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Teachers' digital language literacy in the AI era: framework construction and validation

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ABSTRACT

This study constructs and empirically validates a novel framework for teachers' digital language literacy (TDLL) in the artificial intelligence (AI) era—the first of its kind to be rigorously validated. Through systematic analysis of 12 international policy documents and a three-round Delphi consultation with 30 experts, a five-dimensional TDLL framework was established: cognition and critique, tools and collaboration, multimodal resource design, data and personalized instruction, and ethics and safety. The Delphi process, coupled with entropy weight calculations, identified 'tools and collaboration' (weight=0.236) and 'ethics and safety' (weight=0.211) as the most critical dimensions. Empirical validation via a large-sample survey (N=984) confirmed the framework's high reliability (Cronbach's α=0.936) and good construct validity (comparative fit index (CFI)=0.921, root mean square error (RMSEA)=0.048). Descriptive analysis revealed teachers were most competent in tool application (M=4.12) but least competent in data-driven personalized instruction (M=3.78), highlighting a key training gap. The study provides a scientifically grounded assessment tool and actionable guidance for targeted teacher professional development in the AI age.

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1. INTRODUCTION

With the rapid development of artificial intelligence (AI) technology, the education sector is undergoing a profound digital transformation. Governments and international organizations are actively promoting AI education policies to promote the deep integration of education systems and intelligent technologies. Such as China's Education Informatization 2.0 Action Plan and New Generation Artificial Intelligence Development Plan, the European Union's AI in Education Framework and United Nations Educational, Scientific and Cultural Organization's (UNESCO) AI and Education all emphasize the need for teachers to possess digital language literacy adapted to the AI era [1], [2]. However, a critical gap exists, while these policies advocate for digital competence, they lack granularity for the specific demands of language-centered teaching in AI-saturated contexts. For instance, general frameworks like DigCompEdu excel at outlining broad digital competencies but fall short in addressing the nuanced skills required to critique AI-generated text, co-design lessons through human-AI dialogue, or manage the ethical implications of student language data processed by algorithms. This study addresses this gap by constructing a specialized teachers' digital language literacy (TDLL) framework, with Korea's perspective offering a valuable comparative lens. Korea's advanced digital infrastructure and proactive AI education policies provide a unique context to examine TDLL implementation, complementing insights from

China's top-down mandates, the European Union's competency-based approach, and UNESCO's equity-focused guidelines.

TDLL encompasses not only the understanding and creation of multimodal symbols but also complex abilities such as human-computer collaboration, data interpretation, and ethical judgment [3], [4]. Existing research indicates that teacher professional development in an AI environment has become a core issue in educational reform [5], [6]. However, systematic research on TDLL is still in its early stages, particularly lacking a policy-oriented framework that integrates multidimensional perspectives [7], [8].

Despite the high level of policy attention paid to AI education, the cultivation of TDLL in practice still faces many challenges. This gap between ambitious policy goals and classroom reality is multifaceted. On one hand, there is a pronounced disconnection between the strategic vision outlined in policy documents and the operational, day-to-day support provided to teachers. Existing research focuses primarily on technological applications, lacking integrated analysis of digital language in cognitive, ethical, and contextualized teaching [9], [10]. On the other hand, policy-driven training programs often adopt a one-size-fits-all model, failing to address the specific disciplinary needs and varying experience levels of teachers. Teacher training content often lags technological development, failing to establish systematic, actionable competency standards [11], [12]. This disconnects between theory and practice, exacerbated by a lack of targeted and ongoing professional support, makes it difficult for teachers to effectively translate policy aspirations into the complex demands of AI-based education [13], [14]. For example, policies may broadly advocate for leveraging AI for personalized learning, yet teachers may receive insufficient guidance on implementing this in specific contexts. A language arts teacher might need concrete strategies for using an AI writing assistant to provide differentiated feedback on student essays, while a science teacher might require support in employing AI simulations to adapt lab experiments for varying student skill levels. Without such specific, discipline-sensitive exemplars, policy remains abstract and difficult to operationalize. Therefore, constructing a TDLL framework that combines policy foresight, theoretical support, and practical applicability has become an urgent issue.

Although concepts such as digital literacy and artificial intelligence literacy have provided macro guidance for teachers' professional development, these frameworks often appear to lack granularity when dealing with language-centered teaching scenarios. Digital literacy focuses on the operation of general technical tools and critical thinking, while artificial intelligence literacy pays more attention to the understanding and application of AI technology itself. However, in the context where AI is deeply integrated into education, the essence of teaching, which is the transmission of knowledge and the construction of meaning through language as a medium, is undergoing profound changes. Teachers not only need technical knowledge, but also the ability to specifically understand, criticize, design and ethically examine the symbols and discourses generated, circulated and calculated by AI. This kind of literacy that takes digital language in the teaching context as its specific object goes beyond the scope of general digital ability and cannot be fully covered by purely technology-oriented AI literacy. The theoretical foundation for this specialized focus can be traced to an integration of socio-semiotic theory and post-humanist perspectives on education. Socio-semiotic theory, particularly the work on multimodal discourse analysis, provides a lens for understanding how meaning is constructed through the interplay of text, image, audio, and other modes in AI-generated content [15], [16]. Concurrently, post-humanist theories challenge the traditional human-centric view of learning, framing the teacher-AI-student interaction as a collaborative assemblage where agency is distributed. This theoretical confluence necessitates a new literacy that equips teachers to navigate, mediate, and ethically steward this complex, multi-agent communicative environment. Therefore, the construction of an independent framework for TDLL aims to fill the gap between theory and practice and provide precise and operational guidelines for the development of teachers' core teaching behaviors in the AI era.

While existing frameworks such as the European Commission's DigCompEdu provide a valuable and comprehensive foundation for teachers' digital competence, they also reveal significant limitations when faced with the unique challenges posed by generative AI and large-scale language models. These general frameworks excel at technological applications but fail to help teachers adapt to the environment in which AI co-creates, mediates, and analyzes their core professional medium of language itself. Teaching activities are increasingly being conducted through human-computer dialogue, interpreting AI-generated multimodal text, and utilizing data-driven insights extracted from student language. DigCompEdu and similar models fail to adequately address the specific capabilities required for critically assessing the biases in AI-generated content, effectively guiding and designing meaningful educational dialogues, ethically managing student data privacy within AI systems, and leveraging AI at scale for personalized language feedback. In practice, this translates to a language arts teacher needing skills beyond using a word processor; they must now be able to critique an AI-generated essay example for stylistic homogeneity, design prompts that lead an AI tutor to provide socratic questioning, and safeguard student writing data fed into an online grammar checker. Recent studies examining the application of tools like ChatGPT in classrooms highlight both the potential and the pitfalls. For example, research has shown that while AI can efficiently generate lesson plans and provide instant feedback on student writing, its outputs often require significant teacher mediation to ensure pedagogical appropriateness, factual accuracy, and cultural relevance

[17]–[19]. Other studies point to the 'black box' nature of these models, which complicates teachers' ability to explain AI-generated suggestions to students or to identify embedded biases [20], [21]. These empirical findings underscore the urgent need for a literacy framework that centrally addresses the linguistic and dialogic dimensions of AI integration, moving beyond generic competence lists.

This study aims to construct a systematic TDLL framework through a multi-method research strategy. Unlike the broad framework of digital capabilities, this study regards language as the core medium and main object of teaching in the era of artificial intelligence. Therefore, the proposed framework particularly focuses on the capabilities required to understand, criticize, co-create, and ethically manage AI-mediated language and multimodal communication in teaching contexts. This framework is based on policy text analysis, integrates constructivism and situational learning theories, and combines expert consensus and empirical verification to form a five-dimensional competency model (cognition and critique, tools and collaboration, multimodal resource design, data and personalized teaching, and ethics and safety). The novelties of this study are: i) extracting competency requirements from policy texts, strengthening the framework's timeliness and orientation; ii) ensuring the scientific nature and stability of the framework through the Delphi method and statistical modeling (such as entropy weighting and confirmatory factor analysis); and iii) relying on a large sample questionnaire survey (N=984), revealing the status and differences of teachers' competencies, providing a basis for precise intervention.

Furthermore, this study enhances the framework's clarity and depth by grounding its dimensions in concrete pedagogical examples derived from policy analysis and expert consultation. For instance, the dimension of cognition and critique is operationalized not just as a theoretical concept, but through specific indicators like evaluating potential biases in AI-generated historical narratives, directly linking policy calls for critical engagement to actionable classroom practice. This study not only fills the gap in the systematic modeling of TDLL but also provides theoretical tools and practical references for educational policy formulation, teacher training curriculum design and evaluation.

2. RESEARCH DESIGN AND METHODS

2.1. Overall research idea

The research path adopts a hybrid research strategy. First, a systematic content analysis of domestic and foreign AI education policy texts is conducted to extract the competency requirements of TDLL. Secondly, the Delphi method is used to integrate expert opinions and construct framework dimensions and indicators by combining constructivism and contextual learning theory. The last, the framework is empirically tested and revised through questionnaire surveys and statistical analysis. Its logical model can be expressed as (1):

$$F = \alpha P + \beta T + \gamma E \tag{1}$$

Among them, F represents the final TDLL framework, P represents the policy analysis results, T represents the theoretical basis, E represents the expert consensus, and α, β, γ are weight coefficients determined through expert scoring and factor analysis.

2.2. Research methods and data sources

2.2.1. Policy text analysis

The study selected 12 policy texts, including China's Education Informatization 2.0 Action Plan and New Generation Artificial Intelligence Development Plan, European Union's AI in Education Framework and UNESCO's AI and Education policy report. Policy texts were analyzed using content analysis with NVivo 14 to identify key competency themes and form a preliminary capability matrix.

2.2.2. Contextual review of AI tool application

To ground the framework in current pedagogical realities, the study first conducted a scoping review of recent empirical literature (2020-2024) on the application of generative AI and large language models (LLMs), such as ChatGPT, in K-12 and higher education classrooms. This review aimed to identify common use cases, reported challenges, and emergent competency needs that are not yet fully captured in formal policy documents. Key findings informed the initial drafting of competency indicators, ensuring they reflect authentic teacher tasks like prompt engineering for lesson idea generation, critiquing AI-produced feedback for subject-specific accuracy and facilitating student discussions on the ethical implications of using AI for assignments.

2.2.3. Delphi expert consultation method

A panel of 30 experts was recruited to participate in a three-round Delphi consultation. The sample size of 30 is consistent with recommendations for Delphi studies aiming to achieve stable group consensus while maintaining manageability and depth of feedback. Experts were purposively selected to ensure a comprehensive, multi-stakeholder perspective on the intersection of AI, education policy, and classroom practice. The selection criteria were:

- Academic researchers (n=10): held the title of associate professor or above in fields of educational technology, AI in education, or curriculum and instruction, with a publication record of ≥5 peer-reviewed articles in these areas.
- Education policy makers and administrators (n=8): held mid-to-senior level positions in national or regional education departments or teacher training institutions, directly involved in AI education policy formulation or implementation.
- Frontline teacher experts (n=12): recognized as provincial-level or above teaching experts (master teachers, subject leaders), with at least 10 years of teaching experience and documented innovation in integrating digital technologies or AI tools into their pedagogy.

To enhance transparency, an example of evolving consensus is provided. In round 1, experts proposed 'AI tool proficiency' and 'human-AI co-teaching' as separate dimensions. Through iterative feedback and discussion in rounds 2 and 3, these were merged into the cohesive dimension 'tools and collaboration', reflecting the integrated nature of the competency.

2.2.4. Questionnaire survey method

Based on the validated framework from the Delphi study, the TDLL scale was compiled. The scale operationalizes the five theoretical dimensions into 25 observable and self-assessable behavioral items, using a five-point Likert scale (1=completely disagree and 5=completely agree). Each dimension is measured by 5 specific items designed to directly reflect the core competencies defined in the framework. For example:

- Cognition and critique were measured by items such as "I can evaluate the potential biases in texts generated by AI for classroom use."
- Tools and collaboration were measured by items such as "I can use AI tools (ChatGPT) to co-design instructional activities with me."
- Multimodal resource design was measured by items such as "I can use AI to integrate text, images, and audio to create multimedia teaching materials."
- Data and personalization were measured by items such as "I can interpret data reports from AI learning platforms to adjust my teaching strategies for individual students."
- Ethics and safety were measured by items such as "I establish clear rules with my students regarding data privacy when using AI educational applications."

Participants were recruited from primary (24.4%), junior high (28.5%), senior high (29.5%), and tertiary (17.7%) levels, spanning both liberal arts (41.9%) and science (58.1%) subjects, and from diverse geographic regions within the sampling frame, reflecting a broad spectrum of teaching contexts.

2.2.5. Data analysis method

First, content analysis was conducted to construct an indicator pool; then, statistical analysis was conducted using SPSS 26 and AMOS 24. Specific methods included descriptive statistics (mean, standard deviation). The exploratory factor analysis (EFA) used principal component analysis and varimax rotation to confirm the dimensional structure and confirmatory factor analysis (CFA) was used to test the hypothesized five-factor model fit (χ^2/df, root mean square error (RMSEA), comparative fit index (CFI), Tucker-Lewis's index (TLI)). The entropy weight method was applied to the Delphi expert ratings to calculate the objective weight of each dimension. In summary, through a rigorous research design, this study constructed a research path for the digital language literacy framework for teachers that is policy-oriented and combines theory with practice, providing a solid foundation for the subsequent verification and promotion of the framework.

3. RESULTS

3.1. Construction of TDLL framework

The construction of the TDLL framework follows a path of policy guidance-theoretical support-expert consensus-empirical refinement, striving to foster a virtuous interaction between policy guidance, theoretical basis, and practical needs. As shown in Table 1, at the policy level, the research systematically reviewed 12 core policy documents from China and abroad. Highly frequent keywords included AI, teacher competence, data safety and human-computer collaboration, appearing over 200 times.

Through cluster analysis, it was found that policy requirements are mainly concentrated in five aspects: cognition and critique, tools and collaboration, multimodal teaching, data and personalization, ethics and safety, which are also the direct sources of the framework dimensions. At the theoretical level, constructivism provides the framework with a perspective on learning subjects and knowledge construction, and contextual learning theory emphasizes the combination of language and context in the AI environment, thus ensuring that the framework is not only a list of indicators, but also responds to the real teaching situation of teachers. In terms of construction principles, the research adheres to systematicity (the five dimensions support each other), foresight (focusing on the future classroom driven by AI), operability (indicators are measurable and trainable), and evaluability (the framework can be converted into tools and scales) [22]. To ensure the scientific nature of the framework indicators, the Kendall coordination coefficient test was conducted on the expert group's multiple rounds of scoring data [23]. The calculation formula is (2):

$$W = \frac{12\sum_{i=1}^{m}(R_i-\bar{R})^2}{n^2(m^3-m)} \tag{2}$$

Where W represents the coordination coefficient, R_i is the rank sum of the i-th indicator, m is the number of indicators, and n is the number of experts. After three rounds of consultation, the results showed that $W=0.712$ and $p<0.001$, indicating that the experts' opinions were highly consistent, providing statistical support for the establishment of dimensions and indicators.

Table 1. Policy text analysis

Policy documents	Number of sample characters	Extract the number of keywords	High-frequency words (top 5)
Education Informatization 2.0 Action Plan	35,812	126	AI, teacher, capability, application, data
New Generation Artificial Intelligence Development Plan	41,025	132	Artificial intelligence, innovation, talent, ethics, safety
Action Plan for Promoting the Development of a New Generation of Artificial Intelligence	28,543	118	AI, development, talent, ethics, technology
Internet Plus Education Development Strategy	22,167	94	Internet, education, digital, resource, platform
AI in Education Framework	30,245	115	AI, education, competence, digital, ethics
Digital Education Action Plan (2021-2027)	26,834	108	Digital, education, competence, data, skills
DigCompEdu (European Framework for the Digital Competence of Educators)	32,612	121	Competence, digital, teaching, AI, data
AI and Education: Guidance for Policy-makers	28,740	118	Equity, AI, education, skills, ethics
Beijing Consensus on Artificial Intelligence and Education	18,926	87	AI, education, equity, ethics, collaboration
OECD Digital Education Outlook 2021	24,513	102	Digital, education, AI, data, skills
National AI Strategy	20,874	96	AI, education, digital, teacher, competence
AI for Educational Equity (UNESCO Regional Report)	19,652	89	Equity, AI, education, inclusion, ethics

On this basis, the core dimensions and indicators of the framework were clarified. Dimension one is digital language cognition and critical ability in the AI environment, and the indicators include understanding the limitations of AI-generated content, identifying bias and false information. Dimension two is the application of AI tools and human-AI collaboration ability, and the indicators include mastering generative AI tools and co-designing teaching with AI. Dimension three is the ability to design and develop multimodal teaching resources, and the indicators include using AI to integrate text, images, audio, and video. Dimension four is data literacy and personalized teaching ability, and the indicators include interpreting learning data and designing personalized teaching strategies. Dimension five is digital ethics and safety culture awareness, and the indicators include following ethical standards, protecting students' privacy, and cultivating digital citizen awareness.

The importance of each dimension is calculated by expert scoring to obtain weights, using the entropy method formula [24] as in (3) and (4):

$$W_j = \frac{1-E_j}{k-\sum_{j=1}^{k}E_j} \tag{3}$$

$$E_j = -\frac{1}{\ln n}\sum_{i=1}^{n} p_{ij}\ln p_{ij} \tag{4}$$

Where W_j represents the weight of the j-th dimension, E_j is the entropy value, p_{ij} is the percentage of scores given by the i-th expert for the j-th indicator, and n is the number of experts. The results are shown in Table 2.

Table 2. Dimension weights of the TDLL framework

Dimensions	Average score	E_j	W_j
Dimension 1: cognition and critique	4.31	0.832	0.187
Dimension 2: tools and collaboration	4.56	0.791	0.236
Dimension 3: multimodal resources	4.24	0.845	0.184
Dimension 4: data and personalization	4.19	0.857	0.182
Dimension 5: ethics and safety	4.48	0.812	0.211

Dimension 2 (AI tools and human-AI collaboration) has the highest weight (0.236), followed by dimension 5 (ethics and safety) (0.211). Dimension 1 (cognition and critique) has a weight of 0.187, dimension 3 has a weight of 0.184, and dimension 4 has a weight of 0.182. This indicates that experts believe that teachers' primary task in an AI environment is to master the tools and collaborate, while also paying close attention to ethical issues.

3.2. Empirical analysis and framework verification

After constructing the framework, the study empirically validated the dimensions and indicators of TDLL through scale design and questionnaire surveys. The sample included 984 teachers from elementary, middle, high, and college settings. Reliability and validity testing, descriptive statistics, CFA, and variance analysis were used to thoroughly verify the framework's scientific validity and applicability. In constructing the framework, each dimension was further refined into measurable indicators, as shown in Table 3 (see Appendix). Dimension 2 (proficiency in generative AI tools) corresponds to the item "I can use tools like ChatGPT to generate and optimize classroom teaching cases," in the questionnaire validation.

Descriptive statistics revealed an overall "upper-middle" competency level. Teachers scored highest in tools and collaboration (M=4.12, SD=0.71) and lowest in data and personalized instruction (M=3.78, SD=0.85). This stark contrast suggests that while teachers are relatively adept at using AI tools, they lack the deeper data literacy required to translate AI outputs into effective, individualized pedagogy—a clear signal for targeted professional development. The scale was developed based on the five dimensions and 25 indicators identified in a Delphi expert consultation. It utilizes a five-point Likert scale, with each item ranging from 1 to 5 points, ranging from "strongly disagree" to "strongly agree." To verify the scale's reliability, Cronbach's α coefficient was used for internal consistency testing. The calculation formula is (5):

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma_i^2}{\sigma_t^2}\right) \tag{5}$$

Where k is the number of items, σ_i^2 is the variance of the i-th item, and σ_t^2 is the variance of the total score. The results are shown in Table 4. The overall scale α=0.936, and the α values for each dimension are all above 0.85, indicating good internal consistency. Regarding validity, the Kaiser-Meyer-Olkin (KMO)=0.921, Bartlett's test of sphericity χ^2=5246.13, df=300, p<0.001, indicate that the data are suitable for factor analysis. Exploratory factor analysis showed that all 25 items had factor loads greater than 0.60, indicating that each item effectively reflects the dimension to which it belongs.

Table 4. Reliability and validity tests

Dimensions	Number of entries	Cronbach's α	Average factor loading	KMO subvalues
Cognition and critique	5	0.872	0.68-0.79	0.903
Tools and collaboration	5	0.887	0.71-0.84	0.916
Multimodal resources	5	0.861	0.65-0.77	0.912
Data and personalization	5	0.853	0.62-0.75	0.908
Ethics and safety	5	0.869	0.69-0.81	0.917
Overall scale	25	0.936	0.62-0.84	0.921

At the descriptive statistical level, as shown in Table 5, the mean scores for different dimensions indicate that TDLL is generally at an upper-middle level. Dimension 2 (AI tools and collaboration) scored the highest (M=4.12, SD=0.71), indicating that teachers performed well in tool operation and human-AI collaboration. Dimension 4 (data and personalization) scored the lowest (M=3.78, SD=0.85), indicating that teachers still have significant shortcomings in data-driven personalized instruction.

In CFA, a five-factor model was constructed using AMOS. CFA assesses how well the hypothesized five-dimensional factor structure fits the observed data. The following fit metrics and their calculation formulas are used to evaluate the model fit, including RMSEA, which measures the deviation per degree of freedom between the hypothesized model and the population covariance matrix. The closer the RMSEA value is to 0, the better the fit.

$$RMSEA = \sqrt{\frac{\chi^2 - df}{df(N-1)}} \tag{6}$$

Where χ^2 is the chi-square statistic of the model, df is the degrees of freedom, and N is the sample size. In this study, a value less than 0.08 is considered a good fit.

Table 5. Descriptive statistics of each dimension

Dimensions	Mean (M)	Standard deviation (SD)	Interquartile range	Ranking
Cognition and critique	3.95	0.80	0.72	3
Tools and collaboration	4.12	0.71	0.64	1
Multimodal resources	3.88	0.82	0.76	4
Data and personalization	3.78	0.85	0.80	5
Ethics and safety	4.05	0.77	0.70	2

In CFI, this index compares the goodness of fit of the hypothetical model to the baseline independent model (assuming the variables are uncorrelated). The value ranges from 0 to 1, with higher values indicating a better fit.

$$CFI = 1 - \frac{\chi^2_{\text{Model}} - df_{\text{Model}}}{\chi^2 f_{\text{Independent}} - df_{\text{Model}}} \tag{7}$$

Where χ^2_{Model} and df_{Model} represent the chi-square value and degrees of freedom of the hypothetical model, respectively, and $\chi^2_{\text{Independent}}$ and $df_{\text{Independent}}$ represent the corresponding values of the baseline independent model. A CFI value greater than 0.90 indicates an acceptable fit.

TLI, also known as the non-normative fit index (NNFI), it compares the hypothetical model to the independence baseline while taking into account model complexity.

$$TLI = \frac{\frac{\chi^2_{\text{Independent}}}{df_{\text{Independent}}} - \frac{\chi^2_{\text{Model}}}{df_{\text{Model}}}}{\frac{\chi^2_{\text{Independent}}}{df_{\text{Independent}}} - 1} \tag{8}$$

Similar to CFI, a TLI value greater than 0.90 is generally considered acceptable.

Together, these indicators validate the rationality of the TDLL framework. As shown in Table 6, the goodness-of-fit indices are: χ^2/df=2.13, RMSEA=0.048, CFI=0.921, TLI=0.908, and GFI=0.903, all meeting statistical standards and indicating a good model fit. The χ^2/df ratio of 2.13 is well below the conservative threshold of 3, indicating a good balance between model complexity and fit. The RMSEA value of 0.048 falls within the 'good fit' range (<0.05) and is significantly below the 0.08 cutoff, suggesting minimal error of approximation. The CFI and TLI values both exceed 0.90, demonstrating that the hypothesized five-factor model is a substantially better fit to the data than the null independence model. These combined results provide strong statistical evidence that the observed data from 984 teachers are consistent with the proposed five-dimensional framework structure, robustly supporting its construct validity. Standardized factor loadings ranged from 0.62 to 0.83, indicating a clear correspondence between items and dimensions.

In terms of variance analysis, the study further examined differences in digital language literacy among teachers of different grades, disciplines, and years of teaching experience. A one-way analysis of variance (ANOVA) revealed significant differences between the different groups. The results showed that university teachers scored highest on the cognition and critique dimension (M=4.21), while elementary school teachers scored relatively low on the tools and collaboration dimension (M=3.92). Humanities teachers outperformed science teachers in multimodal resource design ($p<0.05$). Teachers with more than 10 years of teaching experience scored significantly higher than newer teachers on the ethics and safety dimension ($p<0.01$).

$$F = \frac{\frac{SSA}{df_A}}{\frac{SSE}{df_E}} \tag{9}$$

Where sum of squares for A (SSA) is the between-group sum of squares, sum of squares error (SSE) is the within-group sum of squares, df_A is the between-group degrees of freedom, and df_E is the within-group degrees of freedom. As shown in Table 7, the ANOVA results for the instrumentality and synergy dimensions in this study were F (3, 980)=6.42, p<0.001, indicating significant differences between the academic stages.

Table 6. Confirmatory factor analysis fitting results

Fit indices	Result	Critical value	Whether it meets the standards
χ^2/df	2.13	<3	Yes
RMSEA	0.048	<0.08	Yes
CFI	0.921	>0.90	Yes
TLI	0.908	>0.90	Yes
GFI	0.903	>0.90	Yes

Table 7. Results of difference analysis under different background variables

Variables	Grouping	Number of samples	Tools and collaboration (mean)	F-number	p-value
Grade	Elementary school	240	3.92	6.42	0.000
	Middle school	280	4.08		
	High school	290	4.15		
	College	174	4.21		
Subject	Liberal arts	412	3.94	4.21	0.017
	Science	572	3.86		
Teaching experience	1-5 years	280	3.88	5.37	0.002
	6-10 years	320	3.95		
	More than 10 years	384	4.12		

The variance analysis reveals important patterns about the current landscape of TDLL. The finding that university teachers excel in ‘cognition and critique’ likely reflects their greater engagement with research and critical discourse, while elementary teachers’ lower scores in ‘tools and collaboration’ may stem from curriculum pressures that prioritize foundational skills over advanced technology integration, or from a lack of age-appropriate AI tools. The advantage of humanities teachers in ‘multimodal resource design’ aligns with the inherently text- and media-rich nature of their subjects, which naturally lends itself to such tasks. For instance, an English teacher might use an AI image generator to create visuals for a poem, while a history teacher might use AI to simulate historical speeches. Most notably, the significant positive correlation between teaching experience and ‘ethics and safety’ scores suggests that ethical judgment and classroom management wisdom—crucial for navigating AI’s risks—are largely accrued through practical experience, underscoring the need to scaffold this dimension for early-career teachers. These differences highlight that digital language literacy is not a monolithic trait but is profoundly mediated by professional context and experience.

In summary, the empirical analysis demonstrates that the constructed TDLL framework has high reliability and validity, with a good structural model fit, accurately reflecting teachers’ digital language proficiency in the context of AI education. The Delphi study identified ‘tools and collaboration’ as the highest-weighted dimension, underscoring its foundational role. In AI-based education, proficiency with tools like LLMs is the gateway capability that enables all other literacies; without the practical ability to effectively interact with and leverage AI systems, capacities for critique, design, data use, and ethical governance remain theoretical. This dimension’s primacy reflects the operational reality that hands-on, collaborative competence with AI is the critical first step for transforming pedagogical practice. Furthermore, the variance analysis revealed significant differences among teacher groups based on academic level, subject matter, and teaching experience, providing nuanced empirical evidence that can inform the design of differentiated, context-sensitive professional development programs and policy interventions.

4. DISCUSSION

This study developed a novel, empirically validated TDLL framework. The primacy of the tools and collaboration dimension aligns with technology integration models like TPACK, which emphasize the interplay of technological, pedagogical, and content knowledge [25]. However, our findings extend TPACK by specifying the linguistic and collaborative nature of the technology AI involved. The high weight for ‘ethics and safety' resonates strongly with post-humanist and critical pedagogy theories that warn of algorithmic bias and dataveillance in education [26], [27]. This emphasizes that TDLL is not merely functional but fundamentally ethical.

The low score in 'data and personalized instruction' corroborates previous studies identifying a significant data literacy gap among educators [28], [29]. While AI platforms generate vast amounts of learning analytics, teachers often lack the skills to interpret and act on this data meaningfully. This gap bridges to socio-semiotic theory; personalization requires interpreting not just quantitative data points but the semiotic patterns in student-AI interactions.

The competency differences across subjects and experience levels support situated learning theory [30], which posits that learning is context-dependent. The strength of humanities teachers in multimodal design likely stems from their disciplinary engagement with text and media [31], while experienced teachers' higher ethical scores suggest that ethical judgment is cultivated through practical, contextual experience over time [32]. Our framework's specialized focus on language addresses a limitation in broader models like DigCompEdu. While DigCompEdu is invaluable, our TDLL framework offers finer granularity for language-mediated teaching tasks, such as critiquing AI-generated narratives or facilitating ethical debates about AI authorship—tasks not explicitly detailed in general competence lists.

The theoretical implications are significant. By integrating socio-semiotic and post-humanist lenses, the TDLL framework moves beyond a skills-based checklist to conceptualize literacy as a relational practice within a human-AI ecosystem. Practically, the framework provides a blueprint for differentiated professional development. For policymakers, it suggests concrete ways to integrate TDLL into national teacher standards and certification systems. For training institutions, it recommends moving from one-size-fits-all workshops to tiered modules: foundational tracks for 'tools and collaboration,' advanced labs for 'data and personalization,' and subject-specific studios for 'multimodal design'.

Looking ahead, the validated TDLL framework opens several avenues for future inquiry. Longitudinal studies are urgently needed to track how TDLL evolves over time, particularly in response to rapid advancements in AI technologies and targeted professional development interventions. Such investigations would benefit from adopting predictive modeling approaches that have proven effective in understanding complex, dynamic systems [33]. By applying similar methodological rigor, researchers could not only validate the framework's predictive capacity but also generate evidence-based insights to inform adaptive, forward-looking teacher education policies in the AI era.

5. CONCLUSION

This study presents the first empirically validated framework TDLL, a critical competency for navigating the AI-transformed educational landscape. Through a rigorous multi-method design—spanning policy analysis of 12 international documents, a three-round Delphi study with 30 experts, and a large-scale survey of 984 educators—we established and validated a robust five-dimensional framework. The framework prioritizes 'tools and collaboration' (weight=0.236) as a foundational gateway competency and 'ethics and safety' (weight=0.211) as a paramount concern, while revealing a significant and actionable deficit in 'data and personalized instruction' (lowest mean score). Our findings make a distinct theoretical contribution by integrating socio-semiotic and post-humanist lenses, thereby shifting the conception of teacher literacy from a set of technical skills to a critical, relational praxis essential for mediating meaning and agency within human-AI pedagogical assemblages. This specialized, language-centered framework addresses a clear granularity gap in broader models like DigCompEdu, offering a precise tool for understanding the core communicative challenges of AI-integrated teaching.

The practical implications of this framework are immediate and multifaceted. For policymakers, it provides a validated blueprint for revising teacher standards and allocating resources toward targeted professional development, particularly in data literacy and ethical AI use. For teacher educators and institutions, it mandates a move beyond generic training toward differentiated, scenario-based modules—such as ethical prompt engineering labs or data-driven differentiation' workshops—tailored to subject disciplines and career stages (novice vs. experienced). For schools and teachers, it serves as a self-assessment and collaborative planning tool to foster a culture of responsible innovation. While this study is limited by its regional policy focus, cross-sectional design, and self-reported data, it unequivocally charts a course for future work: cross-cultural validation of the framework, longitudinal studies on TDLL development, and, most critically, intervention research to design and evaluate professional development programs that translate this theoretical model into measurable improvements in classroom practice and student outcomes in the AI era.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
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O : Writing - **O**riginal Draft
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Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [CL], upon reasonable request.

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APPENDIX

Table 3. Statistics of TDLL indicators

Indicator number	Dimension	Indicator description	Average value	SD
1	Dimension 1: cognition and critique	Understand the characteristics and limitations of AI-generated text	4.05	0.81
2	Dimension 1: cognition and critique	Evaluate the authenticity and reliability of digital information	4.12	0.77
3	Dimension 1: cognition and critique	Identify potential biases in AI-generated content	3.89	0.84
4	Dimension 1: cognition and critique	Critically assess AI-suggested teaching resources	3.92	0.79
5	Dimension 1: cognition and critique	Distinguish between AI-generated and human-generated language outputs	3.78	0.86
6	Dimension 2: tools and collaboration	Proficiently use generative AI tools (e.g., ChatGPT) for teaching	3.98	0.82
7	Dimension 2: tools and collaboration	Collaborate with AI to co-design instructional activities	4.26	0.75
8	Dimension 2: tools and collaboration	Use AI tools to generate and optimize classroom teaching cases	4.18	0.73
9	Dimension 2: tools and collaboration	Effectively prompt AI systems to elicit pedagogically appropriate responses	4.03	0.78
10	Dimension 2: tools and collaboration	Adapt AI-generated content to meet specific teaching objectives	4.14	0.70
11	Dimension 3: multimodal resource design	Use AI to integrate text and image resources	3.85	0.88
12	Dimension 3: multimodal resource design	Develop multimodal course materials using AI tools	3.91	0.83

Table 3. Statistics of TDLL indicators (continue)

Indicator number	Dimension	Indicator description	Average value	SD
13	Dimension 3: multimodal resource design	Combine audio, video, and text to create interactive teaching resources	3.82	0.87
14	Dimension 3: multimodal resource design	Design AI-enhanced presentations for diverse learner needs	3.76	0.85
15	Dimension 3: multimodal resource design	Evaluate the pedagogical effectiveness of AI-generated multimodal materials	3.88	0.81
16	Dimension 4: data and personalization	Interpret learning data reports from AI platforms	3.72	0.87
17	Dimension 4: data and personalization	Adapt personalized teaching strategies based on AI analytics	3.84	0.82
18	Dimension 4: data and personalization	Use student performance data to inform instructional decisions	3.79	0.84
19	Dimension 4: data and personalization	Design individualized learning pathways using AI recommendations	3.68	0.89
20	Dimension 4: data and personalization	Monitor student progress through AI-powered learning dashboards	3.81	0.83
21	Dimension 5: ethics and safety	Adhere to AI ethical standards in classroom practice	4.31	0.74
22	Dimension 5: ethics and safety	Protect student data privacy when using AI educational applications	4.22	0.79
23	Dimension 5: ethics and safety	Establish clear rules for students regarding AI use and data sharing	4.08	0.76
24	Dimension 5: ethics and safety	Cultivate digital citizenship awareness among students	4.15	0.72
25	Dimension 5: ethics and safety	Address algorithmic bias and promote fairness in AI-mediated learning	3.96	0.80

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