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Can Teacher AI Literacy Reach Those Who Need It Most? Professional Learning, Realised Access, and Cumulative Advantage in TALIS 2024

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Abstract. This study addresses an implementation problem for informatics education: whether teachers' reported participation in AI-related professional learning, interpreted as realised access to one professional learning condition for teacher AI literacy, is associated with declared need or instead follows existing patterns of digital, professional and organisational advantage. The study does not measure teacher AI literacy, AI competence, computing teaching practice, computational-thinking instruction or classroom implementation directly. Rather, it analyses reported participation in AI-related professional learning as a realised opportunity condition for developing teacher AI literacy at scale. Using TALIS 2024 data from 108,136 lower-secondary teachers nested within 10,840 schools across 55 education systems, three-level multilevel linear probability models and random slopes at the education-system level were estimated. Results showed substantial cross-system inequality in reported participation. Variance decomposition located 8.5% of total variation at the education-system level and 9.7% at the school level. Declared need was only partially associated with reported participation: teachers reporting low or moderate need were more likely to have participated in AI-related professional learning than those reporting no need, whereas teachers with the highest need showed no significant advantage. Digital self-efficacy and professional collaboration were consistently associated with higher participation. At the school level, digital resource shortages and school digital leadership support were significant predictors. Random-slope estimates showed that the association between high declared need and participation varied significantly across education systems. The findings suggest that equitable teacher AI literacy requires deliberate opportunity structures, not only competence frameworks or voluntary participation in professional learning.

Key words: teacher AI literacy, informatics education, AI-related professional learning, realised access, cumulative advantage, TALIS 2024

1. Introduction

The integration of artificial intelligence into education systems has generated a new and uneven demand for teacher professional learning. This issue is directly relevant to informatics education because teacher AI literacy is increasingly understood as a condition for enabling teachers to understand AI systems, evaluate their pedagogical uses and limitations, address ethical risks, and mediate AI-supported learning in school contexts (Chiu, 2025; Kohnke et al., 2025). TALIS 2024 data show that the proportion of teachers reporting professional learning on the use of AI for teaching and learning ranges from less than 10% in France to more than 75% in Singapore (OECD, 2025). This gap cannot be explained solely by differences in technological infrastructure or curriculum policy. The central question is therefore not only whether teachers need AI-related professional learning, a point on which there is broad agreement (Bower et al., 2024; Crompton & Burke, 2024), but whether reported participation in such learning, interpreted here as realised access, is distributed in ways that support the equitable development of teacher AI literacy.

This study treats teacher AI literacy not as an individual competence already achieved, but as an implementation challenge for informatics education. As AI literacy becomes part of the broader agenda of computing education, attention cannot be limited to the definition of competence frameworks, curricular expectations or classroom applications (Dilek et al., 2025; Pei et al., 2026). A prior distributive question must be addressed: which teachers report participation in the professional learning opportunities through which such literacy can be developed, and how should this participation be interpreted as realised access

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rather than as objective availability of provision? This question is especially important when AI literacy is expected to extend beyond specialist informatics teachers and become part of the professional repertoire of the wider teaching workforce. From this perspective, reported participation in AI-related professional learning, interpreted as realised access, is not a peripheral professional-development issue. It is a structural condition for whether teacher AI literacy can be scaled equitably across schools and education systems.

Recent research on teachers' AI competence has clarified what it means to be prepared for AI-mediated teaching. A useful distinction has been drawn between AI literacy, understood as knowledge of how AI systems work, their limitations and their ethical implications, and AI competence, understood as the capacity to mobilise such knowledge when designing teaching and learning situations with these technologies (Chiu, 2025). Exploratory evidence further suggests that teachers' AI literacy remains unevenly developed and requires more precise empirical attention in relation to professional preparation (Deshen et al., 2026). At the same time, recent revisions of the TPACK framework have placed stronger emphasis on context, recognising that the integration of emerging technologies depends not only on teachers' individual knowledge, but also on the institutional conditions under which teaching takes place (Petko et al., 2025). In a review of 42 empirical studies involving pre-service and in-service teachers, Zhou et al. (2026) concluded that individual beliefs, professional learning opportunities and cultural factors shape differentiated trajectories of AI competence development across career stages, subject cultures and regional contexts. Taken together, this literature indicates that teacher AI literacy and competence should not be treated only as individual attributes. They also depend on the opportunity structures through which teachers gain access to relevant professional learning.

Existing empirical research has not addressed this opportunity condition with comparable precision. A systematic review of 95 articles published between 2015 and 2024 found that 65% of the literature focused on AI tools designed to support student learning, while teachers' access to specific professional learning opportunities received far less attention (Tan et al., 2025a). The predominance of convenience samples, the overrepresentation of pre-service teachers in relation to practising teachers and the limited use of comparative designs restrict the capacity of the field to determine whether AI-related professional learning reaches those who need it most or those who already hold prior professional advantages (Li et al., 2025; Tan, 2025). This gap is not only thematic. It is also methodological. Without representative large-scale data and models capable of decomposing variation across levels of analysis, it remains difficult to distinguish individual predictors from school-level and system-level opportunity structures in explaining unequal access. For informatics education, this limitation is important because unequal access to teacher professional learning may shape the conditions under which AI literacy is introduced, supported and sustained in school systems.

Individual factors associated with teachers' readiness for AI are consistent with self-efficacy theory and with models of technology adoption. Prior experience with digital tools is a stable predictor of perceived AI self-efficacy (Wang & Chuang, 2024), while technological confidence and perceived social value moderate teachers' intention to prepare students for AI-related learning (Sanusi et al., 2024). Evidence of qualitatively distinct profiles of teacher AI readiness, differentiated by awareness of AI affordances, willingness to integrate AI into the curriculum and operational self-confidence, indicates that teachers do not approach AI-related professional learning from the same starting point (Ramazanoglu & Akın, 2025). This uneven starting point is central to the present study. If access to professional learning for teacher AI literacy depends on prior digital confidence, then professional learning may reinforce existing differences rather than compensate for them. From an analytical perspective, any model seeking to explain access to AI-related professional learning must therefore account for teachers' prior digital capital before estimating the independent role of declared professional learning need.

Experimental and quasi-experimental studies have shown that structured professional learning interventions can improve teachers' AI-related competence. Programmes differing in duration and design have reported gains in technological knowledge, pedagogical competence with AI and willingness to integrate AI into teaching (Le et al., 2026; Moorhouse et al., 2024; Tan et al., 2025b). Transfer to classroom practice also appears more plausible when professional learning is connected to authentic disciplinary problems (Alexandron et al., 2026). Yet evidence that professional learning can support teacher AI literacy when offered does not demonstrate that such learning is equitably distributed. These interventions rarely examine the selection mechanisms that determine which teachers participate, nor do they compare participants with non-participants located in the same educational context. The question of effectiveness and the question of distributive equity are related, but they are not the same. This distinction is central for informatics education: AI literacy initiatives cannot be judged only by the quality of their professional learning designs, but also by whether access reaches teachers and schools with weaker prior digital capacity.

The school is a necessary level of analysis because it mediates between education policy and teachers' everyday professional practice. Recent evidence from K–12 STEM teachers shows that familiarity with generative AI and perceived support needs are unevenly distributed, reinforcing the role of school-level conditions in shaping teachers' opportunities to engage with AI-related professional learning (Cheah & Kim, 2026). Digital leadership, institutional guidelines and protected time for professional learning can affect teachers' opportunities to participate in AI-related professional development (Cheah et al., 2025; Ng et al., 2025). In a study of 532 teachers, Mah et al. (2026) found a positive and significant association between the frequency of participation in AI-related professional learning and the perceived quality of teaching with these technologies. Comparative evidence also points to contextual differentiation: a latent profile analysis of teachers in Germany and Denmark identified distinct configurations of AI use and self-efficacy across national contexts (Mah et al., 2025). The geography of research production reflects a similar imbalance, with a concentration of studies in Anglophone and Asian contexts and limited representation of other education systems (Sperling et al., 2024). These findings justify treating schools and education systems as opportunity structures for teacher AI literacy, rather than as neutral background contexts.

The broader literature on teacher professional development offers useful tools for analysing differential access, although its direct application to AI-related professional learning requires careful specification. Desimone's (2009) model identifies core features of effective professional development, among which collective participation and coherence with school conditions are especially relevant to questions of distribution. Empirical evidence also shows that participation in formal professional development follows a curvilinear pattern across the teaching career, with stronger uptake in mid-career stages and lower participation later on (Richter et al., 2011). AI-related professional learning may depart from these established patterns. It concerns an emerging domain in informatics education in which seniority does not necessarily confer experiential advantage. The most intense professional learning needs may be concentrated among teachers with weaker prior engagement in digital professional development. School-level conditions, including infrastructure, leadership and innovation culture, may also carry greater explanatory weight than in more established domains of teacher learning.

The tension between declared need and prior advantage is captured by the distinction between a compensatory logic and a logic of cumulative advantage. The Matthew effect (Merton, 1968) and its later formulation as a mechanism of cumulative advantage (DiPrete & Eirich, 2006) predict that, when resources are allocated according to relative position rather than need, initial inequalities widen over time. Applied to professional learning for teacher AI literacy, this mechanism leads to a specific expectation: prior digital capital, embeddedness in professional collaboration networks and favourable school conditions should predict access to AI-related professional learning beyond the effect of declared need. The concept of professional capital, structured around human, social and decisional capital, complements this view by stressing that participation in professional learning depends on the density of professional networks and on the organisational capacity of schools to generate opportunities, not only on individual willingness (Hargreaves & Fullan, 2012). A compensatory pattern would imply the opposite. Once teachers' digital and professional capital and school conditions are controlled, declared professional learning need should retain a positive association with access, especially in education systems whose professional learning structures are oriented towards equity.

To the best of our knowledge, no previous large-scale comparative multilevel study has examined whether teachers' access to professional learning for teacher AI literacy follows a compensatory logic or a cumulative advantage logic. Existing studies tend to focus on single-country samples, rarely decompose variation across teachers, schools and education systems, and seldom distinguish analytically between declared need and previously accumulated digital and professional capital (Chiu et al., 2026; Sperling et al., 2024). This gap is especially relevant for informatics education because unequal access to AI-related professional learning may shape the conditions under which teacher AI literacy is introduced into school systems. The present study addresses this gap using TALIS 2024 data, which include specific items on teachers' professional learning in the use of AI for teaching and learning (OECD, 2025). The analyses are based on a common analytic sample of 108,136 lower-secondary teachers nested within 10,840 schools across 55 countries or participating education systems. The study does not measure teacher AI literacy directly. Rather, it examines whether access to one of the professional learning conditions through which such literacy may be developed is distributed according to declared need, prior digital and professional capital, school-level digital conditions and education-system context.

Five research questions guide the analysis:

RQ1. How widely is access to professional learning for teacher AI literacy distributed across participating education systems?

RQ2. To what extent is teachers' declared need for AI-related professional learning associated with the probability of having participated in such learning?

RQ3. Do teachers' prior digital and professional capital predict access to professional learning for teacher AI literacy beyond declared need?

RQ4. Which school-level digital and organisational conditions are associated with a higher probability of access to AI-related professional learning?

RQ5. Does the association between declared need and access to AI-related professional learning vary across education systems?

2. Method

2.1. Study and sample

This study used data from the Teaching and Learning International Survey 2024 (TALIS 2024). TALIS is an international large-scale assessment focused on teachers, principals, schools and the organisational conditions of teaching. The analyses were conducted with lower-secondary teachers and their schools, using the teacher and principal questionnaires. The data have a hierarchical structure, with teachers nested within schools and schools nested within countries or participating education systems.

The initial working file contained 129,617 teacher records across 55 education systems. Because the variables on AI-related professional learning and declared need for professional learning in AI were administered only in the relevant teacher questionnaire forms, the descriptive and explanatory analyses were restricted to teachers with valid information on the study variables. For the main multilevel models including both teacher- and school-level predictors, the final analytic sample comprised 108,136 teachers nested within 10,840 schools and 55 countries or participating education systems. This common analytic sample was also used to re-estimate the teacher-level model before adding school-level predictors, ensuring that model comparisons were not driven by changes in sample composition.

To make the construction of the analytic sample transparent, Table 1 reports the sequential restrictions applied to the initial working file. These restrictions concerned valid information on reported participation in AI-related professional learning, valid information on declared professional learning need, availability of teacher- and school-level predictors, valid teacher sampling weights, and valid clustering identifiers for schools and education systems. The final sample used in the main multilevel analyses comprised 108,136 teachers nested within 10,840 schools across 55 countries or participating education systems.

Table 1. Construction of the analytic sample

Step	Sample restriction	Teachers retained	Teachers excluded at this step	Schools retained	Education systems retained
1	Initial TALIS 2024 lower-secondary teacher file	129,617	—	11,743	55
2	Teachers in questionnaire forms including the AI-related professional learning and AI-related professional learning need items	129,617	0	11,743	55
3	Valid information on reported participation in AI-related professional learning (TT4G21G)	121,283	8,334	11,731	55
4	Valid information on declared need for AI-related professional learning (TT4G24G)	119,989	1,294	11,729	55

Step	Sample restriction	Teachers retained	Teachers excluded at this step	Schools retained	Education systems retained
5	Valid teacher-level predictors and teaching experience	115,289	4,700	11,720	55
6	Successful linkage with school-level predictors from the principal questionnaire	108,143	7,146	10,841	55
7	Valid teacher sampling weights and valid school and education-system identifiers	108,136	7	10,840	55
Final analytic sample	Common sample used in the main multilevel models	108,136	—	10,840	55

Note. The table reports the sequential construction of the common analytic sample used in the main multilevel models. The initial working file had already been restricted to the teacher questionnaire forms in which the AI-related professional learning and AI-related professional learning need items were administered. Exclusions were applied because of missing or non-applicable values in the dependent variable, missing information on declared need, missing teacher- or school-level predictors, missing school-level information from the principal questionnaire, invalid sampling weights, or missing clustering identifiers. The dependent variable was reported participation in AI-related professional learning, interpreted as realised access to one professional learning condition for teacher AI literacy.

Teacher sampling weights were incorporated in all multilevel models. The analyses also retained the three-level structure of the data by specifying schools and education systems as clustering levels. Cases with missing values in the outcome, predictors, weights or clustering variables were excluded from the corresponding models. All missing or non-applicable values in the analysis file were recoded into a common missing-value code before estimation.

A boundary condition of the study should be noted at the outset. TALIS 2024 allows teachers' reported participation in AI-related professional learning to be analysed comparatively, but it does not provide a direct measure of the objective availability, affordability or institutional accessibility of such learning opportunities. Nor does it provide a direct measure of teacher AI literacy, AI competence, computing teaching practice, computational-thinking instruction or classroom implementation. Accordingly, the outcome analysed in this study is reported participation in AI-related professional learning, interpreted as realised access to one professional learning condition for teacher AI literacy. It should not be read as evidence of teachers' achieved AI-literacy competence or as evidence that AI-related professional learning was objectively offered or equally available to all teachers. This distinction is central to the interpretation of the findings.

2.2. Variables

The dependent variable was teachers' reported participation in AI-related professional learning. This information came from TALIS 2024 item TT4G21G. In the teacher questionnaire, respondents were first asked: "Were any of the topics listed below included in your professional learning activities during the last 12 months?" The response categories were "Yes" and "No". The specific topic used in this study was "Using artificial intelligence for teaching and learning". The variable was coded as binary, with 1 indicating reported participation in professional learning on this topic and 0 indicating no reported participation. In conceptual terms, this variable was treated as reported participation in AI-related professional learning, interpreted as realised access to one professional learning condition for teacher AI literacy. It was not treated as a direct measure of the objective availability, affordability or institutional accessibility of AI-related professional learning, nor as a direct measure of teacher AI literacy, AI competence or classroom implementation. Since the multilevel models were specified as linear probability models, coefficients are interpreted as differences in the probability of reported participation in AI-related professional learning, expressed on the observed probability scale.

The main explanatory variable was teachers' declared need for professional learning in artificial intelligence. It was based on TALIS 2024 item TT4G24G. In the teacher questionnaire, respondents were asked: "For each of the areas listed below, please indicate the extent to which you currently need professional learning activities." The specific area used in this study was "Skills for using artificial intelligence for teaching and learning". The response categories were "No need at present", "Low level of need", "Moderate level of need" and "High level of need". For the regression models, the variable was dummy-coded into three indicators: low need, moderate need and high need. Teachers reporting no need were used as the reference category. This categorical specification was preferred over a linear treatment because the descriptive results suggested that the relationship between declared need and reported participation in AI-related professional learning was not monotonic.

Teacher-level digital and professional capital were captured through three continuous TALIS indices. Digital capital was represented by teachers' self-efficacy in using digital resources and tools (T4SEDRT), which captures teachers' perceived capacity to use digital resources and tools in their teaching. Professional capital was represented by two indicators from the teacher collaboration domain: exchange of information and ideas among teachers (T4EXINF) and professional collaboration in lessons among teachers (T4COLES). The former captures more routine forms of professional exchange, whereas the latter refers to more structured and practice-oriented forms of collaboration around teaching. All three teacher-level continuous predictors were grand-mean centred before estimation.

Teaching experience was included as a categorical control variable. Total years of teaching experience were recoded into four groups: five years or less, 6–10 years, 11–20 years and more than 20 years. Teachers with five years of experience or less served as the reference category. This specification allowed the analysis to control for career-stage differences without assuming a linear relationship between teaching experience and access to AI-related professional learning.

School-level predictors were drawn from the principal questionnaire and from TALIS school-level indices. School shortage of digital resources was constructed from two principal-reported items: shortage or inadequacy of digital technology for instruction (TC4G40E) and insufficient Internet access (TC4G40F). Both items were measured on a four-point scale, with higher values indicating greater shortage. The resulting two-item scale showed adequate internal consistency, Cronbach's alpha = 0.781, and was grand-mean centred. School digital leadership support was captured by TC4G28A, which refers to principals' actions to support the integration of digital resources for teaching. This variable was also grand-mean centred. Two additional school-level indices were included: instructional leadership (T4PLEADS) and opportunities for staff participation in school decisions (T4POPPART). Both were grand-mean centred.

The final model therefore combined three analytically distinct sets of predictors: declared professional learning need, teacher-level digital and professional capital, and school-level digital and organisational conditions. This specification made it possible to examine whether reported participation in AI-related professional learning, interpreted as realised access to one professional learning condition for teacher AI literacy, was mainly aligned with teachers' declared needs, with previously accumulated individual and organisational advantages, or with a combination of both logics.

2.3. Data analysis

The empirical strategy was designed to move from description to explanation, and from average associations to cross-system heterogeneity. We began by estimating the weighted prevalence of reported participation in AI-related professional learning, interpreted as realised access to one professional learning condition for teacher AI literacy, in each country or participating education system. These estimates, together with their 95% confidence intervals, were computed taking into account teacher sampling weights and the clustering of teachers within schools. This initial step made it possible to assess how unevenly AI-related professional learning had entered teacher professional development agendas across education systems as an opportunity condition for teacher AI literacy.

The relationship between declared need and access to professional learning for teacher AI literacy was then examined descriptively. For each level of declared need, we estimated the weighted proportion of teachers who reported participation in AI-related professional learning. The association between the two variables was tested using a Rao–Scott design-adjusted test of independence. This analysis offered a first approximation to the compensatory hypothesis: if professional learning were reaching those who needed it most, access should increase progressively with the intensity of declared need.

The multilevel analyses began with a three-level null model, estimated to determine how much of the variation in reported participation in AI-related professional learning, interpreted as realised access, was located at the teacher, school and education-system levels. Because the dependent variable was binary, the models were specified as three-level linear probability models. This specification was preferred for the main analyses for four reasons. First, it allowed the full teacher–school–education-system structure of the data to be retained. Second, it allowed teacher sampling weights to be incorporated consistently across the multilevel models. Third, it provided coefficients that are directly interpretable as percentage-point differences in the probability of reported participation. Fourth, it allowed variance partition coefficients to be calculated on the observed probability scale, which was central to the study's argument about the teacher-, school- and system-level distribution of realised access.

Logistic and probit multilevel specifications were considered as alternative approaches for the binary outcome. However, they were not used as the main specification because their coefficients are less directly interpretable as probability differences and because variance decomposition across three levels is less straightforward on the observed probability scale. For this reason, nonlinear specifications were used as robustness checks rather than as the primary modelling strategy. Variance partition coefficients were calculated from the estimated teacher-, school- and system-level variance components, providing an estimate of the share of total variation attributable to each level.

The explanatory models were built sequentially. The first model included only declared need for professional learning in AI, in order to test whether teachers reporting greater need were more likely to have participated in AI-related professional learning. The next model added teacher-level indicators of digital and professional capital, together with teaching experience. These variables made it possible to assess whether access to professional learning for teacher AI literacy was associated not only with perceived need, but also with teachers' prior digital confidence and professional embeddedness. The final explanatory model incorporated school-level predictors: shortage of digital resources, digital leadership support, instructional leadership and opportunities for staff participation in school decisions. These variables were included to test whether school digital and organisational conditions operated as opportunity structures for teacher AI literacy. The teacher-level and school-extended models were estimated on the same analytic sample, so that differences between them could be attributed to the inclusion of school predictors rather than to changes in sample composition. Model fit was assessed using information criteria, and explanatory capacity was evaluated through the within- and between-level R^2 estimates provided by Mplus (Muthén & Muthén, 1998–2025).

To examine whether the need–access relationship was similar across education systems, we also estimated a random-slope model. In this specification, the effects of low, moderate and high declared need were allowed to vary at the education-system level. School-level variation in these slopes was fixed to zero, and covariances among the random slopes were constrained to zero to keep the model parsimonious. This model addressed a central question of the study: whether declared need is converted into access to professional learning for teacher AI literacy in a consistent way across systems, or whether this conversion depends on the institutional context in which professional development opportunities are organised.

To assess the adequacy of the linear probability specification, we also inspected the predicted probabilities from the final model. This diagnostic was used to determine whether fitted values fell outside the admissible 0–1 range, a known limitation of linear probability models with binary outcomes. The results of this check are reported in the robustness section.

All multilevel models were estimated in Mplus 9 using robust maximum likelihood estimation. Teachers were specified as level 1, schools as level 2, and countries or participating education systems as level 3. Teacher sampling weights were applied throughout the analyses. Continuous predictors were grand-mean centred before modelling. Statistical significance was evaluated using two-tailed tests, and 95% confidence intervals were reported for the main estimates. Multicollinearity was assessed through variance inflation factors, which did not indicate problematic overlap among the predictors included in the final models. Robustness analyses were conducted to assess whether the substantive conclusions were sensitive to the linear probability specification, the presence of out-of-range predicted probabilities, or the use of a common analytic sample across nested models. Throughout the analyses, coefficients were interpreted as associations with access to professional learning for teacher AI literacy, not as effects on teachers' AI literacy competence or classroom use of AI.

The analyses treat TALIS 2024 indicators as internationally harmonised measures collected through a common survey framework. This supports comparative modelling across participating education systems. However, the study does not assume perfect semantic equivalence across contexts. Reported participation in AI-related professional learning, declared need, digital self-efficacy, professional collaboration and school digital conditions may carry different institutional meanings across systems. The estimates should therefore be interpreted as comparative associations based on harmonised indicators, not as evidence of full cross-system measurement equivalence.

3. Results

3.1. Descriptive characteristics of the analytic sample

Table 2 presents the descriptive statistics for the analytic sample. Overall, 42.9% of teachers reported participation in AI-related professional learning during the previous 12 months, whereas 57.1% reported no participation. Regarding declared need, 11.4% of teachers reported no need for professional learning in AI, 20.5% reported a low level of need, 36.6% a moderate level of need, and 31.6% a high level of need. These descriptive figures indicate that access to professional learning for teacher AI literacy was already present in many education systems, but far from universal. The distribution of teaching experience was relatively balanced, with the two largest groups corresponding to teachers with 11–20 years of experience and those with more than 20 years. The continuous teacher-level indicators showed mean values around the TALIS scale centre, with the highest average observed for self-efficacy in using digital resources and tools and the lowest for professional collaboration in lessons among teachers. At the school level, teachers were located in schools with relatively low reported shortages of digital resources, on average, and moderate levels of leadership support for integrating digital resources into teaching.

Table 2. Descriptive statistics for the analytic sample

Variable	**Category / statistic**	**Weighted % / *M***	***SD***
Reported participation in AI-related professional learning	No	57.1	—
	Yes	42.9	—
Declared need for AI-related professional learning	No need	11.4	—
	Low level of need	20.5	—
	Moderate level of need	36.6	—
	High level of need	31.6	—
Teaching experience	5 years or less	19.7	—
	6–10 years	18.4	—
	11–20 years	30.4	—
	More than 20 years	31.6	—
Self-efficacy in using digital resources and tools	Mean / *SD*	11.520	1.958
Exchange of information and ideas among teachers	Mean / *SD*	11.097	1.988
Professional collaboration in lessons among teachers	Mean / SD	9.237	2.118
Instructional leadership	Mean / *SD*	9.913	1.984
Opportunities to participate in school decisions	Mean / *SD*	10.618	1.997
School shortage of digital resources for instruction	Mean / *SD*	1.716	0.837
School leadership support for integrating digital resources for teaching	Mean / *SD*	2.741	0.808

Note. Percentages, means and standard deviations are weighted using teacher sampling weights. Continuous variables are reported in their original, uncentred metrics. School-level variables are assigned to teachers after merging the principal questionnaire with the teacher file; therefore, their descriptive statistics refer to the teacher-level analytic sample rather than to an unweighted distribution of schools. The analytic sample used in the multilevel models comprised 108,136 teachers nested within 10,840 schools and 55 education systems. AI = artificial intelligence; *SD* = standard deviation.

3.2. Cross-system prevalence of access to professional learning for teacher AI literacy

Figure 1 reveals substantial heterogeneity across participating education systems in the proportion of teachers who reported participation in AI-related professional learning. Weighted estimates ranged from 8.86% in France, 95% CI [7.29, 10.43], to 75.69% in Singapore, 95% CI [73.12, 78.25], a difference of 66.83 percentage points between the two extremes. Alongside Singapore, the highest levels were observed in the United Arab Emirates (72.55%; 95% CI [69.57, 75.53]), Korea (61.93%; 95% CI [59.49, 64.36]), and Kazakhstan (60.36%; 95% CI [58.31, 62.40]). At the lower end of the distribution, in addition to France, the lowest prevalence rates were found in the French Community of Belgium (15.51%; 95% CI [13.10, 17.92]), Morocco (20.25%; 95% CI [17.98, 22.53]), and Denmark (20.90%; 95% CI [17.64, 24.16]).

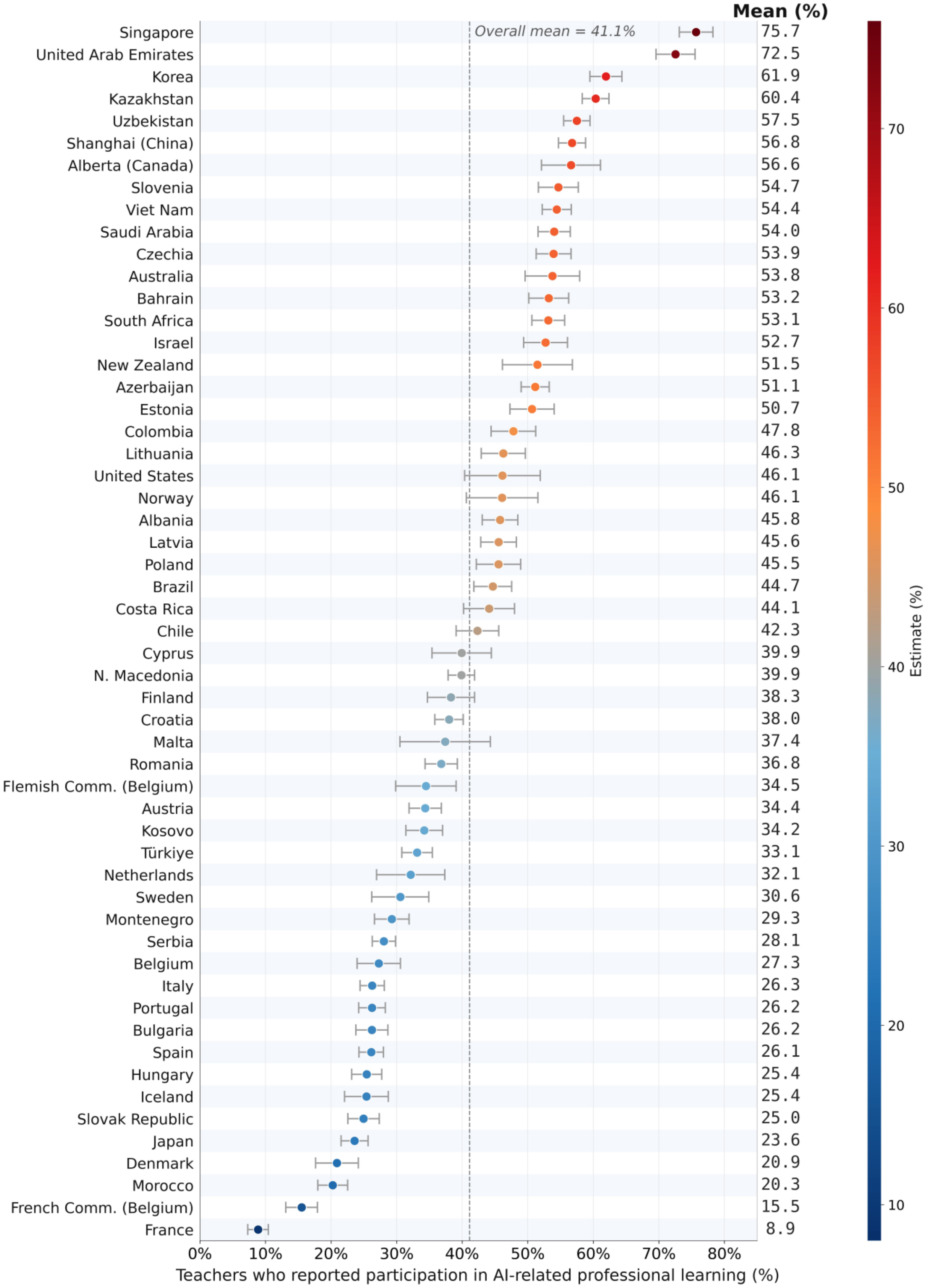

Fig. 1. Percentage of lower-secondary school teachers who reported participation in professional learning on the use of artificial intelligence for teaching and learning, by country or education system (TALIS 2024).

Note. Percentages are weighted estimates. The 95% confidence intervals were estimated accounting for teacher sampling weights and the clustering of teachers within schools. The dependent variable identifies teachers' reported participation in AI-related professional learning during the previous 12 months. The dashed vertical line represents the unweighted mean across participating education systems; the weighted teacher-level analytic-sample percentage is reported in Table 2.

These results indicate that access to professional learning for teacher AI literacy is unevenly distributed across education systems. In some contexts, more than half of teachers reported participation in AI-related professional learning, whereas in others the proportion barely reached one quarter of the teaching workforce, or even fell well below that threshold. This wide descriptive gap suggests that the professional learning conditions required to support teacher AI literacy are advancing at markedly uneven speeds. It also provides early evidence of international disparities in the capacity of education systems to offer professional learning opportunities related to AI as an emerging domain of informatics education. Against this background, the following analyses examine whether access to AI-related professional learning follows primarily a compensatory logic, associated with declared professional learning needs, or a cumulative logic, linked to teachers' digital, professional, and organisational capital.

3.3. Bivariate association between declared need and access to professional learning for teacher AI literacy

Table 3 presents the bivariate association between declared need for AI-related professional learning and the proportion of teachers who reported participation in AI-related professional learning. The results show a statistically significant association between the two variables, according to the Rao–Scott design-adjusted test of independence, $F(2.918, 1476.460) = 29.395$, $p < 0.001$. However, the observed pattern does not follow a strictly linear relationship between professional learning need and actual access to professional learning.

Among teachers who reported no need for AI-related professional learning, 31.33% reported participation in AI-related professional learning, 95% CI [28.79, 33.87]. This proportion increased markedly among those reporting a low level of need, reaching 44.45%, 95% CI [41.89, 47.02], and reached its highest value among teachers with a moderate level of need, at 47.52%, 95% CI [45.47, 49.58]. However, among teachers reporting a high level of need, the proportion reporting participation in AI-related professional learning decreased to 41.82%, 95% CI [39.70, 43.94].

This pattern provides only partial support for a compensatory logic. On the one hand, declaring some degree of professional learning need is associated with a higher prevalence of access than declaring no need at all. In this respect, professional learning for teacher AI literacy appears to reach more frequently those teachers who recognise a need for further professional development in this area. On the other hand, the group with the highest level of need does not show the highest level of access, suggesting that the most intense needs do not necessarily translate into greater professional learning opportunities.

This pattern may be read as an initial indication of an unmet-need gap in the opportunity structure for teacher AI literacy. Access appears to be concentrated especially among teachers who report low or moderate needs, while part of the teaching workforce with the strongest perceived needs may remain less connected to effective professional development circuits. This association should nevertheless be interpreted with caution, given the cross-sectional and self-reported nature of both variables: having participated in AI-related professional learning may reduce perceived need, but it may also increase teachers' awareness of new professional learning demands. For this reason, the subsequent multivariate analyses examine whether this relationship remains once teachers' digital and professional capital, as well as school organisational conditions, are taken into account.

Table 3. Bivariate association between declared need for AI-related professional learning and reported participation in AI-related professional learning

Declared need for AI-related professional learning	% reporting participation in AI-related professional learning	95% CI
No need	31.33	[28.79, 33.87]
Low level of need	44.45	[41.89, 47.02]
Moderate level of need	47.52	[45.47, 49.58]
High level of need	41.82	[39.70, 43.94]

Note. Percentages refer to the weighted proportion of teachers who reported participation in AI-related professional learning on the use of artificial intelligence for teaching and learning within each level of declared professional learning need. The 95% confidence intervals were estimated accounting for teacher sampling weights and the clustering of teachers within schools. The association between the two variables was statistically significant according to the Rao–Scott design-adjusted test of independence, $F(2.918, 1476.460) = 29.395$, $p < 0.001$.

3.4. Variance in access to professional learning for teacher AI literacy between schools and education systems

The previous descriptive results suggest that access to professional learning for teacher AI literacy is unevenly distributed across education systems. The next question is whether this inequality is merely a compositional feature of the teacher population or whether it is also structured by the contexts in which teachers work. To address this issue, a three-level null multilevel model was estimated, with teachers nested within schools and schools nested within countries or participating education systems. Because the outcome was dichotomous, the variance decomposition was estimated using a multilevel linear probability model, which allowed the hierarchical structure of the data and the teacher sampling weights to be retained. The resulting variance partition coefficients are therefore interpreted on the observed probability scale.

The model confirmed that access to AI-related professional learning varied significantly at each level of the educational structure. The largest share of variance was located at the teacher level, as expected, with an estimated variance of 0.197, SE = 0.005, 95% CI [0.188, 0.206]. However, differences between schools and between education systems were far from negligible. The between-school variance was 0.023, SE = 0.002, 95% CI [0.019, 0.027], while the between-system variance was 0.020, SE = 0.003, 95% CI [0.014, 0.027].

The variance partition coefficients indicate that 81.8% of the total variation in access to AI-related professional learning was located at the teacher level, 95% CI [79.0, 84.6]. The remaining 18.2% was located above the individual teacher level, 95% CI [15.4, 21.0], with 9.7% attributable to differences between schools, 95% CI [8.0, 11.4], and 8.5% to differences between countries or education systems, 95% CI [5.7, 11.3]. This distribution is substantively relevant: almost one fifth of the variability in access to AI-related professional learning is associated with contextual levels rather than with individual teachers alone.

These findings support the use of a multilevel analytical strategy and sharpen the central argument of the study. Access to professional learning for teacher AI literacy is not simply an individual attribute or a matter of personal demand. It is also embedded in school-level and system-level opportunity structures. In practical terms, this means that teachers with similar needs may face different probabilities of receiving AI-related professional learning depending on the school in which they work and the education system in which that school is located. The following models therefore examine whether this contextual variation can be partly explained by teachers' declared professional learning needs, their digital and professional capital, and the organisational conditions of schools.

Table 4. Three-level null multilevel model for reported participation in AI-related professional learning

Parameter	Estimate	*SE*	95% CI
Variance components			
Teacher-level variance	0.197	0.005	[0.188, 0.206]
Between-school variance	0.023	0.002	[0.019, 0.027]
Between-system variance	0.020	0.003	[0.014, 0.027]
Variance partition coefficients			
Teacher-level VPC (%)	81.8	1.4	[79.0, 84.6]
School-level VPC (%)	9.7	0.9	[8.0, 11.4]
System-level VPC (%)	8.5	1.4	[5.7, 11.3]
Contextual VPC: school + system (%)	18.2	1.4	[15.4, 21.0]

Note. A multilevel linear probability model was estimated with teachers nested within schools and schools nested within countries or participating education systems. The dependent variable identifies teachers' reported participation in AI-related professional learning. Variance partition coefficients indicate the proportion of variance located at each level of analysis. Estimates incorporate teacher sampling weights. VPC = variance partition coefficient; *SE* = standard error; CI = confidence interval.

3.5. Declared need as a predictor of access to professional learning for teacher AI literacy

The first explanatory model examined whether declared need for AI-related professional learning in artificial intelligence translated into a higher probability of reported participation in AI-related professional learning, once the nesting of teachers within schools and education systems was taken into account. This model provides the first direct test of the compensatory hypothesis. If access to professional learning for teacher AI literacy were primarily distributed according to need, teachers reporting stronger needs should be those most clearly reached by professional learning opportunities. Teachers reporting no need for AI-related professional learning were used as the reference category.

The results indicate that need matters, but not in the straightforward way that a fully compensatory model would predict (Table 5). Compared with teachers who reported no need, those reporting a low level of need showed a 7.7 percentage-point higher probability of reported participation in AI-related professional learning, $b = 0.077$, $SE = 0.010$, 95% CI [0.057, 0.097], $p < 0.001$. The association was strongest among teachers reporting a moderate level of need: their probability of access was 10.7 percentage points higher than that of teachers reporting no need, $b = 0.107$, $SE = 0.018$, 95% CI [0.072, 0.142], $p < 0.001$. However, the coefficient for teachers reporting a high level of need was smaller and did not reach conventional levels of statistical significance, $b = 0.043$, $SE = 0.026$, 95% CI [-0.008, 0.095], $p = 0.099$.

This pattern is analytically important because it complicates a simple compensatory reading of the results. AI-related professional learning appears to reach teachers who acknowledge some degree of need, but it does not reach most clearly those who declare the greatest need. The strongest association is observed for moderate need, not high need. In substantive terms, this suggests that access to professional learning may be organised less around the intensity of need than around a more selective form of responsiveness: teachers with low or moderate needs may be sufficiently close to existing professional learning circuits to enter them, whereas those reporting high need may remain less effectively reached by these opportunities.

The contribution of declared need was statistically significant but modest. The within-level R^2 was 0.007, indicating that declared need accounted for only a small share of teacher-level differences in access. More importantly, the contextual structure of inequality remained almost unchanged. In the null model estimated on the same analytic sample, 18.2% of the variance was located above the individual teacher level; after introducing declared need, this proportion remained at 17.8%. Specifically, 9.4% of the variance was still located between schools, 95% CI [7.7, 11.1], and 8.4% between education systems, 95% CI [5.7, 11.1]. Thus, declared need is not irrelevant, but it is clearly insufficient. Access to professional learning for teacher AI literacy cannot be understood only as a response to teachers' perceived professional learning needs. The persistence of school- and system-level variance suggests that other forms of advantage, digital, professional and organisational, may shape who is actually able to benefit from emerging opportunities for professional development.

Table 5. Three-level multilevel linear probability model predicting reported participation in AI-related professional learning from declared need

Predictor / Parameter	Estimate	*SE*	95% CI	*p*
Fixed effects				
Low level of need	0.077	0.010	[0.057, 0.097]	< 0.001
Moderate level of need	0.107	0.018	[0.072, 0.142]	< 0.001
High level of need	0.043	0.026	[-0.008, 0.095]	0.099
Variance components				
Teacher-level residual variance	0.196	0.005	[0.187, 0.205]	< 0.001
Between-school variance	0.022	0.002	[0.018, 0.026]	< 0.001
Between-system variance	0.020	0.003	[0.014, 0.026]	< 0.001
Variance partition coefficients				
Teacher-level VPC (%)	82.2	1.4	[79.5, 85.0]	< 0.001
School-level VPC (%)	9.4	0.8	[7.7, 11.1]	< 0.001
System-level VPC (%)	8.4	1.4	[5.7, 11.1]	< 0.001
Contextual VPC: school + system (%)	17.8	1.4	[15.0, 20.5]	< 0.001
Model information				

Predictor / Parameter	Estimate	*SE*	95% CI	*p*
Teacher-level R^2	0.007	0.001	—	< 0.001
AIC	138,935.99	—	—	—
BIC	139,003.12	—	—	—
Teachers	108,136	—	—	—
Schools	10,840	—	—	—
Education systems	55	—	—	—

Note. A three-level multilevel linear probability model was estimated with teachers nested within schools and schools nested within countries or participating education systems. The dependent variable identifies teachers' reported participation in AI-related professional learning. The reference category for declared professional learning need is “No need”. Coefficients are expressed as probability differences; for example, 0.077 indicates a 7.7 percentage-point higher probability of reported participation in AI-related professional learning relative to teachers reporting no need. Estimates incorporate teacher sampling weights. VPC = variance partition coefficient; SE = standard error; CI = confidence interval.

3.6. Digital and professional capital as opportunity structures for teacher AI literacy

The previous model showed that declared need was not, by itself, enough to explain who gains reported participation in AI-related professional learning, interpreted as realised access. The next step was therefore to examine whether access to professional learning for teacher AI literacy is also shaped by teachers’ digital and professional capital, and by the digital opportunity structure of the school. Two models were estimated on the same analytic sample. The first included teacher-level predictors: declared need, digital self-efficacy, professional exchange, professional collaboration, and teaching experience. The second added school-level indicators of digital resource shortages, digital leadership support, instructional leadership, and opportunities for staff participation in school decisions.

The teacher-level model confirmed that access to AI-related professional learning is strongly patterned by prior digital and professional resources (Table 6). Teachers with low and moderate declared need remained more likely to report participation in AI-related professional learning than teachers reporting no need, with estimated differences of 6.9 and 9.7 percentage points, respectively. However, teachers reporting high need did not differ significantly from those reporting no need. Direct contrasts between need categories further confirmed the non-linear pattern. Teachers reporting high need showed a lower probability of access than those reporting moderate need, $\Delta = -0.066$, $SE = 0.010$, 95% CI [-0.087, -0.046], $p < 0.001$. They also showed a slightly lower probability of access than teachers reporting low need, $\Delta = -0.039$, $SE = 0.019$, 95% CI [-0.077, -0.001], $p = 0.045$. In contrast, moderate need was associated with higher access than low need, $\Delta = 0.027$, $SE = 0.011$, 95% CI [0.006, 0.048], $p = 0.011$. This pattern indicates that the highest declared need does not translate into the highest probability of access, strengthening the interpretation of an unmet-need gap rather than a fully compensatory allocation of AI-related professional learning.

The clearest individual predictor was teachers’ self-efficacy in using digital resources and tools. A one-unit increase in digital self-efficacy was associated with a 4.1 percentage-point higher probability of reported participation in AI-related professional learning, net of declared need, collaboration, and experience. Professional collaboration also mattered: teachers working in more collaborative professional environments were more likely to access AI-related professional learning, whereas the exchange of information and ideas among teachers showed only a very small positive association. By contrast, teaching experience contributed little once these forms of digital and professional capital were taken into account. The only significant coefficient was found among teachers with more than 20 years of experience, who showed a 2.9 percentage-point lower probability of access relative to teachers with five years of experience or less.

Adding school-level predictors did not change the teacher-level results, which remained practically identical. This stability is important: the associations between digital self-efficacy, collaboration, declared need and access are not artefacts of school composition. At the same time, the school-level model showed that access to AI-related professional learning is also shaped by the digital conditions of the school. Schools reporting greater shortages or inadequacy of digital resources showed lower average access to AI-related professional learning, whereas schools where principals more frequently supported the integration of digital resources for teaching showed higher access. In substantive terms, a one-unit increase in school digital leadership support was associated with a 2.4 percentage-point higher probability of access, while a one-unit increase in digital resource shortage was associated with a 0.9 percentage-point lower probability.

General instructional leadership and opportunities for participation in school decision-making were not statistically significant.

This distinction is theoretically informative. The school effect is not a generic leadership effect, nor simply a participatory climate effect. It is specifically tied to the school's digital infrastructure and to leadership actions directed at integrating digital resources into teaching. Access to AI-related professional learning therefore appears to follow a logic of accumulated capacity: teachers with stronger digital self-efficacy and schools with stronger digital leadership are better positioned to enter emerging AI-related professional learning circuits, while schools facing greater digital shortages are less likely to do so.

The variance decomposition reinforces this interpretation. In the teacher-level model, 16.3% of the remaining variance was located above the individual level, with 9.2% between schools and 7.2% between education systems. After adding school-level predictors, the contextual share remained very similar, at 16.2%, with 9.1% between schools and 7.1% between systems. The school-level predictors explained a small but statistically significant portion of between-school variation, $R^2 = 0.018$. Thus, the observed school variables capture only part of the contextual structure behind access to professional learning for teacher AI literacy. The broader conclusion remains clear: access is not merely an individual outcome, but neither is it fully explained by the school indicators included here. It is produced at the intersection of teacher capital, school digital capacity and wider system-level opportunity structures.

Table 6. Three-level multilevel linear probability models predicting access to AI-related professional learning from teacher- and school-level predictors

Predictor / parameter	**Model 2**			**Model 3**		
	b	***SE***	***p***	***b***	***SE***	***p***
Teacher-level predictors						
Low declared need for AI-related professional learning	0.069	0.009	< 0.001	0.069	0.009	< 0.001
Moderate declared need for AI-related professional learning	0.097	0.016	< 0.001	0.097	0.016	< 0.001
High declared need for AI-related professional learning	0.031	0.023	0.176	0.031	0.023	0.175
Post-estimation contrasts between need categories						
High need vs low need	—	—	—	-0.039	0.019	0.045
High need vs moderate need	—	—	—	-0.066	0.010	< 0.001
Moderate need vs low need	—	—	—	0.027	0.011	0.011
Self-efficacy in using digital resources and tools	0.041	0.002	< 0.001	0.041	0.002	< 0.001
Exchange of information and ideas among teachers	0.004	0.001	0.001	0.004	0.001	0.001
Professional collaboration in lessons among teachers	0.026	0.002	< 0.001	0.026	0.002	< 0.001
Teaching experience: 6–10 years	-0.002	0.006	0.738	-0.002	0.006	0.718
Teaching experience: 11–20 years	-0.008	0.007	0.272	-0.008	0.007	0.255
Teaching experience: more than 20 years	-0.029	0.008	< 0.001	-0.029	0.008	< 0.001
School-level predictors						
School shortage of digital resources	—	—	—	-0.009	0.004	0.008
School digital leadership support	—	—	—	0.024	0.004	< 0.001
Instructional leadership	—	—	—	-0.002	0.001	0.146
Opportunities to participate in school decisions	—	—	—	0.000	0.001	0.717
Variance components						
Teacher-level residual variance	0.188	0.004	< 0.001	0.188	0.004	< 0.001
School-level residual variance	0.021	0.002	< 0.001	0.020	0.002	< 0.001
System-level variance	0.016	0.003	< 0.001	0.016	0.003	< 0.001
Variance partition coefficients						
Teacher-level VPC (%)	83.7	1.4	< 0.001	83.8	1.4	< 0.001
School-level VPC (%)	9.2	0.9	< 0.001	9.1	0.9	< 0.001
System-level VPC (%)	7.2	1.2	< 0.001	7.1	1.2	< 0.001

Predictor / parameter	Model 2			Model 3		
	b	***SE***	***p***	***b***	***SE***	***p***
Contextual VPC: school + system (%)	16.3	1.4	< 0.001	16.2	1.4	< 0.001
Model information						
Teacher-level R^2	0.064	0.003	< 0.001	0.064	0.003	< 0.001
School-level R^2	—	—	—	0.018	0.004	< 0.001
AIC	133,847.90	—	—	133,773.60	—	—
BIC	133,972.60	—	—	133,936.70	—	—
Teachers	108,136	—	—	108,136	—	—
Schools	10,840	—	—	10,840	—	—
Education systems	55	—	—	55	—	—

Note. Models are three-level multilevel linear probability models with teachers nested within schools and schools nested within countries or participating education systems. The dependent variable identifies whether teachers reported participation in AI-related professional learning on the use of artificial intelligence for teaching and learning. Coefficients are expressed as probability differences. Teacher-level reference categories are: no declared need for AI-related professional learning and five years of teaching experience or less. Continuous teacher- and school-level predictors were grand-mean centred. Post-estimation contrasts between need categories were computed from the fully adjusted model using linear combinations of the estimated need coefficients. They compare probability differences between declared-need categories; the main need coefficients use "no need" as the reference category. Dashes indicate parameters or contrasts not estimated for that model. Estimates incorporate teacher sampling weights. VPC = variance partition coefficient; *SE* = standard error.

3.7. Cross-system variation in the need–access association for teacher AI literacy

The previous models treated the association between declared need and access to professional learning for teacher AI literacy as if it were common across education systems. This assumption may be too restrictive, because education systems may differ in the extent to which teachers' declared professional learning needs are associated with realised access to AI-related professional learning. To examine this cross-system heterogeneity, a three-level random-slope model was estimated in which the effects of low, moderate and high declared need were allowed to vary across countries or participating education systems.

The results confirm that the need–access association for professional learning linked to teacher AI literacy is not internationally homogeneous (Table 7). On average, teachers reporting low need showed a 7.2 percentage-point higher probability of reported participation in AI-related professional learning than teachers reporting no need. The corresponding difference for moderate need was 9.6 percentage points. In contrast, the average effect of high need remained small and statistically non-significant, at 2.7 percentage points. This reproduces the central pattern observed in the fixed-slope models: access to AI-related professional learning is associated with some degree of declared need, but the highest level of need does not, on average, translate into the clearest advantage in access.

However, the random-slope variances substantially qualify this average pattern. The slopes for low, moderate and high need all varied significantly across education systems. The variation was modest for low need, larger for moderate need, and largest for high need. This is the most important finding of the model: the weak average association between high need and access should not be read as evidence that high need is irrelevant everywhere. Rather, it indicates that the association between high declared need and realised access differs across education systems. In some systems, teachers who report high need appear to be more frequently connected to AI-related professional learning; in others, high need remains weakly connected, or disconnected, from access to such opportunities.

This finding sharpens the multilevel argument of the study, but it should not be interpreted as evidence of specific system-level mechanisms. The model shows that the relationship between declared need and access to professional learning for teacher AI literacy is not uniform across education systems. It does not identify whether this heterogeneity is explained by national AI strategies, funding arrangements, mandatory participation schemes, governance models or other policy instruments, because these factors were not included as measured predictors. The same declared need may therefore be more strongly associated with access in some systems than in others, but the institutional sources of this variation remain open to further investigation. Access to professional learning for teacher AI literacy is thus shaped by a multilevel opportunity structure in which teacher digital and professional capital, school digital capacity and cross-system heterogeneity all matter, without implying that the present model identifies the specific policy arrangements behind system-level differences.

Table 7. Random slopes at the education-system level for declared need as a predictor of access to AI-related professional learning

Random slope	**Mean slope**	***SE***	***p***	**Slope variance**	***SE***	***p***
Low need vs no need	0.072	0.009	< 0.001	0.001	0.001	0.012
Moderate need vs no need	0.096	0.015	< 0.001	0.007	0.002	< 0.001
High need vs no need	0.027	0.020	0.190	0.014	0.004	< 0.001

Note. Random slopes were estimated at the education-system level in a three-level multilevel linear probability model with teachers nested within schools and schools nested within countries or participating education systems. The dependent variable identifies whether teachers reported participation in AI-related professional learning on the use of artificial intelligence for teaching and learning. The reference category for declared need is “no need”. The model controls for teacher-level digital self-efficacy, professional exchange, professional collaboration, teaching experience, and school-level digital resource shortages, digital leadership support, instructional leadership and opportunities for participation in school decisions. Coefficients are expressed as probability differences. Estimates incorporate teacher sampling weights. The model does not include direct measures of national AI strategies, funding arrangements, mandatory participation rules or other system-level policy instruments; therefore, the random slopes should be interpreted as evidence of cross-system heterogeneity, not as evidence of specific policy mechanisms.

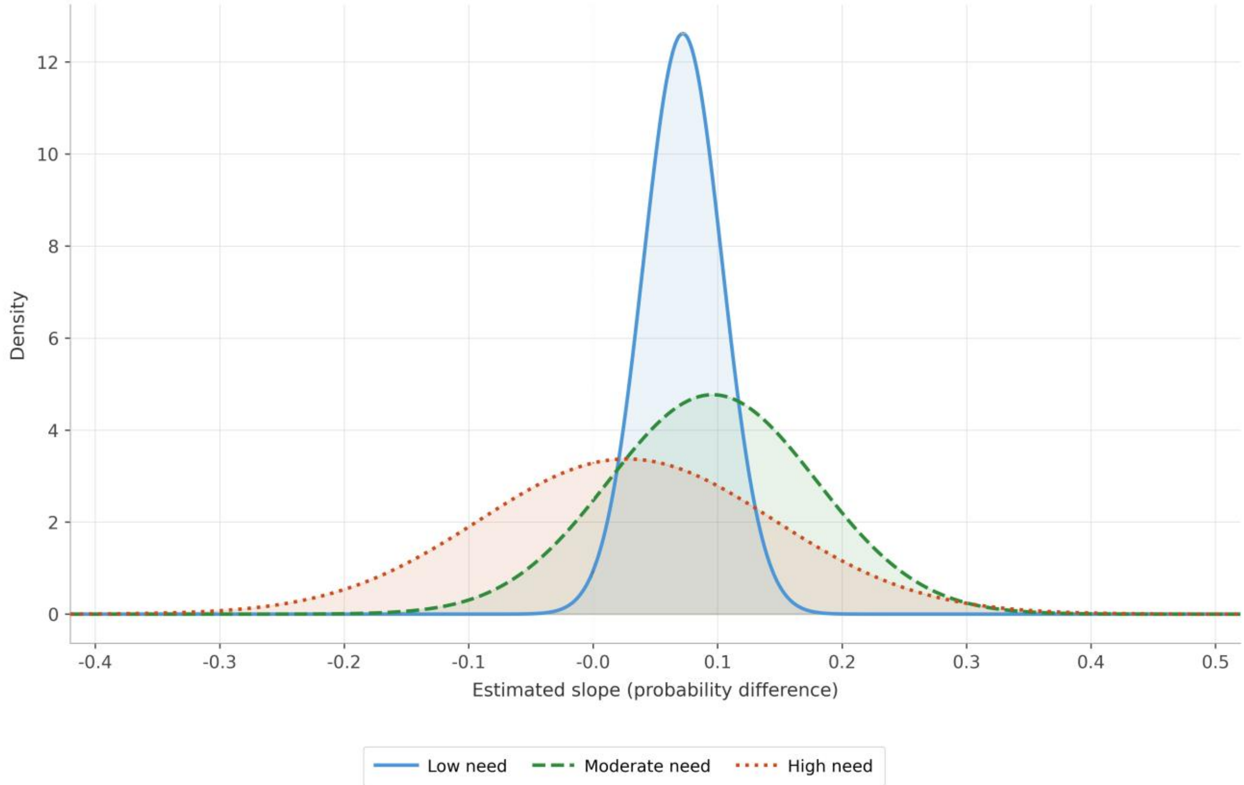

Fig. 2. Simulated distribution of slopes at the education-system level for declared professional learning need predicting reported participation in AI-related professional learning

Note. Curves represent the normal distribution implied by the estimated mean slope and slope variance from the random-slope model. The vertical dashed line marks zero. Shaded areas show the range within ±1 SD of the mean slope for each need level. Low need: mean slope = 0.072, slope variance = 0.001, p = 0.012. Moderate need: mean slope = 0.096, slope variance = 0.007, p < 0.001. High need: mean slope = 0.027, p = 0.190; slope variance = 0.014, p < 0.001. A wider distribution indicates greater cross-system heterogeneity in the need–access association.

3.8. Robustness checks for the opportunity-structure interpretation

Several robustness checks were conducted to assess whether the main findings about reported participation in AI-related professional learning, interpreted as realised access to one professional learning condition for teacher AI literacy, depended on model specification, sample composition or the use of a linear probability model for a binary outcome (Table 8).

One concern was whether the comparison between the teacher-level and school-extended models could be affected by changes in the estimation sample. To address this issue, both models were estimated on the same analytic sample as the final model. The results were highly stable. The coefficients for declared need, digital self-efficacy, professional exchange, professional collaboration and teaching experience remained virtually unchanged after school-level predictors were added. In particular, the non-linear pattern of declared need was replicated: low and moderate need were positively associated with access to professional learning for teacher AI literacy, whereas high need was not significantly associated with access on average. The strongest teacher-level association also remained unchanged, with digital self-efficacy consistently predicting a higher probability of access to AI-related professional learning.

The linear probability specification was also examined directly. Fixed-part predicted probabilities from the final model were inspected to assess whether fitted values fell outside the admissible 0–1 range, a known limitation of linear probability models with binary outcomes. Predicted probabilities ranged from -0.07 to 0.77, with a mean of 0.410. Only 60 cases fell outside the admissible range, representing 0.06% of the analytic sample; all of them were below 0, and no predicted probability exceeded 1. This indicates that the linear probability model provided an adequate approximation for the observed binary outcome, while retaining the advantage of coefficients that are directly interpretable as percentage-point differences in realised access.

Table 8. Robustness checks for the final model

Check	Purpose	Result	Implication
Fixed-part predicted probabilities from the linear probability model	Assess whether predicted probabilities fell outside the 0–1 interval	Predicted probabilities ranged from -0.07 to 0.77. Only 60 cases fell outside the admissible range, representing 0.06% of the analytic sample; all were below 0 and none exceeded 1.	The linear probability specification provides an adequate approximation to the binary outcome.
Common analytic sample across explanatory models	Rule out changes due to sample composition	The teacher-level and school-extended models were estimated on the same analytic sample of 108,136 teachers. Teacher-level coefficients remained virtually unchanged after adding school-level predictors.	Model comparisons are not driven by changes in the estimation sample.
Multicollinearity diagnostics	Assess overlap among predictors	Variance inflation factors remained below conventional thresholds, with the highest value below 2.50.	The main associations are not artefacts of predictor redundancy.
Alternative three-level multilevel logistic specification	Assess whether substantive conclusions depend on the linear probability model	The direction and inferential pattern of the main associations were replicated in the alternative three-level multilevel logistic specification.	The conclusions are not driven by the linear probability specification.

Note. The table summarizes robustness checks conducted for the final multilevel model. Predicted probabilities refer to the fixed part of the final linear probability model. The analytic sample comprised 108,136 teachers nested within 10,840 schools across 55 education systems.

To examine whether the conclusions depended on the link function used for the binary outcome, the final model was re-estimated using an alternative three-level multilevel logistic specification with the same fixed-effect predictors and clustering structure. This analysis was not intended to replace the main linear probability model, but to test whether the direction and inferential pattern of the central associations were sensitive to the modelling approach. The alternative logistic specification led to the same substantive conclusions. Low and moderate declared need remained positively associated with reported participation in AI-related professional learning, whereas high declared need did not show a clear positive association on average. Digital self-efficacy and professional collaboration remained positively associated with participation. At the school level, digital resource shortages remained negatively associated with participation, while school digital leadership support remained positively associated with participation. These results indicate that the main interpretation is not an artefact of the linear probability specification.

The random-slope model provided an additional robustness check for the interpretation of declared need. Although high declared need did not predict access on average, its slope varied significantly across education systems. This means that the apparent lack of compensation for teachers with the highest need is not uniform across countries, but depends on the institutional context in which professional learning opportunities are organised.

These checks support the robustness of the opportunity-structure interpretation. Access to professional learning for teacher AI literacy is not distributed only according to declared need. It is consistently associated with teachers' prior digital and professional capital, with the school's digital opportunity structure, and with education-system differences in the extent to which declared need is converted into access.

4. Discussion

The central contribution of this study is to reposition teacher AI literacy as a distributive challenge in informatics education. The study does not ask whether teachers are already AI literate, nor whether they use AI competently in classroom practice. TALIS 2024 does not allow such claims. Instead, the study examines a prior condition: whether teachers gain access to the professional learning opportunities through which AI literacy may be developed. This distinction matters because the expansion of AI literacy in schools will not depend only on competence frameworks, curriculum documents or exemplary professional learning designs. It will also depend on whether access to professional learning reaches teachers and schools with weaker prior digital capacity.

The findings show that this access is not distributed as a simple response to declared need. Teachers reporting low or moderate need were more likely to have participated in AI-related professional learning than those reporting no need, whereas the highest-need group did not show a significant advantage in the multilevel models. At the same time, access was consistently associated with digital self-efficacy, professional collaboration and specific school-level digital conditions. The pattern is therefore not one of pure exclusion, but neither is it fully compensatory. AI-related professional learning appears to reach teachers who are already partly connected to digital and professional opportunity structures more effectively than those who declare the strongest need.

This finding extends research on AI literacy and teacher AI competence by shifting attention from competence definitions to the distribution of the professional learning opportunities through which such competence may be developed. Recent work has clarified the forms of knowledge teachers require to understand, evaluate and pedagogically mediate AI systems (Chiu, 2025; Kohnke et al., 2025; Pei et al., 2026; Tagare et al., 2025). Updated models of technology integration have also stressed that teachers' capacity to work with emerging technologies is shaped by contextual and institutional conditions, not only by individual knowledge (Petko et al., 2025). The present study adds that access to the professional learning through which teacher AI literacy may be developed is itself unequally distributed.

The cross-system differences observed in the study show that professional learning for teacher AI literacy has not entered education systems evenly. The gap between France and Singapore exceeded 66 percentage points, and the null model located meaningful shares of variance at both the school and education-system levels. These findings resonate with previous reviews showing that the empirical literature on AI in education remains unevenly distributed across regions, samples and institutional contexts (Sperling et al., 2024; Tan et al., 2025a). They also address a limitation identified in recent reviews of AI and teacher professional development: much of the literature has focused on tools, perceptions or localised interventions, whereas less is known about who gains access to AI-related professional learning in large-scale comparative settings (Li et al., 2025; Tan, 2025). From this perspective, access is not a secondary implementation detail. It is a structural condition for equitable teacher AI literacy development in schools.

The non-linear association between declared need and access is the most relevant result for the compensatory argument. A needs-responsive model of professional learning for teacher AI literacy would imply that teachers with the highest declared need should be the most clearly connected to learning opportunities. That pattern was not observed. The highest-need group did not show the strongest access, either descriptively or in the multilevel models. This does not mean that teachers with high need are excluded from AI-related professional learning. It means that existing opportunity structures do not convert high declared need into participation in a systematic way. The result points to a possible unmet-need gap: some teachers recognise a strong need for AI-related professional learning, but this recognition is not reliably transformed into access.

The cumulative advantage perspective provides a useful interpretation of this pattern, although it should not be read as causal evidence. The Matthew effect and the broader theory of cumulative advantage suggest that access to valuable resources tends to favour actors already better positioned to identify, request or use them (DiPrete & Eirich, 2006; Merton, 1968). In this study, teachers with stronger digital self-efficacy were more likely to have participated in AI-related professional learning, even after declared need and other professional characteristics were taken into account. This finding is consistent with work showing that AI self-efficacy and digital confidence are central to teachers' readiness to engage with AI-related practices (Sanusi et al., 2024; Wang & Chuang, 2024). The contribution of the present study is to show that digital self-efficacy is not only relevant as an outcome of preparation or as a predictor of AI adoption. It is also associated with entry into the professional learning pathways through which teacher AI literacy may be developed.

This interpretation aligns with evidence showing that AI readiness profiles are unevenly distributed within the profession (Ramazanoglu & Akın, 2025). Studies of AI-related professional development show that structured interventions can improve teachers' AI competence, but rarely examine the prior selection processes determining who participates (Le et al., 2026; Tan et al., 2025b). Demonstrating that professional learning can support teacher AI literacy is not the same as demonstrating that access to such learning is equitable.

Professional collaboration also contributed independently to access. The distinction between collaboration and lighter forms of information exchange is important. The latter showed only a small association, whereas more structured professional collaboration was more clearly related to participation. This result is consistent with the broader literature on teacher professional development, where collective participation and coherence with the professional context are central features of effective learning opportunities (Desimone, 2009). It also fits the concept of professional capital, which stresses that teachers' development depends not only on individual human capital, but also on social and organisational conditions that support shared learning and professional judgement (Hargreaves & Fullan, 2012). In the context of teacher AI literacy, collaboration appears to act as an opportunity structure: it connects teachers to practices, expectations and information that may facilitate participation in AI-related professional learning.

The school-level findings refine this interpretation. General instructional leadership and opportunities for participation in school decisions were not significant predictors once other variables were considered. By contrast, digital resource shortages and leadership directed towards technology integration were associated with access. This suggests that the organisational conditions linked to professional learning for teacher AI literacy are specifically digital rather than generic. Schools with stronger digital capacity and clearer school digital leadership support appear better positioned to connect teachers with AI-related learning opportunities. This result is consistent with studies showing that school strategies, leadership support and organisational readiness condition teachers' engagement with generative AI in K–12 settings (Cheah et al., 2025; Cheah & Kim, 2026; Ng et al., 2025). It also helps explain why school context cannot be treated as a neutral background variable in the implementation of teacher AI literacy.

The finding on digital resource shortages is especially important. Schools affected by digital shortages may face a double disadvantage: fewer material conditions for experimenting with AI-mediated teaching and fewer professional learning opportunities to compensate for that lack of capacity. This pattern is relevant for informatics education because teacher AI literacy cannot be scaled equitably if schools with weaker digital conditions are also less connected to professional learning opportunities. In this sense, digital infrastructure and professional learning should not be treated as separate policy domains. They form part of the same opportunity structure for teacher AI literacy implementation.

The random-slope model adds a cross-system dimension to this argument. On average, high declared need was not a significant predictor of access, but its association with access varied significantly across education systems. This result prevents a simplistic interpretation of the average effect. High need is not irrelevant everywhere; rather, the relationship between need and access differs across systems. The present study cannot determine which system-level arrangements explain this variation, because national AI strategies, funding mechanisms, mandatory participation requirements and other policy instruments were not included as measured predictors. The result should therefore be interpreted as evidence of cross-system heterogeneity, not as evidence of specific institutional mechanisms. Future comparative research should examine whether differences in AI policy design, professional development governance, funding models or accountability arrangements help explain why some systems appear more capable than others of converting declared need into realised access.

These results have direct implications for the design of professional learning for teacher AI literacy. Where provision relies predominantly on voluntary participation, teachers with stronger digital confidence and denser professional networks will systematically benefit more, reproducing cumulative advantage rather than compensating for unequal starting points. A more equitable approach requires deliberate allocation criteria anchored in need assessment rather than in prior capacity. Table 9 summarises the main empirical patterns identified in this study, the equity risk each pattern entails, and a corresponding implementation implication for professional learning design.

Table 9. Empirical patterns, equity risks, and implementation implications for equitable professional learning design in teacher AI literacy

Empirical pattern	**Equity risk**	**Implementation implication**
Teachers with the highest declared need do not show the highest reported participation	Unmet-need gap	Prioritise high-need teachers in AI-literacy professional learning allocation, replacing self-selection with active outreach
Lower digital self-efficacy is consistently associated with lower participation	Self-selection by confidence	Offer scaffolded entry-level AI-literacy training designed for teachers with limited prior digital experience
School digital resource shortages are associated with lower access to AI-related professional learning	Double disadvantage	Extend preferential professional learning support to schools with weaker digital infrastructure, treating resource shortage as an eligibility criterion rather than a disqualifying barrier
Professional collaboration is a positive predictor of participation, independent of declared need	Network advantage	Use professional learning communities as a deliberate implementation channel to reach teachers who are less connected to existing AI-related professional development circuits
The association between declared need and reported participation varies significantly across education systems	Policy contingency	Monitor realised access periodically as a diagnostic equity indicator, disaggregated by education system, region, school type, and teacher need level

Note. Each row corresponds to one empirical pattern identified in the multilevel and random-slope models reported in this study. Equity risk labels describe the distributional mechanism implied by the pattern. Implementation implications refer to professional learning design and policy rather than to individual teacher behaviour.

The study therefore contributes to informatics education by moving the focus from AI readiness to the distribution of access to professional learning for teacher AI literacy. The question is not only whether teachers are ready for AI, whether AI literacy can be defined, or whether professional development can improve teachers' competence. It is also whether access to that learning is distributed in a way that reduces or reproduces existing professional inequalities. The evidence from TALIS 2024 suggests that current access patterns are not neutral. They are associated with prior digital confidence, professional collaboration and school digital capacity. Without deliberate compensatory design, professional learning for teacher AI literacy may strengthen the same inequalities that inclusive AI literacy policies seek to address.

5. Conclusions

This study examined whether access to professional learning for teacher AI literacy is distributed according to declared need or according to previously accumulated digital, professional and organisational advantage. Using TALIS 2024 data from 108,136 lower-secondary teachers nested within 10,840 schools across 55 education systems, the study provides large-scale comparative and multilevel evidence on a necessary opportunity condition for the development of teacher AI literacy.

The findings show that access is only partially aligned with declared need. Teachers reporting low or moderate need were more likely to have participated in AI-related professional learning than teachers reporting no need, whereas those reporting the highest need did not show a significant advantage in the multilevel models. This pattern does not support a fully compensatory interpretation. Rather, it suggests that existing professional learning structures may reach teachers who are already close to AI-related development opportunities more effectively than those with the strongest perceived need.

The results also indicate that access is patterned by prior digital and professional capital. Digital self-efficacy and professional collaboration were consistent predictors of participation. At the school level, digital resource shortages were associated with lower access, while school digital leadership support was associated with higher access. General instructional leadership and opportunities for participation in school decisions were not significant predictors once digital and organisational conditions were considered. These findings suggest that the opportunity structure for teacher AI literacy is specifically digital and organisational, not merely a reflection of general school leadership.

The multilevel and random-slope results add a system-level contribution. A meaningful share of variance was located between schools and education systems, and the association between high declared need and access varied significantly across systems. The conversion of need into access is therefore institutionally contingent. In some systems, professional learning provision appears better positioned to reach teachers with stronger needs; in others, access remains more closely tied to prior advantage. For informatics education, this is a central equity issue: teacher AI literacy cannot be implemented equitably if the professional learning needed to develop it is distributed through mechanisms that reproduce existing differences in digital confidence, collaboration and school capacity.

The study has important strengths, but also clear limitations. Its main strength lies in providing comparative, multilevel evidence on access to AI-related professional learning across a large number of education systems. However, TALIS 2024 does not provide a direct measure of teacher AI literacy, AI competence, computing teaching practice, computational-thinking instruction or classroom implementation. The outcome analysed here captures participation in AI-related professional learning, not the content, duration, quality or transfer of that learning. The cross-sectional design does not allow causal inference. The measures are self-reported and may carry different meanings across education systems. In addition, the random-slope model shows that the association between declared need and access to AI-related professional learning varies across education systems, especially for teachers reporting high need. However, the models do not include direct measures of national AI strategies, professional development funding, mandatory participation rules or other system-level policy arrangements. For this reason, these mechanisms should be treated as hypotheses for future research rather than as explanations identified by the present analysis.

Future research should extend this work in three directions. First, longitudinal studies should examine whether access to AI-related professional learning leads to later gains in teacher AI literacy, classroom use and pedagogical judgement. Second, comparative qualitative research should analyse why some systems convert declared need into access more effectively than others. Third, future studies should move beyond participation and examine the quality, content and equity effects of professional learning, especially for teachers with low digital self-efficacy and for schools with weaker digital infrastructure.

The main conclusion is that teacher AI literacy cannot be implemented equitably through competence frameworks alone. Before teachers can develop the knowledge, judgement and pedagogical capacity required to mediate AI in schools, they must have access to meaningful professional learning opportunities. The evidence from TALIS 2024 shows that this access is not neutral. It is patterned by digital self-efficacy, professional collaboration, school digital capacity and system-level differences in the conversion of need into opportunity. The contribution of this study is therefore deliberately bounded but substantively important: it does not provide evidence of achieved teacher AI literacy; it provides evidence of unequal access to one of the conditions through which such literacy may be developed. For informatics education, this boundary is not merely a limitation. It defines the equity problem that the field needs to confront.

Declarations

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Competing interests

The authors declare no competing interests.

Ethics approval and consent to participate

Not applicable. This study uses secondary anonymised TALIS 2024 data and does not report primary research involving human participants or identifiable personal data collected by the authors.

Data availability

TALIS 2024 data are subject to OECD access conditions. The analysis syntax and variable recoding decisions are available from the corresponding author upon reasonable request, subject to the terms of use of the TALIS data.

Generative AI disclosure

During the preparation of the manuscript, ChatGPT was used as a support tool for language review, improving clarity of expression, and editing selected sections of the text. The authors critically reviewed all suggestions, verified the academic and statistical content, and take full responsibility for the final version of the article.

Author contributions

Both authors contributed equally to the conception, development, writing, review, and final approval of the manuscript.

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