Fawns, 2019). AI literacy is thus understood not merely as an individual cognitive attribute or disposition, but as the capacity to mobilize knowledge, skills, and critical judgment in contextually appropriate pedagogical decisions. These competencies are functionally interconnected but need not develop simultaneously or to the same degree: conceptual understanding can inform the evaluation of AI outputs, while practical engagement can provide opportunities to develop and refine such understanding. Their educational significance lies not in achieving equally high scores across domains, but in their effective coordination when teachers select, evaluate, adapt, or reject AI-supported materials and activities. Accordingly, an asymmetrical competence profile is not inherently a deficiency; it becomes potentially consequential when limitations in particular competencies constrain informed pedagogical decisions. The present study examines the empirical organization and relative levels of selected self-reported indicators without assuming that theoretically defined competencies necessarily emerge as distinct factors. Whether higher AI literacy translates into improved teaching practice and learning outcomes remains an empirical question requiring further investigation.

2.2 Factors Associated with AI Literacy

Research suggests that AI literacy is associated with individual competencies, prior experience, educational opportunities, and institutional contexts (Laupichler et al., 2022; Zhao, Wu, & Luo, 2022; Tan, Cheng, & Ling,

2025; Ayyoub et al., 2025; Zhu et al., 2025; Lan et al., 2026). Digital competence and computational thinking may provide foundations for understanding AI systems (Celik, 2023), while attitudes, perceived usefulness, and access to technology can influence opportunities for engagement (Ayanwale et al., 2022; Ayyoub et al., 2025; Celik, 2023). Experience with AI tools has also been associated with higher self-reported AI literacy (Lan et al., 2026). However, these factors are not interchangeable: technological familiarity, positive attitudes, and AI literacy represent related but distinct constructs. With prior AI-related education or training is particularly relevant to teachers' professional learning. Previous research has associated AI-related education and professional development with higher levels of AI literacy (Ding et al., 2024; O'Dea et al., 2024; Ayyoub et al., 2025; Lademann et al., 2026). However, whether these associations vary across AI-literacy dimensions remains insufficiently understood.

General educational attainment represents a related but distinct factor. Advanced academic qualifications may provide analytical and research-related competencies, yet they do not necessarily involve formal education in AI. Highest degree attained should therefore not be treated as a proxy for AI-specific training. Similarly, educational level may be associated with AI literacy through differences in professional responsibilities, disciplinary specialization, technological exposure, and institutional resources (Lan et al., 2026). However, educational sector and academic qualifications may themselves be closely related, complicating the interpretation of their separate associations with AI literacy.

Beyond these individual associations, the educational level at which teachers teach (hereafter, teaching level) may moderate the relationship between prior AI-related training and self-reported AI literacy. Primary, secondary, and higher education differ in curricular demands, professional responsibilities, institutional resources, and opportunities to apply AI-related knowledge. In primary education, AI-related learning may be particularly relevant to differentiated instruction, foundational learning, and age-appropriate pedagogical practices. In secondary education, its application may be shaped by subject specialization, curriculum requirements, and assessment demands. In higher education, research activities, disciplinary specialization, and opportunities to engage with advanced technologies may provide additional contexts for applying AI-related knowledge. These differences may shape how teachers apply and consolidate knowledge acquired through training, potentially influencing the strength of its association with specific AI-literacy competencies. However, the direction and magnitude of these associations cannot be predicted a priori, as each educational sector presents distinct opportunities and constraints for AI-related professional learning.

Although reviews document growing interest in teachers' AI literacy (Kong, Cheung, & Zhang, 2023; Lintner, 2024), evidence remains limited on how prior AI-related training, teaching level, and academic qualifications are jointly associated with teachers' overall self-reported AI literacy and its constituent dimensions. Particularly underexplored is whether the association with training varies across educational sectors and competencies. Examining these relationships among primary, secondary, and higher-education teachers in Greece may clarify how professional and educational characteristics relate to different self-reported AI-literacy profiles.

3. Aims and hypotheses

To address this gap, the present study aims to investigate the self-reported AI literacy of in-service teachers across primary, secondary, and higher education in Greece. More specifically, it examines the empirical structure of the AI-literacy indicators, the overall level of self-reported AI literacy, and the extent to which AI literacy and its identified dimensions are associated with educational level, prior AI-related education or training, and highest degree attained. The study addresses the following research questions:

RQ1. What is the empirical structure of the self-reported AI-literacy indicators, and how do teachers score on the dimensions identified?

RQ2. What is the overall level of self-reported AI literacy among in-service teachers in Greece?

RQ3. How are teachers' overall self-reported AI literacy and its identified dimensions associated with teaching

level and prior AI-related education or training, after accounting for highest degree attained?

Based on previous research, the following hypotheses were formulated:

H1. Teachers will exhibit an uneven self-reported AI-literacy profile, characterized by greater confidence in critically evaluating AI and recognizing its ethical implications than in understanding its underlying concepts and technical mechanisms.

H2. Prior AI-related education or training will be positively associated with teachers' self-reported AI literacy across its identified dimensions, although the magnitude of these associations may vary depending on the competencies examined.

H3. Teaching level will moderate the association between prior AI-related education or training and self-reported AI literacy, with the magnitude of this association varying across educational sectors and AI-literacy dimensions.

4. Materials and methods

Sample - The analytic sample comprised 1,173 in-service teachers working in primary, secondary, and higher education in Greece. Of these, 431 were primary-school teachers, 625 were secondary-school teachers, and 117 were higher-education teachers. The sample included 935 women, 231 men, and 7 participants recorded under another or unspecified gender category. Participants were aged between 30 and 65 years and were recruited from different regions of Greece through professional-development activities in which attendance was mandatory. Importantly, although participation in these programmes was compulsory, participation in the research was entirely voluntary and was not a requirement of the professional-development activities. The study therefore employed a large, non-probability convenience sample. All participants provided informed consent prior to participation. Data were collected anonymously and used exclusively for research purposes. Participants were informed that participation was voluntary and that they could withdraw at any stage without consequences. The study adhered to the applicable ethical guidelines for research involving human participants.

Instrument development and data collection - Data were collected using a self-report questionnaire developed by the author to assess teachers' self-reported AI literacy and to collect supplementary information on their views, experiences, and professional-development needs regarding AI in educational contexts. The questionnaire comprised 22 questions in Greek, including 20 closed-ended items and two open-ended questions. The first section (Questions 1–6) collected demographic and professional background information, including age, teaching subject, highest degree attained, educational level taught, and previous AI-related education or training. In the present study, educational level, highest degree attained, and prior AI-related education or training were examined in relation to teachers' self-reported AI literacy.

The second section (Questions 7–16) comprised ten self-report items assessing different aspects of AI literacy. Responses were recorded on a five-point Likert-type scale indicating the extent to which each statement was true of the respondent, ranging from 1 (not at all true of me) to 5 (completely true of me). Item development followed a systematic, literature-informed, deductive approach. First, an extensive review of the literature was undertaken to identify and map the different conceptual dimensions and parameters of AI literacy. This process resulted in a comprehensive inventory of AI-literacy competencies that informed the initial test specifications. Drawing on this conceptual mapping and existing AI-literacy instruments, particularly those developed by Wang et al. (2023) and Laupichler et al. (2023), an initial pool of 25 candidate items was generated.

To assess content validity, the 25 items written in Greek were evaluated by a multidisciplinary panel of eight experts. The expert panel comprised four researchers with expertise in AI literacy and AI education, two specialists in educational measurement and questionnaire development, and two experts familiar with the target population and its educational context. This composition was intended to support the evaluation of the items' conceptual

relevance, alignment with the intended construct dimensions, clarity, and contextual appropriateness. Following Lawshe's (1975) approach, experts independently rated each item using three categories: essential, useful but not essential, or not necessary. Content Validity Ratios (CVRs) were calculated to assess expert agreement regarding item essentiality. Only items with a CVR of at least 0.75, the critical value for a panel of eight experts, were retained (Ayre & Scally, 2014). Six of the ten retained items achieved unanimous expert agreement (CVR = 1.00), exceeding the critical value of 0.75 for eight experts. Four additional items achieved CVR values of 0.75, meeting the critical threshold, and were therefore retained in the test. The final instrument comprised ten items addressing self-perceived conceptual and technical AI knowledge, practical use of AI applications, critical evaluation of AI-generated information, and awareness of ethical issues and AI-related risks (see Table 1).

Table 1

Content Validity Ratios of the 10 items.

	Item wording	Essential (1)	Useful but not essential (2)	Not necessary (3)	Proportion essential	CVR
AIL1	I can explain the difference between different types of Artificial Intelligence (e.g., supervised learning, unsupervised learning, reinforcement learning)	7	1	0	87.5%	0.75
AIL2	I know what an algorithm is	7	1	0	87.5%	0.75
AIL3	I can explain how machine learning works	7	1	0	87.5%	0.75
AIL4	I can explain what large language models are	8	0	0	100.0%	1.00
AIL5	I can explain what a neural network is	8	0	0	100.0%	1.00
AIL6	I can use everyday AI applications (e.g., chatbots, automatic text correction, voice commands)	8	0	0	100.0%	1.00
AIL7	I have experience using machine learning or data analysis tools	7	1	0	87.5%	0.75
AIL8	I am confident in my ability to critically evaluate information provided by Artificial Intelligence	8	0	0	100.0%	1.00
AIL9	I am confident in my ability to understand and discuss ethical issues related to Artificial Intelligence (e.g., algorithmic bias, privacy)	8	0	0	100.0%	1.00
AIL10	I am aware of the potential risks associated with the use of Artificial Intelligence	8	0	0	100.0%	1.00

Rather than assigning the ten items a priori to predefined subscales, their empirical structure was examined through exploratory factor analysis. Responses were subsequently used to derive the AI-literacy dimensions identified empirically in the present study. The ten-item set demonstrated good overall internal consistency (Cronbach's $\alpha = .882$); reliability estimates for the empirically identified dimensions are reported in the Results section. Additional closed-ended items (Questions 17–20) examined teachers' views of AI in education, perceived educational applications of AI, and professional-development needs. Two open-ended questions invited participants to elaborate on their experiences, concerns, and expectations regarding AI in educational practice. Although the questionnaire generated both quantitative and qualitative data, only the quantitative data relevant to the aims of the present study are analyzed here.

Data were collected between February 2025 and November 2025 in the context of compulsory professional-development programmes coordinated by Public School Counselors responsible for teacher professional development in Greece and delivered by the author. Additional participants were recruited through professional-development initiatives organized by university Teaching and Learning Centers. The questionnaire was administered immediately before the substantive AI-related content of the professional-development session was delivered. Consequently, responses to the AI-literacy items were not based on knowledge acquired during the session in which data collection occurred. Likewise, the variable concerning prior AI-related education or training referred exclusively to participants' previous experience and did not include the professional-development activity during which the questionnaire was administered. Participation in the study was voluntary, was not a requirement for participation in the professional-development programme, and responses were collected anonymously.

Statistics - Statistical analyses were conducted using IBM SPSS Statistics, Version 21, supplemented where necessary by computational procedures for parallel analysis and McDonald's omega. To address RQ1, the empirical structure of the AI-literacy items was examined using exploratory factor analysis (EFA). Exploratory factor analysis was conducted on the correlation matrix of the AI-literacy items using principal-axis factoring with oblique rotation. Sampling adequacy was assessed using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity. The number of factors to retain was determined through parallel analysis with 1,000 random permutations. Principal-axis factoring with oblique rotation was then used to identify the underlying factor structure. Internal consistency of the resulting dimensions was assessed using Cronbach's alpha and McDonald's omega.

The overall self-reported AI-literacy score was calculated for each participant as the arithmetic mean of the ten AI-literacy items (AIL1–AIL10). Higher scores indicated higher levels of self-reported AI literacy. Composite scores for the two empirically identified dimensions were calculated by averaging the corresponding items: AIL1–AIL5 and AIL7 for Conceptual–Technical AI Literacy, and AIL8–AIL10 for Critical–Ethical AI Literacy. AIL6 was retained as a separate indicator of Practical AI Use because it did not load uniquely on either factor. Descriptive statistics were used to examine the overall level of self-reported AI literacy and the levels of the identified dimensions, thereby addressing RQ2. Differences between the identified dimensions were examined using paired-samples t-tests.

To address RQ3, a multivariate general linear model (GLM) was conducted with the empirically derived Conceptual–Technical and Critical–Ethical AI Literacy scores as dependent variables and teaching level, prior AI-related education or training, and highest degree attained as predictors. The teaching-level × prior-training interaction was included to examine whether the association between previous AI-related training and AI literacy differed across educational sectors. This interaction was specified a priori on substantive grounds, as teaching level was expected to reflect differences in professional responsibilities, institutional contexts, and opportunities for AI-related learning that could moderate the association between prior training and self-reported AI literacy. Significant multivariate effects were followed by univariate tests for each AI-literacy dimension. Practical AI Use (AIL6), which did not load uniquely on either factor, was analyzed separately using a univariate GLM with the same predictors. Overall, AI Literacy was also examined using a separate univariate GLM. Significant teaching-level × prior-training interactions were further examined through simple-effects analyses based on model-estimated marginal means. Specifically, the association between prior training and each AI-literacy outcome was examined within each teaching level, adjusting for highest degree attained. Differences between training-related contrasts across teaching levels were formally tested. Estimated mean differences were reported with 95% confidence intervals, and Holm's sequential procedure was applied to the p-values of multiple comparisons. Finally, associations among the categorical predictors were examined using chi-square tests of independence and Cramér's V to assess potential overlap between teaching level, prior AI-related training, and highest degree attained. To assess the robustness of the findings given the association between teaching level and highest degree attained, sensitivity analyses were conducted by repeating the GLMs without highest degree as a predictor.

Statistical significance was set at $\alpha = .05$. Effect sizes for the general linear models (GLM) were reported as partial eta squared (ηp^2). Values of approximately .01, .06, and .14 were interpreted as small, medium, and large effects, respectively, following Cohen (1988).

5. Results

5.1 RQ1: Empirical Structure of the AI-Literacy Indicators

To address RQ1, the empirical structure of the ten AI-literacy indicators was examined using exploratory factor analysis. Principal-axis factoring with oblique rotation was applied to the correlation matrix of the items. The data were suitable for factor analysis, as indicated by a Kaiser–Meyer–Olkin value of .893 and a significant

Bartlett's test of sphericity, $\chi^2(45) = 5805.19$, $p < .001$. Parallel analysis with 1,000 random permutations supported the retention of two factors. The first three observed eigenvalues were 5.073, 1.164, and .957; only the first two exceeded the corresponding 95th-percentile eigenvalues generated under random permutations. Principal-axis factoring was therefore conducted specifying two factors.

As shown in Table 2, the first factor comprised AIL1–AIL5 and AIL7, with salient loadings ranging from .396 to .892, and was interpreted as Conceptual–Technical AI Literacy. The second factor comprised AIL8–AIL10, with loadings ranging from .674 to .855, and was interpreted as Critical–Ethical AI Literacy. AIL6, assessing practical use of everyday AI applications, cross-loaded on both factors (.421 and .306) and was therefore excluded from the composite scores and retained as a separate indicator of Practical AI Use.

Table 2

Factor Loadings of the AI-Literacy Indicators.

Item	Conceptual–Technical AI Literacy	Critical–Ethical AI Literacy
AIL1	.396	−.111
AIL2	.618	−.048
AIL3	.892	−.021
AIL4	.686	−.071
AIL5	.874	.040
AIL6	.421	.306
AIL7	.715	−.017
AIL8	.034	.674
AIL9	−.032	.855
AIL10	.028	.779
Cronbach's α	.858	.817
McDonald's ω	.913	.870

*Note. Factor loadings were obtained using principal-axis factoring on the correlation matrix of the AI-literacy items with oblique rotation. Bold values indicate salient loadings (≥ .30). AIL6 cross-loaded on both factors and was therefore excluded from the composite scores and retained as a separate indicator of Practical AI Use. KMO = .893; Bartlett's test of sphericity, $\chi^2(45) = 5805.19$, $p < .001$. Parallel analysis with 1,000 random permutations supported a two-factor solution.

Both empirically identified dimensions demonstrated satisfactory internal consistency. The Conceptual–Technical dimension showed a standardized Cronbach's α of .858 and McDonald's ω of .913, while the Critical–Ethical dimension yielded α = .817 and ω = .870. These findings indicate that the AI-literacy indicators organized into two broader, related dimensions, alongside a separate indicator of practical AI use.

5.2 RQ2: Overall Level of AI Literacy and Levels Across the Identified Dimensions

To address RQ2, the overall level of self-reported AI literacy and the levels of the empirically identified dimensions were examined. The sample demonstrated a mean overall AI-literacy score of M = 1.82 (SD = .58), with scores ranging from 1.00 to 4.80, indicating scores concentrated toward the lower end of the five-point response scale. A marked imbalance was evident across the empirically identified dimensions. Conceptual–Technical AI Literacy showed the lowest mean (M = 1.55, SD = .61), whereas Critical–Ethical AI Literacy was substantially higher (M = 2.37, SD = .76). Practical AI Use, represented by AIL6, occupied an intermediate position (M = 1.83, SD = .80). A paired-samples t-test confirmed that Critical–Ethical AI Literacy was significantly higher than Conceptual–Technical AI Literacy, $t(1172) = 43.14$, $p < .001$. Thus, teachers' responses indicated higher self-reported scores on critical–ethical awareness and confidence items.

As shown in Table 3, self-reported conceptual and technical AI knowledge was generally low across educational levels. Particularly low overall means were observed for experience with machine-learning or data-analysis tools (AIL7, M = 1.30, SD = .64), knowledge of algorithms (AIL2, M = 1.40, SD = .81), and knowledge

of neural networks (AIL5, M = 1.40, SD = .75). Knowledge of machine learning (AIL3, M = 1.60, SD = .84) and large language models (AIL4, M = 1.64, SD = .82) was also relatively limited. Knowledge of the main types of AI (AIL1) was somewhat higher overall (M = 1.97, SD = .98), with primary-education teachers reporting the highest mean on this item. Higher-education teachers generally reported higher scores on several of the remaining conceptual and technical indicators, particularly knowledge of algorithms and neural networks and experience with machine-learning or data-analysis tools, although the comparatively large standard deviations indicate considerable heterogeneity within the higher-education group.

Table 3

Descriptive Statistics for AI-Literacy Items by Educational Level.

Questions	Primary		Secondary		Higher		TOTAL	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
AIL1	2.47	1.25	1.63	0.58	1.95	.72	1.97	.98
AIL2	1.30	.66	1.34	.71	2.13	1.28	1.40	.81
AIL3	1.65	.84	1.48	.72	2.00	1.19	1.60	.84
AIL4	1.72	.86	1.56	.73	1.79	1.00	1.64	.82
AIL5	1.37	.66	1.30	.61	2.01	1.24	1.40	.75
AIL6	1.74	.68	1.75	.69	2.52	1.26	1.83	.80
AIL7	1.40	.64	1.16	.42	1.71	1.15	1.30	.64
AIL8	2.79	1.08	2.84	1.03	3.25	1.30	2.86	1.08
AIL9	1.96	.83	2.00	.80	2.39	1.06	2.03	.85
AIL10	2.16	.73	2.20	.66	2.56	.88	2.22	.72

In contrast, the highest overall mean was observed for confidence in critically evaluating information provided by AI (AIL8, M = 2.86, SD = 1.08), followed by awareness of potential risks associated with AI use (AIL10, M = 2.22, SD = .72) and perceived ability to understand and discuss ethical issues related to AI (AIL9, M = 2.03, SD = .85). The same general asymmetry was evident across primary, secondary, and higher education, although higher-education teachers tended to report stronger AI-related competence overall. This pattern suggests that teachers' self-reported AI literacy is characterized less by uniformly low competence across all areas than by uneven development, with critical and ethical awareness exceeding conceptual and technical understanding.

5.3 RQ3: Associations With Teaching Level, Prior AI Education or Training, and Highest Degree Attained

The analyses revealed significant teaching-level × prior-training interactions across the four AI-literacy outcomes, indicating that the association between prior AI-related education or training and self-reported AI literacy varied across educational sectors. Follow-up comparisons showed positive training-related differences at all three teaching levels, with the largest differences generally observed among higher-education teachers. Table 4 presents the adjusted mean differences and corresponding 95% confidence intervals.

Table 4

Adjusted Differences in Self-Reported AI Literacy Between Teachers With and Without Prior AI-Related Training, by Teaching Level

AI-Literacy Outcome	Teaching Level	Adjusted Mean Difference	95% CI
Overall AI Literacy	Primary	0.496	[0.401, 0.591]
	Secondary	0.392	[0.312, 0.472]
	Higher education	1.099	[0.901, 1.296]
Conceptual–Technical AI Literacy	Primary	0.470	[0.370, 0.569]
	Secondary	0.389	[0.305, 0.473]
	Higher education	1.244	[1.037, 1.452]
Critical–Ethical AI Literacy	Primary	0.562	[0.429, 0.696]
	Secondary	0.407	[0.295, 0.520]
	Higher education	0.869	[0.591, 1.147]
Practical AI Use	Primary	0.457	[0.317, 0.597]
	Secondary	0.361	[0.243, 0.479]
	Higher education	0.913	[0.622, 1.204]

Note. Adjusted mean differences represent contrasts between participants with and without prior AI-related education or training (Yes − No), estimated from general linear models controlling for highest degree attained. Positive differences indicate higher self-reported AI-literacy scores among participants with prior training. Confidence intervals are unadjusted 95% intervals. All within-teaching-level contrasts were statistically significant after Holm correction for multiple comparisons (adjusted $p < .001$).

The teaching-level × prior-training interaction was statistically significant for Overall AI Literacy, $F(2, 1165) = 21.24$, $p < .001$, $\eta^2_p = .035$. Simple-effects analyses showed that teachers reporting previous AI-related training had significantly higher adjusted overall AI-literacy scores than those without previous training in primary, secondary, and higher education (all Holm-adjusted $p < .001$; Table 4). Formal comparisons of the training-related contrasts indicated that the association was significantly stronger in higher education than in primary education (difference between contrasts = 0.602, 95% CI [0.384, 0.821], Holm-adjusted $p < .001$) and secondary education (difference between contrasts = 0.707, 95% CI [0.494, 0.920], Holm-adjusted $p < .001$). The difference between primary and secondary education was not statistically significant after adjustment ($p = .097$).

The multivariate analysis of the two empirically identified AI-literacy dimensions revealed a significant teaching-level × prior-training interaction, $F(4, 2330) = 14.48$, $p < .001$. Follow-up univariate analyses showed that the interaction was particularly pronounced for Conceptual–Technical AI Literacy, $F(2, 1165) = 28.24$, $p < .001$, $\eta^2_p = .046$. Simple-effects analyses indicated significantly higher adjusted Conceptual–Technical AI Literacy scores among participants with previous AI-related training at all three teaching levels (all Holm-adjusted $p < .001$; Table 4). Comparisons of training-related contrasts demonstrated that the association was significantly stronger in higher education than in primary education (difference between contrasts = 0.775, 95% CI [0.544, 1.005], Holm-adjusted $p < .001$) and secondary education (difference between contrasts = 0.855, 95% CI [0.631, 1.079], Holm-adjusted $p < .001$). The difference between primary and secondary education was not statistically significant (Holm-adjusted $p = .224$).

The teaching-level × prior-training interaction was also statistically significant for Critical–Ethical AI Literacy, $F(2, 1165) = 5.12$, $p = .006$, $\eta^2_p = .009$, although the effect size was smaller than that observed for Conceptual–Technical AI Literacy. Simple-effects analyses revealed significantly higher adjusted scores among participants reporting previous AI-related training at all three teaching levels (all Holm-adjusted $p < .001$; Table 4). The training-related contrast was significantly larger in higher education than in secondary education (difference between contrasts = 0.462, 95% CI [0.162, 0.761], Holm-adjusted $p = .008$). However, the differences between higher and primary education and between primary and secondary education were not statistically significant after adjustment (both Holm-adjusted $p = .102$).

Practical AI Use was examined separately because AIL6 did not load uniquely on either factor. The teaching-level × prior-training interaction was statistically significant, $F(2, 1165) = 5.98$, $p = .003$, $\eta^2_p = .010$. Simple-effects analyses showed significantly higher adjusted Practical AI Use scores among participants with previous AI-related training at all three teaching levels (all Holm-adjusted $p < .001$; Table 4). The association was significantly stronger in higher education than in primary education (difference between contrasts = 0.456, 95% CI [0.133, 0.778], Holm-adjusted $p = .011$) and secondary education (difference between contrasts = 0.552, 95% CI [0.238, 0.866], Holm-adjusted $p = .002$). The difference between primary and secondary education was not statistically significant (Holm-adjusted $p = .300$).

Chi-square tests of independence revealed a weak association between teaching level and prior AI-related training, $\chi^2(2) = 9.02$, $p = .011$, Cramér's $V = .088$. A substantially stronger association was observed between teaching level and highest degree attained, $\chi^2(4) = 655.08$, $p < .001$, $V = .528$. Prior AI-related training was also weakly associated with highest degree attained, $\chi^2(2) = 16.24$, $p < .001$, $V = .118$.

Notably, 115 of the 117 higher-education teachers held a doctoral degree, indicating considerable overlap between teaching level and educational attainment. This association limits the extent to which their independent contributions can be distinguished and warrants caution when interpreting estimates adjusted for highest degree attained. Sensitivity analyses excluding highest degree attained confirmed that the teaching level × prior training interaction remained statistically significant for Conceptual–Technical AI Literacy ($p < .001$), Critical–Ethical AI Literacy ($p = .004$), and Practical AI Use ($p = .003$).

6. Discussion

The present study examined the empirical structure, overall level, and correlates of self-reported AI literacy among 1,173 in-service teachers across primary, secondary, and higher education in Greece. Three findings are particularly noteworthy: the AI-literacy indicators clustered into two broader dimensions rather than reproducing the domains of existing frameworks; teachers reported substantially higher critical–ethical than conceptual–technical scores; and the positive association between prior AI-related training and self-reported AI literacy varied significantly across educational sectors, with particularly large differences among higher-education teachers.

Regarding RQ1, exploratory factor analysis identified two dimensions, Conceptual–Technical AI Literacy and Critical–Ethical AI Literacy, while the item measuring Practical AI Use cross-loaded on both factors and was retained separately. This structure differs from Wang et al.'s (2023) four-domain framework of awareness, use, evaluation, and ethics, although the conceptual content of those domains remains represented in the present instrument. Conceptual–Technical AI Literacy primarily reflects knowledge of AI mechanisms and related technologies, whereas Critical–Ethical AI Literacy combines perceived ability to evaluate AI-generated information, understanding and discussing ethical issues, and awareness of AI-related risks. The convergence of critical and ethical indicators is conceptually plausible, given their shared emphasis on evaluating AI outputs and consequences (Long & Magerko, 2020; Ng et al., 2021). It is also compatible with broader multidimensional conceptualizations of AI literacy (Casal-Otero et al., 2023; Almatrafi et al., 2024). The distinction between AI literacy and ethical awareness is also reflected in Du et al. (2024), who found a positive association between the two constructs among Chinese K–12 teachers. While their study examined ethical awareness as a separate construct associated with AI literacy, the present exploratory analysis identified a combined Critical–Ethical dimension within its particular set of self-report indicators.

Nevertheless, the two-factor solution should not be interpreted as evidence that AI literacy inherently consists of only two dimensions or that evaluation and ethics are indistinguishable competencies. Unlike Wang et al.'s (2023) instrument, which was developed around theoretically specified constructs, the present study used a shorter, researcher-developed item set and an exploratory approach. The resulting structure may therefore reflect item coverage, conceptual overlap, and measurement characteristics. Similarly, the cross-loading of Practical AI Use suggests that everyday engagement with AI applications shares features with both dimensions, but a single item cannot establish an independent practical competence domain. These findings underline the importance of examining the empirical structure of AI-literacy measures rather than assuming that theoretically defined domains will necessarily emerge as separate factors in every population. Importantly, the identified factor structure is sample- and item-dependent, and its stability and equivalence across educational sectors remain unestablished in the absence of confirmatory factor analysis (CFA) and measurement invariance testing.

Regarding RQ2, the mean overall self-reported AI-literacy score was relatively low. More importantly, teachers displayed a pronounced asymmetry between Conceptual–Technical AI Literacy and Critical–Ethical AI Literacy, supporting H1, which predicted higher self-reported confidence in critically evaluating AI and recognizing its ethical implications than in understanding its underlying concepts and technical mechanisms. Practical AI Use occupied an intermediate position. At the item level, particularly low scores concerned experience with machine-learning or data-analysis tools, knowledge of algorithms, and knowledge of neural networks. By contrast, perceived ability in critically evaluating AI-generated information was the highest-scoring item. These findings are consistent with previous research documenting limitations and unevenness in teachers' AI-related knowledge and competencies. Traga-Philippakos and Rocconi (2025) reported variation in teachers' familiarity with AI concepts and applications, while Sperling et al. (2024) highlighted the need to consider different forms of professional knowledge when conceptualizing teachers' AI literacy. More specifically, the present findings partly align with Kesen Mutlu (2025), who reported relatively low overall GenAI literacy among Turkish EFL teachers, with particularly low scores in design and evaluation but comparatively higher scores in ethics. Both studies therefore suggest an uneven profile of self-reported AI literacy, although they differ in the relative position of critical evaluation: whereas evaluation was among the lowest-scoring dimensions in Kesen Mutlu's study,

confidence in critically evaluating AI-generated information was the highest-scoring item in the present study. This divergence may reflect differences in the operationalization of evaluation and the populations examined. The present study extends this literature by documenting the asymmetry between conceptual–technical and critical–ethical indicators in a large sample encompassing primary, secondary, and higher education in Greece. However, because these indicators assess self-perceived knowledge, experience, and awareness rather than demonstrated competence, the observed asymmetry should not be interpreted as evidence of superior critical-evaluation ability.

The expression "awareness without conceptual depth" captures this asymmetry in teachers' responses, but requires careful interpretation. The study did not establish that participants could accurately evaluate AI outputs while lacking the knowledge necessary to do so. Rather, participants reported greater confidence in critical evaluation and greater awareness of AI-related risks than knowledge of underlying technical concepts. These differences may reflect genuine variation in perceived competencies, but they may also be influenced by item characteristics: conceptual–technical items referred to specific concepts and technologies, whereas critical–ethical items asked about confidence, awareness, or the ability to discuss broader issues. Accordingly, the observed difference should not be treated as a demonstrated discrepancy between actual critical competence and technical knowledge. Performance-based assessments and instruments with more comparable item formulations are needed to establish whether the same asymmetry characterizes teachers' demonstrated abilities.

The pattern nevertheless raises an important educational question. Teachers are increasingly expected to evaluate AI-generated materials, identify unreliable outputs, and address ethical risks, yet the present findings suggest that their perceived familiarity with these responsibilities is not matched by equally high self-reported understanding of AI mechanisms (Karaduman, 2025). This tension is compatible with concerns raised in the literature about fragmented AI competencies and the distinction between routine technological engagement and informed pedagogical use (Ng et al., 2021; Sperling et al., 2024; Author, in press). It should be understood as a possible mismatch between expanding professional expectations and teachers' reported preparation, rather than as evidence of objectively inadequate teaching competence. In the emerging post-AI educational context, the relevant challenge is not simply increasing exposure to AI tools but supporting the conceptual understanding and professional judgment required for their educational use.

RQ3 yielded particularly informative findings concerning prior AI-related education or training. Consistent with H2, teachers reporting previous training had significantly higher adjusted scores on Overall AI Literacy, Conceptual–Technical AI Literacy, Critical–Ethical AI Literacy, and Practical AI Use at all three educational levels. These positive associations are consistent with studies linking AI-related professional development to stronger AI-literacy outcomes (Ding et al., 2024; O'Dea et al., 2024; Ayyoub et al., 2025; Lademann et al., 2026). Importantly, the present findings extend this literature by examining training-related differences separately within primary, secondary, and higher education rather than treating teachers as a homogeneous professional group.

The teaching-level × prior-training interaction was statistically significant for all four outcomes, supporting H3. For Overall AI Literacy, the association between prior AI-related training and self-reported literacy was considerably stronger among higher-education teachers than among those working in primary or secondary education, with the smallest difference observed in secondary education. Formal comparisons confirmed that the higher-education contrast was significantly larger than both school-sector contrasts, whereas the primary–secondary difference was not statistically significant. Thus, the most distinctive finding is not merely that teachers with previous training reported higher AI literacy, but that the magnitude of this association differed substantially by educational sector.

This pattern was especially evident for Conceptual–Technical AI Literacy. Both comparisons involving higher education were statistically significant after Holm correction. This result is noteworthy because conceptual–technical understanding was the lowest-scoring dimension overall, yet the association with previous training was particularly large in the higher-education subgroup. One possible interpretation is that prior AI-related learning may be more closely connected to opportunities for specialized technological or research-related engagement in

higher education. However, the study did not assess training content, institutional support, or subsequent applications of AI knowledge, so this explanation remains provisional.

The interactions for Critical–Ethical AI Literacy and Practical AI Use were also significant, although their estimated effect sizes were smaller. For Critical–Ethical AI Literacy, the training-related difference was significantly larger in higher than in secondary education, but the other between-sector comparisons were not significant after adjustment. For Practical AI Use, the higher-education contrast exceeded those in both primary and secondary education. These findings indicate that the relationship between previous training and self-reported AI literacy is context-sensitive, but not identical across outcomes. The larger interaction effect size for Conceptual–Technical AI Literacy is descriptively noteworthy; however, the study did not formally test whether training associations differed between the two AI-literacy dimensions. Such a cross-dimensional conclusion would therefore be unwarranted.

The role of educational level and highest degree attained also requires careful interpretation. Higher-education teachers generally reported higher scores on several conceptual–technical indicators and on everyday practical AI use, whereas differences in critical–ethical indicators were less pronounced. These patterns may reflect differences in disciplinary specialization, research practices, and opportunities to engage with AI-related technologies, as suggested by the contextual perspective developed in Section 2.2 (Lan et al., 2026). However, educational level was strongly associated with highest degree attained: 115 of the 117 higher-education participants held doctoral degrees. This substantial overlap limits the extent to which sector-specific associations can be distinguished from those related to academic qualifications. The results therefore do not establish that employment in higher education, or possession of a doctoral degree, independently accounts for stronger AI-literacy scores. Nevertheless, sensitivity analyses excluding highest degree confirmed the robustness of the teaching level × prior training interactions across the three outcomes. Thus, although sector and qualification effects cannot be fully disentangled, the observed differences in training-related associations were not dependent on including academic qualifications in the models.

An additional implication concerns the distinction between general academic qualifications and AI-specific professional learning. Advanced degrees do not necessarily entail systematic education in AI, and associations with prior AI-related training should not be interpreted as interchangeable with educational attainment. Importantly, the cross-sectional design precludes causal conclusions about training effectiveness. Teachers with greater motivation, prior technological experience, or confidence may have been more likely to seek AI-related training, while unequal access to professional-development opportunities may also have influenced participation. Furthermore, training was assessed through self-reported participation without information on its content, duration, or quality. These considerations are particularly relevant to the large training-related contrasts observed in higher education, which should be interpreted as associations rather than evidence of stronger training effects.

Overall, the findings suggest several priorities for professional development. First, the low conceptual–technical scores indicate a need to address foundational AI concepts, including algorithms, machine learning, model training, and system limitations, without assuming that teachers require programming expertise. Second, the higher critical–ethical scores should not be taken as grounds for reducing attention to critical evaluation or ethical decision-making. Instead, professional learning should connect conceptual understanding with the verification of AI-generated information, recognition of bias, protection of student data, and judgments about appropriate educational applications. Such an approach is consistent with multidimensional accounts of AI literacy (Long & Magerko, 2020; Ng et al., 2021) and with the Content and AI-Integrated Learning framework, which emphasizes the integration of AI within disciplinary learning and pedagogical purposes (Gavriilidou, 2025).

Third, the significant teaching-level × training interactions argue against assuming that a single professional-development model will be equally relevant across educational sectors. Primary and secondary teachers may require examples closely connected to classroom planning, student learning, assessment, and safeguarding, whereas higher-education programmes may also address research-related applications, disciplinary specialization,

and advanced AI concepts. These are proposed design considerations rather than intervention effects demonstrated by the present study. Their effectiveness should be evaluated through comparative and longitudinal research.

Professional development should therefore be pedagogically situated rather than organized exclusively around technological functionality. Boud and Brew (2013) emphasize professional learning through teaching practice and collegial engagement, while Baran, Correia, and Thompson (2011) caution against technology integration that privileges tools over pedagogical transformation. Similarly, Fawns (2019) and Selwyn (2010) situate educational technologies within wider pedagogical, institutional, and sociotechnical relationships. Applied to AI literacy, these perspectives support professional learning that combines conceptual explanation with authentic teaching and learning tasks: evaluating AI-generated resources, adapting materials to learners' needs, and designing activities in which students verify AI-generated information, identify inaccuracies, and justify their reasoning rather than accepting AI outputs uncritically. Such provision also requires institutional guidance and support; individual teachers cannot be expected to resolve questions of responsible AI integration through personal competence alone.

Overall, the study contributes evidence that teachers' self-reported AI literacy is unevenly distributed across competencies and that its association with previous AI-related training varies substantially by educational sector. Its distinctive contribution lies in combining an exploratory examination of AI-literacy indicators with adjusted, sector-specific comparisons of training-related differences. The findings support a shift from generic calls for greater AI literacy toward more differentiated professional learning, while highlighting the need for performance-based assessment, stronger instrument validation, and research capable of distinguishing training effects from pre-existing differences between teachers.

7. Conclusions and limitations

To the best of our knowledge, this is the first large-scale study to examine self-reported AI literacy comparatively across primary, secondary, and higher education in Greece. Drawing on data from 1,173 in-service teachers, the study provides evidence of generally low self-reported AI literacy, with substantially higher scores on critical–ethical than conceptual–technical indicators. This uneven profile, described as "awareness without conceptual depth," concerns perceived rather than demonstrated competencies and should be interpreted in light of the instrument's characteristics. Beyond documenting this asymmetry, the study's principal contribution is identifying significant differences across educational sectors in the association between prior AI-related training and self-reported AI literacy. Although positive training-related associations were observed across all three sectors, they were particularly pronounced for Conceptual–Technical AI Literacy in higher education. These findings extend previous research by demonstrating that the relationship between prior training and perceived AI competencies varies according to educational context.

The findings support the development of differentiated, pedagogically grounded professional development that integrates conceptual understanding, practical application, critical evaluation, and ethical judgment. Teacher education should also incorporate authentic tasks involving the evaluation and adaptation of AI-generated explanations, learning materials, assessments, and feedback, rather than focusing exclusively on familiarity with AI tools.

Several limitations should be acknowledged. The reliance on self-report data precludes conclusions about demonstrated AI competence, while differences in item wording and specificity may have contributed to the observed asymmetry. The researcher-developed instrument requires further validation, and Practical AI Use was assessed through a single item. The convenience sample limits generalizability, while the cross-sectional design, potential self-selection into training, and unequal access to professional-development opportunities preclude causal interpretations of training-related associations. Moreover, previous training was measured without distinguishing its content or duration. The smaller higher-education subgroup, the substantial overlap between teaching level and academic qualifications, and the absence of CFA and measurement invariance testing further limit the interpretation of cross-sector comparisons, as dimensional equivalence cannot be assumed.

Future studies should validate the two-factor structure through CFA in independent samples and examine measurement invariance across primary, secondary, and higher education before drawing stronger conclusions about cross-sector differences. Future research should, also, combine self-report and performance-based measures, using instruments with comparable item formulations, to determine whether the observed asymmetry reflects genuine differences in competencies or measurement-related effects. Longitudinal and intervention studies should examine how different forms of AI-related training influence specific competencies across educational sectors. Importantly, research should also investigate whether improvements in AI literacy translate into more informed pedagogical decisions and higher-quality AI-supported teaching materials and learning activities.

Declaration of AI and AI-Assisted Technology Use During the preparation of this manuscript, the author used Perplexity (Perplexity AI) to proofread the text and improve its grammar, clarity, and readability. Following this use, the author reviewed and edited the text as necessary and takes full responsibility for the final content of the manuscript**.**

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