Hierarchical Characteristics and Cultivation Mechanism of Teachers' Data Literacy in the Context of Digital Transformation

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ABSTRACT Efficient data acquisition, intelligent analysis, and adaptive decision-making are fundamental capabilities for modern digital engineering systems. To address the limitations of homogeneous teacher training under digital transformation, this study proposes a hierarchical diagnosis and progressive cultivation framework for teacher data literacy based on multimodal assessment and latent profile analysis. A context-embedded evaluation tool integrating situational judgment, behavioral retrospection, and ethical dilemma tasks was developed and applied to 1,263 teachers to identify four distinct competency levels. Based on the diagnosed developmental characteristics, a four-stage cultivation mechanism incorporating intelligent recommendation, competency dashboards, and micro-certification was established and iteratively optimized through design-based research. Experimental results demonstrate that the proposed framework achieves an upward competency migration rate of 60.7%, significantly outperforming conventional training approaches, while the competency dashboard provides the greatest independent contribution to performance improvement. The hierarchical and evidence-driven strategy effectively enhances personalized learning trajectories and supports scalable digital capability development. Beyond educational applications, the proposed multimodal profiling and adaptive optimization framework provides a practical reference for intelligent information processing, data fusion, human-centered decision support, and adaptive sensing architectures, offering potential guidance for data-driven optimization and intelligent management in electromagnetic wave analysis, antenna-enabled sensing systems, and propagation-oriented engineering applications.

INDEX TERMS data-driven intelligence, multimodal assessment, latent profile analysis, adaptive decision-making, electromagnetic information processing

I. INTRODUCTION

DIGITAL transformation is reshaping the operational logic of basic education with unprecedented depth, and the shift from experience-driven to data-driven teaching decisions has become an irreversible trend [1]. As the core implementers of teaching activities, teachers' ability to effectively acquire, understand, analyze, and apply data directly determines the quality of implementation of precision teaching and evidence-based improvement [2]. However, current teacher data literacy training generally adopts a large-scale, standardized, and uniform supply model, assuming that all teachers are at a homogeneous starting point in terms of ability, ignoring the hidden hierarchical differentiation within the teacher group in dimensions including data cognition, analytical application, and ethical decision-making [3,4]. This "one-size-fits-all" training paradigm leads to lower-level teachers feeling apprehensive and hesitant when faced with advanced analytical content, while higher-level teachers are forced to repeat basic operational training. A serious structural mismatch exists between training content and real development needs, and the dilemma of high input and low conversion has not been broken for a long time.

Academics have accumulated a relatively rich research foundation around the above issues. For example, Lee et al. pointed out through a systematic review that teachers' data literacy is not just a single data processing ability, but a multi-dimensional structure that includes data understanding, interpretation, use, communication and ethical judgment [5]; Boesdorfer et al. further found that teachers' understanding of "data" in real teaching practice is significantly different, and different teachers' depth and initiative in using data to improve teaching are not consistent [6]. In terms of training intervention, Filderman et al.'s meta-analysis showed that data literacy training for K-12 teachers can significantly improve teachers' data interpretation and data-driven decision-making abilities [7]; Puccioni and Desir emphasized that digital tools can promote teachers to carry out collaborative data analysis and data-driven decision-making [8]. At the same time, Ruhter and Karvonen pointed out that professional development projects have a positive effect on improving teachers' data decision-making abilities, but their effectiveness is often affected by the suitability of training content and the degree of contextual support [9]; Fuchs et al. proposed from the perspective of data-driven individualized support that teachers need to obtain more operational and continuous feedback technical support in order to truly transform data into teaching actions [10]. McCammon et al.'s research on pre-service teacher data decision-making training also shows that different intervention methods have different effects on promoting teachers' data use ability [11]; Dülger et al.'s research on teacher dashboards further illustrates that visual feedback tools can help teachers monitor the teaching process and improve learning support strategies [12]. However, existing studies mostly stay at the level of single dimension or experience grouping, lack empirical hierarchical classification based on large sample potential profile analysis, and the training mechanism design is rarely connected with the refined hierarchical diagnosis results, making it difficult to achieve accurate matching of "level-person-policy".

At the methodological level, latent profile analysis, as an individual-centered classification technique, can identify potential groups with substantial differences based on the individual's response patterns on multidimensional indicators. Agathangelou et al. used latent profile analysis to identify teachers' professional development needs, demonstrating that this method can reveal different developmental types within the teacher group and provide a basis for customized professional development [13]. Torsney et al. also used latent profile analysis to distinguish different types of teachers' motivational structures, indicating that this method is suitable for explaining internal differences in the teacher group that are masked by the mean [14]. Meanwhile, design research provides important methodological support for the generation, testing, and iteration of training mechanisms. Lim and Nguyen pointed out that design research can promote teacher learning in real educational situations through repeated design, implementation, and modification [15]. Peters-Burton et al. further demonstrated that teachers' participation in the design research process can also become an important path for professional development, helping to promote the simultaneous occurrence of teaching practice and mechanism optimization [16]. However, most existing studies use LPA for current status description, rarely forming a closed loop with training mechanism design, and lack a connecting path to transform hierarchical diagnostic results into intervention starting points. This paper aims to integrate latent profile analysis and design research methods to make implicit hierarchical characteristics explicit as the starting point for training, constructing a systematic framework of "hierarchical diagnosis—mechanism matching—evidence-based optimization."

In summary, this study aims to explore the hierarchical characteristics of teachers' data literacy in the context of digital transformation, and accordingly construct a corresponding progressive training mechanism. The study first develops a context-embedded multimodal assessment tool. Based on assessment data from 1263 primary and secondary school teachers (covering diverse disciplines including STEM, humanities, and arts across both primary and middle school levels), latent profile analysis is used to identify four levels of data literacy. To ensure logical validity, the study characterizes discipline-specific feature maps and developmental breakpoints, accounting for the distinct data application needs of different subject areas. Then, based on the zone of proximal development theory, a four-stage progressive training mechanism of "cognitive activation —skill proficiency—teaching integration—ecological co-creation" is constructed, embedding dynamic supply elements such as intelligent recommendation, competency dashboards, and micro-certification. Finally, quasi-experimental design and hierarchical regression analysis are used to examine the transfer effect of the mechanism and the independent contribution of each element.

II. METHODS

A. DEVELOPMENT OF CONTEXT-EMBEDDED MULTIMODAL ASSESSMENT TOOL

Effective diagnosis of teachers' data literacy first requires a "measuring stick" that can truly measure the gap in ability. Existing assessment tools mostly rely on self-report scales or general data analysis items, stripping teachers of the real-world context of data in their daily work. Therefore, this study, based on the real lifecycle of data flow in teaching, developed a multimodal assessment tool embedded in teaching contexts. Its overall dimensional structure and evidence integration logic are shown in Figure 1.

There were four steps in the development of the tool. Stage 1: Dimension construction and scenario library development. Drawing on the data-driven decision-making model, the study team defined teachers' data literacy as data cognition, analytical application and ethical decision-making. A series of semi-structured interviews were administered with 28 frontline teachers from six primary and middle schools to identify frequent data usage patterns in teaching and assessment processes, and in school-parent interactions, to generate 47 scenarios. The second stage involved item development. For the data cognition dimension, 25 situational judgment questions were designed, containing common traps of misinterpretation, to assess teachers' data knowledge of statistical concepts and data charts. For the analytical application dimension, 8 retrospective questions on behavioral events were developed, asking teachers to recall their actual teaching experiences of teaching adaptation based on data. The rating system was 0-3 levels based on the evidence chain of "identifying the problem - connecting data

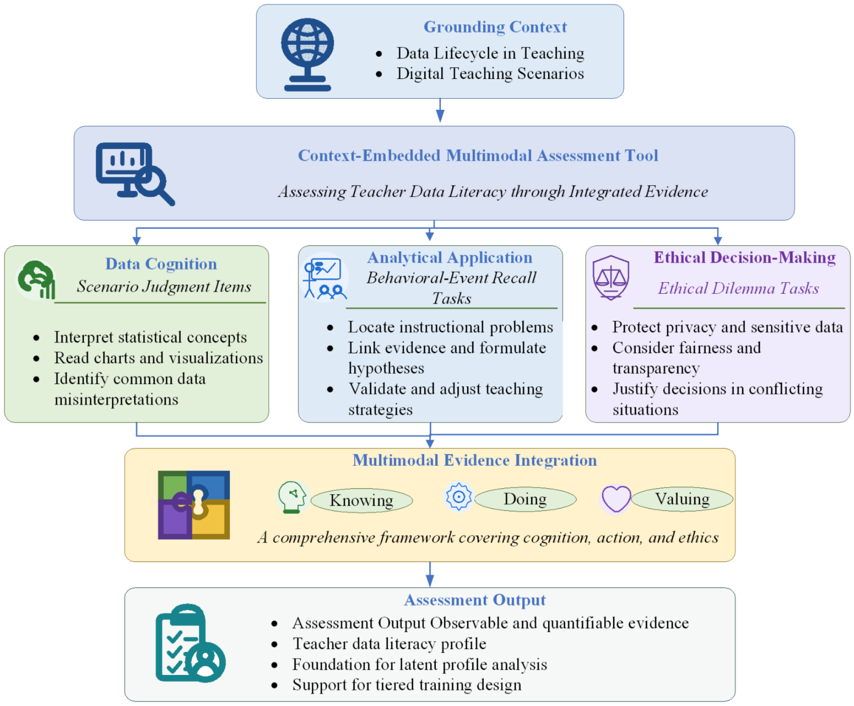

FIGURE 1. Dimensional Model of the Context-Embedded Multimodal Assessment Tool for Teachers' Data Literacy

- proposing hypotheses - verifying improvements." For the ethical decision-making dimension, 5 dilemma tasks were designed, depicting situations of data privacy and fairness dilemmas, and based on three scoring dimensions: privacy protection, fairness, and transparency. In the third stage, the items were reviewed and verified by experts. Seven experts in the domain reviewed the items through three rounds of Delphi process, deleting items with a content validity ratio less than 0.78, and finally selecting 23 questions of situational judgment, 6 questions of behavioral event recall and 4 questions of the dilemmas tasks. The fourth stage involved pre-testing and testing the reliability and validity [17-19]. The pre-testing outcomes with 217 non-sample teachers confirmed that the confirmatory factor analysis three-factor model had a good fit, with combined reliability of each dimension from 0.82 to 0.89, mean variance sample size (MVSS) greater than 0.50, inter-rater consistency coefficient (ICC) of 0.85, and total Cronbach's α coefficient of 0.88, as shown in Table 1 for details of each indicator.

The essence of the assessment tool is contextual embedding and multimodal evidence information. Contextual embedding judgment questions are collected at the level of data interpretation ability cognition, behavioral event retrospection are collected at the level of data application transferability behavior, and ethical dilemma tasks are collected at the level of data ethical sensitivity value judgment. Three kinds of evidence collection based on different levels construct the whole set of three-tiered structure assessment model "knowledge-action-morality".

B. HIERARCHICAL CLASSIFICATION BASED ON LATENT PROFILE ANALYSIS

This paper uses individual-centered latent profile analysis to model the data, attempting to extract hidden structural stratification from teachers' answer patterns on the three types of assessment tasks. Analysis proceeds with the standardized scores of the three dimensions of the assessing instrument as explicitly indicated indicators, and profile models for 1 to 6 latent categories are fitted. Estimation of model parameters is done with robust maximum likelihood; each model is calculated 50 times with randomly chosen initial values to prevent local optima from disturbing the judgment. The changing trends of the model fit indices are shown in Figure 2.

The comparison of fit indices shows a clear inflection point: from class 1 to class 4, the AIC, BIC, and aBIC values decreased continuously and significantly, and the p-values of LMRT and BLRT are both less than 0.001; when the number of classes increases to 5, the decrease slows down significantly, and the two likelihood ratio tests are not significant for the first time, indicating that the five-class model is over-extracted. Considering both goodness of fit and interpretability, the four-class model is accepted as the optimal solution, with an entropy value of 0.86 and average posterior classification probabilities for each profile ranging from 0.83 to 0.92, indicating good classification accuracy. Kruskal-Wallis tests and post-hoc pairwise comparisons further confirm that the differences among the four groups in the three dimensions of data cognition, analytical application, and ethical decision-making are all significant, indicating that these levels are not accidental products of

TABLE 1. Summary of Reliability and Validity Indicators of the Assessment Tool

Indicator type	Dimension / Level	Value	Criterion
Content validity	All items	CVR $\geq$ 0.78	Retained after Delphi panel review
Construct validity	Three-factor model (overall)	χ^2/df = 2.34, CFI = 0.93, TLI = 0.91, RMSEA = 0.062, SRMR = 0.048	Good model fit
Convergent validity	Data cognition	CR = 0.89, AVE = 0.66	CR $>$ 0.70, AVE $>$ 0.50
Convergent validity	Analysis application	CR = 0.84, AVE = 0.58	
Convergent validity	Ethical decision-making	CR = 0.82, AVE = 0.55	
Internal consistency reliability	Full scale	Cronbach's α = 0.88	α $>$ 0.80
Internal consistency reliability	Data cognition	α = 0.87	
Internal consistency reliability	Analysis application	α = 0.82	
Internal consistency reliability	Ethical decision-making	α = 0.79	
Inter-rater reliability	Behavioral-event recall + ethical dilemma tasks	ICC = 0.85 (three raters)	ICC $>$ 0.75

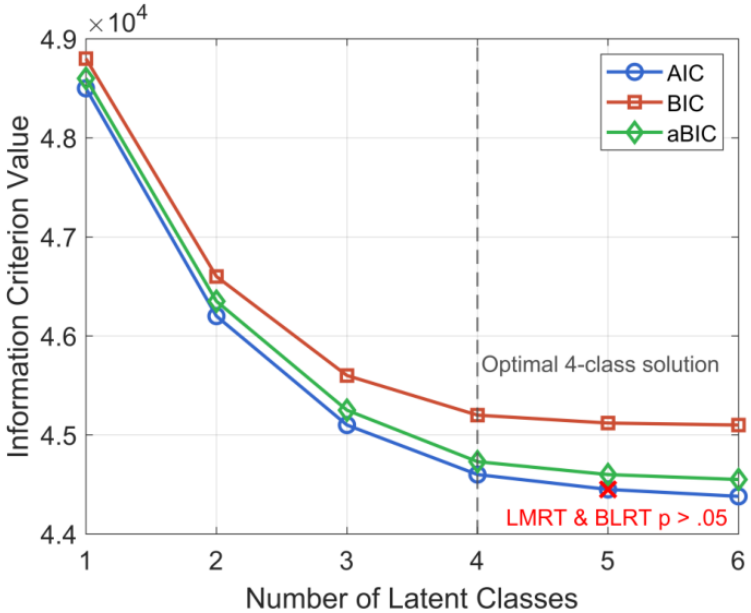

FIGURE 2. Comparison of Fit Indices for Potential Profile Models

statistical modeling, but rather have substantially different behavioral characteristics in each core dimension.

Based on this, the research group named the four levels according to the three-dimensional mean profile and behavioral characteristics. The first type, "Technology-Aware", scores low in all three dimensions, they take data as an external regulatory tool and adopt an avoidance and wait-and-see attitude. The second type, "Mechanical Execution", they are aware of statistical knowledge and have basic ethical awareness, but they can not independently turn data into teaching hypotheses, that is, they are "knowing but not using well" . The third type, "Strategy Integration", they are excellent in cognitive and analytical applications, they finished a closed-loop reasoning from identifying problems to verification and improvement, while ethical sensitivity is weak, they could sacrifice individuals' privacy protection in order to improve the efficiency of data release . The fourth type, "Intelligent Creation", they rank first in all three dimensions especially in ethics, they can integrate multi-source data flexibly for optimizing teaching and further establish school-based data sharing and discussion mechanisms, they play a key node role in diffusing data culture.

Figure 3 reveals that the average values of the three axes from "Technology-Aware" to "Intellectual Creation" do not rise evenly, but rather show a phased capability leap: the leap from "Technology-Aware" to "Mechanical Execution" is mainly a breakthrough in cognitive entry; the key leap from "Mechanical Execution" to "Strategy Integration" is reflected in the dramatic rise of the analysis and application axis; and the leap from "Strategy Integration" to "Intellectual Creation" is more reflected in the significant upward tilt of the ethical decision-making axis. This suggests that the process of data literacy development is not a balanced accumulation of all the dimensions, but rather a cognition barrier in the beginning, a change barrier in the middle and an ethical barrier in the end. The four levels form four qualitatively different capability segments in terms of measurement, rather than high, middle and low. The gradation has a big middle and small ends. The "mechanical execution type" accounts for nearly 40%, forming the basic foundation

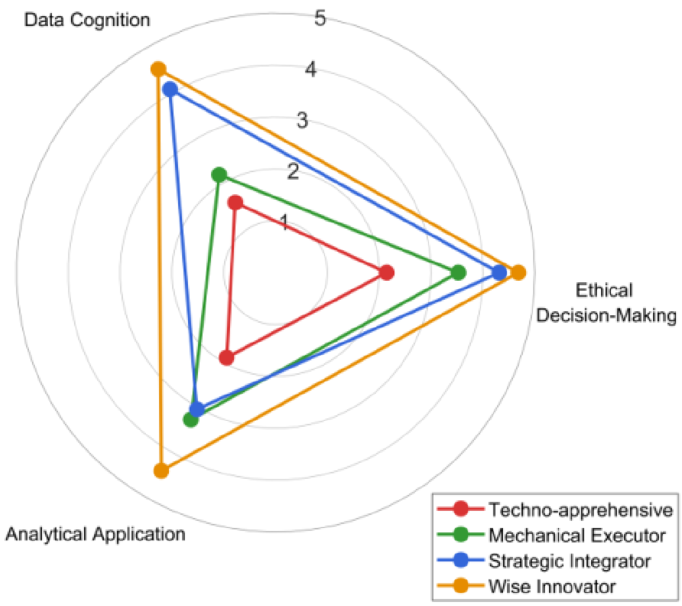

FIGURE 3. Radar Chart of Four-Level Data Literacy Characteristics

of current teachers' data literacy. This characteristic means that if training is still uniformly provided to the "average teachers", nearly half of the "mechanical execution type" teachers are unable to achieve a qualitative change towards strategy integration due to the lack of support in the analysis and application links. The smaller proportion of "intellectual creation type" teachers also stagnate in their development due to the lack of high-level challenges [20]. The Kruskal-Wallis test combined with the Dunn-Bonferroni correction post-hoc pairwise comparison further confirmed that the differences in the four levels in the three dimensions were all significant. The results are summarized in Table 2.

The overall distribution of the 1263 teachers shows that the "technology-aware type" and "mechanical execution type" teachers account for 70.0%. The hierarchical distribution is clearly a pyramidical structure, and the lower-level teachers are the foundation of current data literacy. This distribution pattern has implications for training design: if the training is still provided uniformly to "average teachers", the 30% of "technology-aware" teachers are challenged by the cognitive gap, the 40% of "mechanical execution" teachers are unable to leap qualitatively to the level of strategy integration due to the lack of analytical and application support, and the 10% of "intellectual creation" teachers stagnate due to the lack of challenges. The hierarchical classification is completed to provide an empirical basis for converting the theory of zone of proximal development into a four-level training mechanism. Since the subsequent experiments require excluding teachers who lack data from the pre-test or who have not completed the training, the hierarchical structure of the subsample for the experiments is slightly different from the whole sample (see experimental setup), but LPA remains unaffected.

C. MAPPING DEVELOPMENTAL FAULT LINES AND ANALYTICAL PATHS

While the potential profile analysis divided teachers' data literacy into four statistically significant groups, the mean dimensional values alone cannot reveal the location of the 'developmental fault lines'—the specific conceptual or behavioral barriers that prevent teachers from advancing to the next stage. Consequently, this study coded the textual and ethical dilemma responses of teachers' behavioral events at each level segment by segment, attempting to draw a progressive path map marking these critical cognitive and practical faults. The coding was done in two rounds. The first iteration of the analysis of 126 retrospective texts from teachers described as "technology-aware" and "mechanically compliant" showed that the former constantly expressed challenges of "not knowing where to access the data platform" and "giving up as soon as they see a table," suggesting that the fundamental problem of the former is the absence of a meaningful link between data and teaching. The latter, while capable of repeating the meaning of the data, consistently expressed passive phrases such as "I collect what the school asks me to collect" with a lack of reasoning from data interpretation to hypotheses in their action chain. This implies that the differences between these two levels are not cognitive, but rather the awareness shift from "data is an external task that is not relevant to me" to "data is

TABLE 2. Mean Dimensions and Multiple Comparison Results for the Four Levels

Dimension	Techno-apprehensive (n=379)	Mechanical Executor (n=505)	Strategic Integrator (n=253)	Wise Innovator (n=126)	H	Post-hoc
Data Cognition	2.21 ± 0.72	3.48 ± 0.69	4.29 ± 0.57	4.71 ± 0.40	337.64^{***}	$1 < 2 < 3 < 4$
Analytical Application	1.62 ± 0.53	2.23 ± 0.65	4.01 ± 0.54	4.55 ± 0.44	508.91^{***}	$1 < 2 < 3 < 4$
Ethical Decision-Making	1.92 ± 0.75	3.31 ± 0.73	3.09 ± 0.70	4.44 ± 0.49	282.53^{***}	$1 < 3 < 2 < 4$

Note: $^{***}p < 0.001$; post-hoc comparisons used Dunn-Bonferroni correction, with numbers 1–4 representing technologically alert, mechanically executive, strategically integrated, and intellectually creative types, respectively; "<" indicates the former is significantly lower than the latter, and all listed pairwise comparisons showed adjusted $p < 0.001$.

my teaching tool." The second round of coding compared 95 retrospective texts and ethical dilemma responses from "mechanical execution" and "strategy integration" types. It was found that "strategy integration" teachers were able to present a complete reasoning chain from locating the problem to associating data and then to verifying and improving, but they showed a significant lag in ethical sensitivity in the dilemma task, tending to put the efficiency value of data disclosure above privacy protection; while "intellectual creation" teachers generally dealt with both transparency and protection value demands at the same time when faced with the same situation. The divergence between the two levels in ethical decision-making marks the final threshold from "making good use of data" to "making good use of data and treating people well" [21,22].

D. DESIGN OF FOUR-STAGE PROGRESSIVE TRAINING MECHANISM DRIVEN BY THE ZONE OF PROXIMAL DEVELOPMENT

Based on the theory of the zone of proximal development, this study transforms the identified gaps into a non-linear, multi-entry intervention framework. Unlike traditional sequential pipelines, each teacher is dynamically mapped to a specific starting stage based on their diagnostic profile, bypassing redundant modules. This adaptive branching ensures that 'Strategy Integration' teachers, for instance, engage directly with ethical dilemmas rather than repeating basic cognitive tasks, thereby achieving true individualized trajectory optimization rather than a standard one-way progression. The "cognitive activation" stage is aimed at "technology-aware" teachers, using low cognitive load data stories and simplified panels that are close to the actual situation of the class as scaffolds to help them establish a preliminary meaningful connection between data and teaching; the "skill proficiency" stage is aimed at "mechanical execution" teachers, using "hypothesis-verification" deduction tasks and fill-in-the-blank scaffolding to promote the shift from passive interpretation to autonomous questioning; the "teaching integration" stage focuses on "strategy integration" teachers, using ethical dilemma debates and ethical deduction logs to leverage value reflection and make up for the shortcomings of ethical sensitivity; the "ecological co-creation" stage provides "wisdom creation" teachers with roles such as peer review and school-based research to prevent development stagnation [23]. There are three dynamic support components of the mechanism. The smart recommendation engine provides different cases, scaffolding or future resources according to the teacher's level, subject tags, or real-time learning blind spots. Specifically, for the cultivation of data ethics, the system recommends value-conflict scenarios and reflective logs rather than simple technical tasks, bridging the gap between automated recommendation and value-based competency development. The competency dashboard provides a simulation of the growth process with bar graphs or a 3D literacy radar chart, particularly making the subtle ethical dimension explicit, allowing teachers to self-monitor the progress and solve the orientation problem of "where have I been in my learning?". Micro-certification is automatically triggered when key tasks are completed at each stage to formally evangelize competency and open the next stage's resource door, solving the incentive problem of "what have I learned?". The three components combine to form a micro-learning loop in each stage: "diagnosis entry—scaffolded learning—performance certification—repositioning". The whole process is not a timetable, but an interactive learning navigation system. In the learning stage, the dashboard tracks the variations of competency dimensions. When any stagnation is detected, the intelligent recommendation system reverts to the previous scaffolding or new tasks. When the leap standard is achieved, the stage is automatically promoted, so the teacher always faces challenges with support. This responsive supply model of "one policy per level" transforms the hidden hierarchical differences into the next steps for each teacher.

E. DUAL-CIRCUIT ITERATIVE ADAPTATION BASED ON DESIGN RESEARCH

There could inevitably be gaps between the paper design and mechanism framework and the implementation in actual training situations that could need to be iterated multiple times. How high should be built the scaffolding such that it is just a little bit higher than the current level? Could it be that the recommended content was "just what teachers need"? Could it be that the presentation of the dashboards were user-friendly for teachers at different levels? These questions could not be predicted in the design draft. Therefore, this study selected a design research approach to carry out two rounds of iterative experiments in the teacher development center in two regions, eastern and central China. Only in this way could the mechanism reveal problems, receive feedback, and further improve in a real environment.

The first round of iteration covered 127 teachers in a city in eastern China. The project team systematically collected problem signals through background behavior logs, weekly feedback questionnaires, and monthly focus groups. Three design flaws were exposed in the first month of operation. First, the intelligent recommendation only matches content at the hierarchical level, resulting in primary school teachers being pushed high school physics data cases, leading to a serious mismatch in context. Second, the fill-in-the-blank scaffolding in the “skill proficiency” stage lacks exemplary anchors that can be imitated, and teachers generally report that they “stare at the blanks and don’t know what to write.” Third, the competency dashboard lacks dynamic updates, and the frequency of teacher visits has declined significantly since the fourth week. In response to the above problems, the research team implemented the first three corrections in the second round: upgrading the recommendation logic to a three-dimensional cross-matching of “hierarchy + grade level + subject” and adding manual review in the cold start stage; embedding complete deduction demonstrations by anonymous teachers and more specific semi-structured sentences in the scaffolding; and adding a weekly “dynamic snapshot” function to the dashboard to maintain the motivation for follow-up visits with continuous new information [24]. The second round of iteration was conducted among 98 teachers in a city in central China. After the correction, the recommendation click rate increased by 34 percentage points compared to the first round, the active deduction completion rate increased from 61% to 83%, and the four-week follow-up rate of the dashboard increased from 38% to 71%. However, a new problem emerged during implementation: some “tech-aware” teachers experienced task pauses at the transition between stages. Namely, their previous successful experiences were not yet solidified, and the anxiety emerged again when facing the independent reasoning. Therefore, an optional “buffer period” between the two stages is added, i.e., let teachers continue with the low-risk extension exercises in stage 2 or let them just take the learning logs of the peers who passed to the next stage before they independently started the new stage. The two rounds of design samples were mainly used for mechanism iteration and operational process optimization. If some of the above teachers could be included in the subsequent formal experiment, this paper controlled for the regional and batch differences in the formal analysis to alleviate the impact of iterative experience on effect estimation.

III. RESULTS AND DISCUSSION

A. EXPERIMENTAL SETUP

This study employed a quasi-experimental design. From 1263 teachers who completed the baseline assessment, 53 individuals with incomplete pre-test data or who did not complete the full training were excluded, leaving a final effective sample of 1210. These teachers were randomly assigned to an experimental group (610 participants) and a control group (600 participants) based on school cluster randomization. The pretest hierarchical distribution was balanced between the two groups (L1≈30%, L2≈40%, L3≈20%, L4≈10%), exhibiting a clear pyramid shape (L1 and L2 combined accounted for 70%). The experimental group received a coordinated intervention combining a four-stage progressive training mechanism, intelligent recommendation, competency dashboard, and micro-certification, while the control group maintained regular intensive training. Context-embedded multimodal assessment tools were used for both pre- and post-tests, with learning behavior logs and micro-certification records collected simultaneously. This study was approved by the Ethics Committee of Yong’an Open University, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

B. EXPERIMENT

1) Validation of the hierarchical structure of data literacy

To assess the accuracy and discriminative ability of the four-level model obtained from the potential profile analysis, a validity test was carried out on 1263 pretest data. In terms of classification accuracy, the average posterior probability of the four levels ranged from 0.83 to 0.92, all above the judgment threshold value of 0.80; the global entropy of the model was 0.86, higher than the critical value of 0.80, suggesting that classification of individuals is accurate and the potential profiles are well separated. As for external discrimination, a Kruskal-Wallis H test was used to explore the differences between the four levels (independent variable) in three standardized dimensions (dependent variables). The results indicated that there were significant differences between levels in data cognition ($H = 342.78$, $p < 0.001$), analytical application ($H = 512.36$, $p < 0.001$), and ethical decision-making ($H = 278.65$, $p < 0.001$), and all post hoc comparisons were significant (adjusted $p < 0.001$), which confirmed that there were significant differences between levels in core competency dimensions. The radar chart of level characteristics (Figure 3) also shows that “technologically alert” is low in all three dimensions; “mechanically executive” has moderate cognition and ethics but weak analytical application; “strategy integration” has excellent cognition and analytical application, but low ethical decision-making; and “intellectual creation” has high scores in all three dimensions, particularly significantly higher in ethical decision-making, showing that ethical decision-making is a crucial turning point in top-level data literacy. In summary, the four-level structure meets the psychometric requirements in terms of classification accuracy, profile independence, and external discrimination, and its validity is strongly supported.

2) Experiment on the Evaluation of the Transfer Effect of the Training Mechanism at Different Levels

To examine the real effect of the training mechanism on the transfer of teachers' data literacy at different levels, this study adopted a quasi-experimental pre- and post-test design. 1210 primary and secondary school teachers were randomly divided into an experimental group (610 people) and a control group (600 people). The experimental group received a one-semester four-stage progressive training intervention, covering four stages: cognitive activation, skill mastery, teaching integration, and ecological co-creation, and incorporating intelligent recommendation and micro-certification; the control group participated in the same amount of regular intensive training. Both the pre- and post-tests used a context-embedded multimodal assessment tool to collect evidence on data cognition, analysis and application, and ethical decision-making. Based on potential profile analysis, teachers were assigned to corresponding levels, and a transfer matrix was generated. The focus was on comparing the upward transfer rate and changes in the level distribution pattern between the two groups.

Figures 4(a-b) present the pre- and post-test transfer matrices of teachers' data literacy levels in the experimental and control groups, respectively. After receiving the four-level progressive training mechanism, the experimental group achieved an overall upward transfer rate of 60.7%, while the control group only achieved 22.0% ($\chi^2 = 189.4$, $p < 0.001$). The post-test level distribution changed from the pre-test (L1 and L2 combined accounting for 70%) to (L2, L3, and L4 combined accounting for 90.8%), indicating a significant optimization of the level structure. Simultaneously, the experimental group showed a significantly higher improvement in the institutionalization level of data-driven teaching behavior (Cohen's $d = 0.89$) than the control group ($d = 0.21$), confirming that the training mechanism not only promoted individual level advancement but also reshaped the overall data literacy landscape of the teaching community.

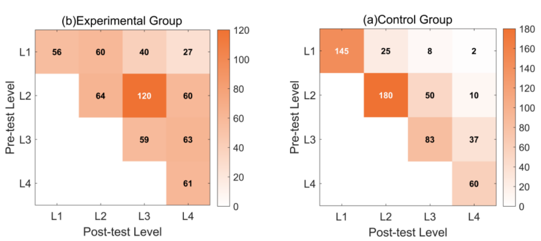

FIGURE 4. Evaluation of the Transfer Effect of the Training Mechanism at Different Levels

3) Analysis of the Contribution of Key Elements in the Training Mechanism

To reveal the specific impact of the training elements, we analyzed three core components. First, 'intelligent recommendation' is operationally defined as the algorithmic matching of pedagogical cases to a teacher's subject-specific blind spots. Second, the 'competency dashboard' serves as a real-time visual feedback interface displaying 3D radar charts of progress. Third, 'micro-certification' refers to the digital badge system that validates modular skill acquisition. Stratified regression was then used to investigate the incremental variance of these defined elements on post-test scores, this study tested the 610 teachers in the experimental group through a stratified regression analysis. With baseline test scores as control variables, the usage behavior indicators of the three core components of the system - the frequency of recommended resource adoption, the number of times the dashboard was viewed actively, and the number of micro-certifications earned - were entered into the regression equation in a progressive manner to investigate the incremental variance explained by the post-test scores of teachers' literacy after the introduction of the three elements. The results are presented in Table 3.

TABLE 3. Stratified Regression Results of Key Factors in Data Literacy Improvement

Step	Variable Entered	β	ΔR^2	F Change	p
1	Baseline score	0.42	0.176	—	< 0.001
2	Frequency of intelligent recommendation adoption	0.28	0.064	41.53	< 0.001
3	Active views of the competency dashboard	0.31	0.089	63.72	< 0.001
4	Number of micro-credentials earned	0.19	0.033	22.15	< 0.001

All three key elements made significant independent incremental contributions to teachers' data literacy. Among them, the interactive competency dashboard had the highest independent explanatory power ($\Delta R^2 = 0.089$, $\beta = 0.31$, $p < 0.001$), followed by the frequency of intelligent recommendation adoption ($\Delta R^2 = 0.064$, $\beta = 0.28$, $p < 0.001$), while the number of micro-certifications acquired, although having a slightly smaller effect, still reached a significant level ($\Delta R^2 = 0.033$, $\beta = 0.19$, $p < 0.001$). These three elements collectively explained 36.2% of the total variance in post-test scores (cumulative $R^2 = 0.362$), and the visualized self-monitoring mechanism centered on the competency dashboard contributed 47.8% of the total incremental explanatory power, indicating that making implicit growth processes explicit is a key lever driving the development of teachers' data literacy.

IV. CONCLUSION

This research transcends the limitations of uniform training by validating a transition model where 60.7% of participants successfully migrated to higher competency tiers. The results imply that the shift from 'technology-aware' to 'intellectual creation' is not merely a quantitative increase in data skills, but a fundamental transformation in professional identity and ethical agency. This provides a scalable paradigm for personalized professional development in the digital age.

AUTHOR CONTRIBUTIONS

Xia Yin designed, collected and analyzed the data, and drafted the manuscript. Xia Yin conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Xia Yin participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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HUMAN RESEARCH SUBJECTS

This study was approved by the Ethics Committee of Yong'an Open University, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

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Not applicable.

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