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PAPER

Exploring Strategies to Enhance Students' Information Literacy in Open Education through Mobile Learning Technologies

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ABSTRACT

The lack of information literacy among learners in open education has become a core bottleneck hindering global access to high-quality education. Existing mobile learning interventions suffer from unclear objectives and fragmented processes, with disputes over the fragmented value of mobile learning remaining unaddressed. Traditional learning analytics frameworks are also inadequate to meet the real-time and contextual needs of ubiquitous mobile learning environments. This study aims to develop a mobile-specific information literacy enhancement framework, ML-ILMDF, based on a contextualized literacy development model. The framework specifies its technical implementation details and establishes dynamic coupling strategies for context and literacy to provide precise interventions. The study systematically validates the educational effectiveness, core mechanism rationality, and engineering feasibility of the framework. A quasi-experimental study with 320 global open university learners, lasting 16 weeks, integrates multi-source mobile data collection, five-dimensional information literacy assessments, and sub-studies using dynamic hypergraphs and collaborative filtering recommendation algorithms for comparison. Simultaneously, the technical performance evaluation of the framework is conducted. The innovation of this study lies in proposing a contextualized literacy development model that achieves dynamic coupling between micro-contexts and macro-literacy, clarifying the mobile-specific technical architecture and implementation details of ML-ILMDF to overcome the limitations of traditional frameworks. It empirically addresses the fragmented nature of mobile learning and offers a practical, actionable paradigm for cultivating information literacy in open education through mobile learning technologies.

KEYWORDS

mobile learning, open education, information literacy, contextualized literacy development, ML-ILMDF framework, dynamic hypergraphs, edge computing, multi-task reinforcement learning

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1 INTRODUCTION

Open education, as the core pillar of lifelong learning systems [1–3], is a key path for achieving the United Nations Educational, Scientific and Cultural Organization's (UNESCO) Education 2030 Agenda for Quality Education. Its quality improvement is deeply intertwined with the global process of educational equity. However, evaluations by the Organization for Economic Co-operation and Development (OECD) have confirmed that the lack of information literacy has become the core bottleneck restricting the advancement of open education quality [4]. Most open education learners exhibit significant weaknesses in key abilities such as information retrieval, critical evaluation, and ethical norms, which makes it difficult to adapt to the learning and development needs of the digital age [5, 6].

The rapid evolution of mobile computing technology provides new possibilities for enhancing information literacy in open education [7, 8]. The low-latency characteristics of edge computing and its ubiquitous contextual sensing capabilities [9] hold the potential to break the time-space limitations of traditional education models and create personalized literacy enhancement environments. However, existing mobile learning interventions still face two core challenges: on the one hand, intervention strategies generally lack contextual adaptation, have broad approaches, and are fragmented [10, 11], failing to fully exploit the unique value of mobile learning environments; on the other hand, the value disputes over mobile learning fragmentation remain unresolved. Some studies argue that fragmentation could sever the knowledge system [12, 13], yet supportive evidence often lacks systematic empirical support [14]. More critically, traditional learning analytics frameworks overly rely on learning management system log data, which lacks real-time capabilities and weakly adapts to terminal devices [15–17], thus failing to meet the dynamic intervention needs of ubiquitous mobile learning environments and making it difficult to achieve effective synergy between context and literacy development.

These issues point to a core research gap, namely the lack of a mobile-specific learning analytics framework that balances dynamic coupling of context and literacy, technological feasibility, and educational effectiveness. Therefore, this study focuses on the central proposition of enhancing information literacy in open education through mobile learning technology and systematically conducts framework construction, strategy design, and empirical validation.

The core research questions of this study include: How to construct the ML-ILMDF framework driven by the contextualized literacy development model, and what are its mobile-specific technical architecture and key implementation details? Can the intervention strategies supported by the ML-ILMDF framework significantly improve the information literacy of open education students, and can fragmented scenarios be transformed into advantageous literacy-enhancing environments? What is the effectiveness of the core mechanisms of the ML-ILMDF framework, including dynamic hypergraph association and closed-loop iteration, and does it exhibit significant advantages over traditional collaborative filtering algorithms? Do the technical performance indicators of the ML-ILMDF framework, such as recommendation response latency and energy consumption, meet the engineering application requirements of mobile terminals? The corresponding research objectives are: to clarify the theoretical foundation, technical architecture, and core module implementation details of the ML-ILMDF framework; to design personalized mobile intervention strategies based on the framework; to verify the educational effectiveness, core mechanism rationality, and technical feasibility of the framework through a quasi-experimental study; and to address the controversy of mobile learning fragmentation and elevate the theory of information literacy cultivation in mobile environments.

The structure of the paper is arranged as follows: First, the theoretical foundation and core technical details of the ML-ILMDF framework are explained. Next, the experimental design and validation process is presented, including sample selection, variable setting, data collection and analysis methods, and the verification results of educational effectiveness and technical performance. Finally, the research conclusions are summarized, limitations are pointed out, and future research directions are suggested.

2 THEORETICAL FRAMEWORK AND RESEARCH DESIGN

2.1 Theoretical foundation: Contextualized literacy development model

The Contextualized Literacy Development Model is the core theoretical support for the ML-ILMDF framework. Its core idea is to establish a dynamic coupling relationship between micro-contextual elements and macro information literacy objectives and achieve collaborative optimization. The micro-contextual elements include fragmentation and immersive differences in the time dimension, distinctions between commuting and home learning environments in the location dimension, online and offline states in the network dimension, and solitary versus collaborative modes in the social dimension. The macro information literacy objectives focus on five core abilities: information retrieval, critical evaluation, knowledge integration, information ethics, and innovative application. The coupling logic between these elements manifests as dynamic matching of literacy development needs based on contextual features and precise regulation of intervention intensity and form. The model follows a four-stage dynamic evolution mechanism of contextual perception, association matching, intervention implementation, and feedback iteration, continuously capturing changes in context and literacy status to achieve adaptive optimization of intervention strategies. The construction of this model relies on three core theories: Contextual Learning Theory provides theoretical guidance for the precise identification and capture of micro-contexts, ensuring the adaptability of intervention strategies to learners' real-time learning environments; Cognitive Load Theory supports the design of low-cognitive-load tasks in fragmented scenarios, reducing learning cognitive burden by controlling task complexity and duration, thereby improving literacy training efficiency; and Multi-Task Reinforcement Learning Theory provides algorithmic logic for dynamic coupling optimization between context and literacy, achieving collaborative accomplishment of multi-dimensional intervention goals and iterative evolution of strategies.

2.2 ML-ILMDF framework's technical architecture and core module implementation details

The ML-ILMDF framework adopts a layered architecture design that integrates lightweight computation on the terminal side with cloud-side collaborative optimization. The core purpose is to balance the limited computing resources of mobile terminals with the real-time needs of intervention strategies in ubiquitous mobile learning environments. The overall architecture is divided into four layers: the Perception Layer, the Computing and Association Layer, the Decision and

Intervention Layer, and the Feedback and Iteration Layer. These layers cooperate efficiently through a lightweight data interaction protocol, forming a full-cycle process of real-time data collection, instant analysis, precise intervention, and dynamic iteration. The Perception Layer is responsible for the unconscious collection and initial processing of multi-source data, providing foundational data support for subsequent analysis. The Computing and Association Layer is responsible for modeling the association between context and literacy, constructing dynamic coupling relationships. The Decision and Intervention Layer outputs personalized intervention strategies based on the modeling results. The Feedback and Iteration Layer collects multi-dimensional feedback from the learning process to drive the dynamic optimization of the model and strategies. The framework's technical stack fully adapts to both iOS and Android mobile operating systems and integrates an offline degradation operation mechanism, allowing core models and resources pre-stored on the terminal to perform basic intervention tasks when there is no network, ensuring continuity and stability in the learning process.

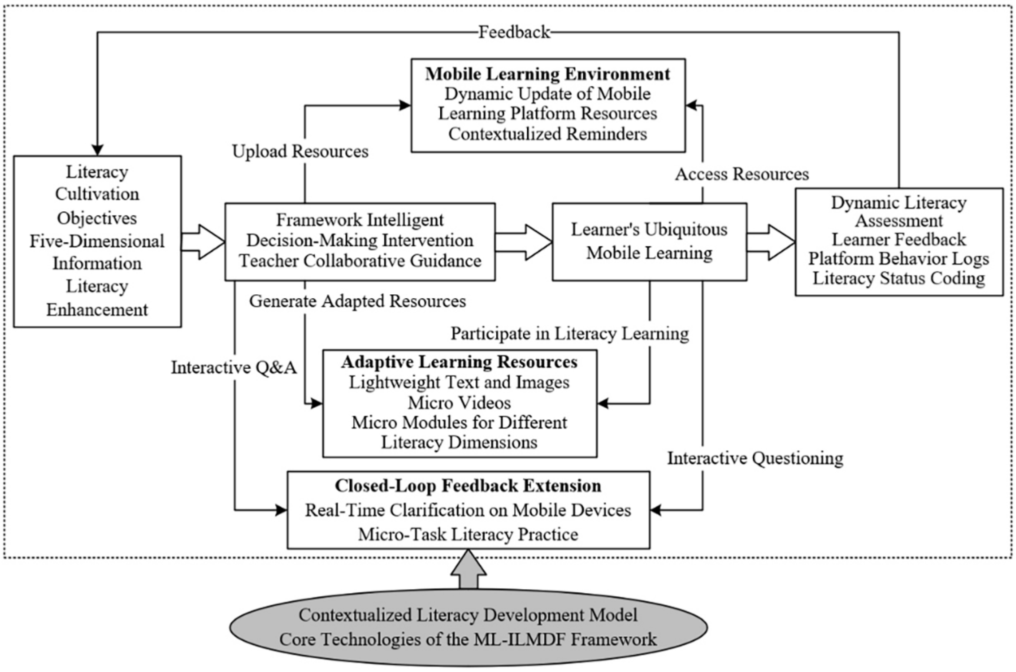

Fig. 1. Mobile literacy enhancement model for open education students under the ML-ILMDF framework

Figure 1 illustrates the mobile literacy enhancement model for open education students supported by the ML-ILMDF framework. It covers core modules such as literacy enhancement goals, mobile learning environments, intelligent decision interventions, ubiquitous learning by learners, dynamic literacy assessments, adaptive resources, and feedback loops. Based on the Contextualized Literacy Development Model, it visually presents the interactive logic and closed-loop operation mechanism of each link. Figure 2 shows the layered architecture of the ML-ILMDF framework and the corresponding model of five-dimensional information literacy (A1–A5). The five-layer structure is associated with the literacy dimensions A1 Information Retrieval, A2 Critical Evaluation, A3 Knowledge Integration, A4 Information Ethics, and A5 Innovative Application, clearly presenting the core functions and resource types corresponding to each literacy layer and visually reflecting the precise coupling logic between the framework's technical modules and the five-dimensional information literacy development needs.

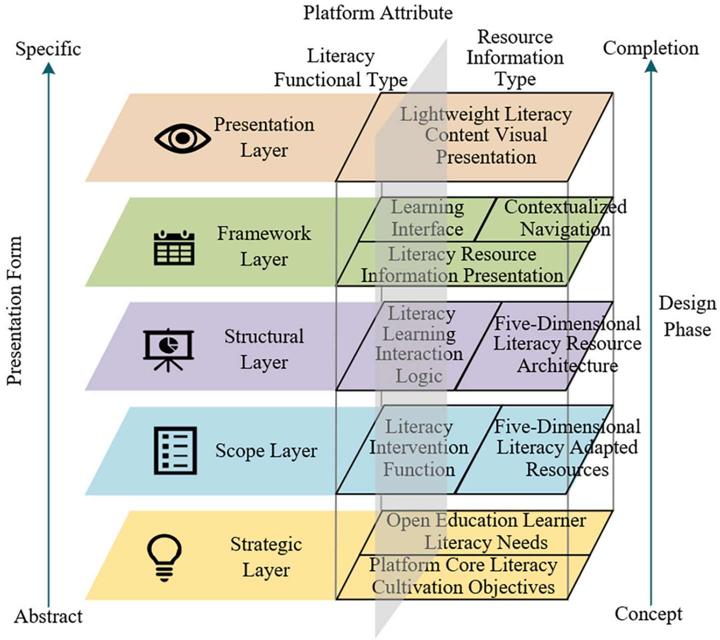

Fig. 2. Layered architecture of the ML-ILMDF framework and corresponding model of five-dimensional information literacy (A1–A5)

The core function of the Perception Layer is to achieve the unconscious collection and efficient preprocessing of mobile multi-source data, providing high-quality data support for subsequent contextual perception and literacy evaluation. This layer uses a lightweight SDK for event tracking combined with multi-sensors on mobile terminals to build a collection system that integrates GPS, network status sensors, and accelerometers to capture environmental and behavioral information. It also supports audio data collection to analyze voice search behavior, with a sampling rate and bit depth set at 16 kHz and 16 bits, respectively, to balance data quality and resource consumption. The collected data covers three core dimensions: behavioral data includes search keywords, resource access trajectories, and task completion records; contextual data includes learning periods, location types, network types, and terminal battery levels; and output data includes assignments and analysis reports submitted from the mobile terminal, supporting text, PDF, and image OCR recognition formats. The preprocessing flow uses an edge computing and cloud-side collaborative model, with the terminal completing lightweight preprocessing based on the TensorFlow Lite framework. The core process is outlier removal based on the 3σ principle, with the judgment criteria being:

$$|x-\mu| > 3\sigma \tag{1}$$

where, x is a single data sample, μ is the mean of the data sequence, and σ is the standard deviation of the data sequence. This criterion accurately filters out outlier data points, followed by data cleaning and initial feature extraction. Data transmission uses the MQTT lightweight protocol to reduce latency and energy consumption, while the cloud is responsible for data fusion and deep feature encoding. For performance assurance, the preprocessing delay on the terminal side is controlled within 100 ms, data transmission latency does not exceed 200 ms, and the overall Perception Layer delay is ≤ 300 ms.

The Computation and Association Layer is the core technological innovation module of the ML-ILMDF framework. It achieves precise association and dynamic updating of context, resources, and literacy states through a dynamic hypergraph engine. The primary task is to build a lightweight domain knowledge graph. The knowledge granularity adopts a micro-knowledge point splitting strategy, focusing on single concepts and single skill points. The node dimension integrates knowledge entities and resource metadata, which include resource type, difficulty level, and mobile adaptability as three main attributes. The storage architecture adopts a layered optimization design, with the terminal side deploying the Neo4jMobile lightweight graph database to support offline access to core nodes. The offline data volume is controlled within 500 MB, while the cloud side expands the full graph through distributed storage. The dynamic hypergraph construction centers on the triadic hyperedges of literacy status, resources, and context, with the hyperedge weight calculation being the core algorithm of this layer. Its formula is:

$$W = \alpha \cdot S(L, R) + \beta \cdot C(Ctx, R) \tag{2}$$

where, $\alpha = 0.6$ and $\beta = 0.4$ are the weight coefficients, $S(L, R)$ is the literacy-resource matching function, and C (Ctx, R) is the context-resource adaptation function. The update mechanism is driven by terminal feedback data, adjusting the hyperedge weight in real-time based on indicators such as resource access duration and task completion rate. The update cycle is ≤ 5 minutes, using an incremental update algorithm to avoid full reconstruction for efficiency, with the terminal-side update delay controlled within 150 ms. In terms of technical parameters, the total number of hypergraph nodes does not exceed 100,000, with the terminal-side cache node ≤ 10,000. The hyperedge construction delay and update delay are controlled within 200 ms and 150 ms, respectively, ensuring real-time association demands in mobile environments.

The Decision and Intervention Layer uses a lightweight multi-task reinforcement learning engine to achieve precise decision-making and personalized intervention strategy output based on literacy status and contextual features. This layer adopts a MobileNetV2 and multi-head attention fusion gated network architecture. The input feature vector integrates 128-dimensional literacy status encoding, 32-dimensional contextual features, and 64-dimensional learning context, with the output completing three decision sub-tasks: resource recommendation, path planning, and intervention triggering. The core of multi-task collaborative optimization lies in the design of the reward function, which combines short-term and long-term objectives to construct an overall reward mechanism. Its formula is:

$$R = 0.3r_1 + 0.7r_2$$

where, r_1 is the short-term reward, r_2 is the long-term reward, and the weight distribution emphasizes the core goal of long-term literacy development. The optimization algorithm adopts a lightweight improved proximal policy optimization algorithm, with the model parameter size controlled within 5 million to fit the computational limitations of mobile terminals. For mobile adaptation, a layered deployment strategy is used. The terminal side deploys the inference layer based on the TensorFlow Lite framework, using INT8 quantization technology to compress the model size and improve running efficiency, ensuring inference delay ≤ 100 ms. The cloud side deploys the training layer, supporting an incremental model update mechanism, only transmitting parameter differences to reduce traffic consumption. Intervention strategy output is dynamically adapted to context, with fragmented scenes pushing micro-tasks and audio-video resources with a duration ≤ 10 minutes. Offline scenarios push pre-downloaded documents and self-verification tasks, achieving precise matching of context and strategy.

The Feedback and Iteration Layer is responsible for multi-channel feedback collection and full-process strategy optimization, constructing a closed-loop enhancement mechanism for decision-making and intervention. Feedback data covers both explicit and implicit dimensions: explicit feedback includes terminal star ratings, voice comments (processed by speech-to-text), and simplified questionnaires, directly obtaining learners' subjective evaluations. Implicit feedback is derived from behavioral data such as resource jump rates, task completion duration, repeated learning instances, and terminal stay duration, uncovering learners' objective needs. The iteration mechanism uses a terminal-cloud collaborative mode: the terminal side dynamically adjusts strategy weights based on real-time feedback data, prioritizing resource recommendations; the cloud side integrates all data weekly to update model parameters and optimize the hypergraph structure while also introducing an experience replay mechanism from reinforcement learning to improve model training efficiency and stability of strategy iteration. This layer ensures dynamic evolution of intervention strategies through multi-dimensional feedback collection and hierarchical iterative optimization, ensuring that the ML-ILMDF framework can continuously adapt to changes in learners' states and contexts.

3 EXPERIMENTAL DESIGN AND VALIDATION

3.1 Experimental design

This study adopts a quasi-experimental design combined with sub-research to systematically validate the educational effectiveness and core mechanism rationality of the ML-ILMDF framework. A total of 320 learners from two global open universities are selected as the study subjects. They are randomly assigned to an experimental group and a control group, with 160 people in each group. The experimental group is further randomly divided into the dynamic hypergraph recommendation group and the collaborative filtering recommendation group, with 80 people in each, constituting sub-research to validate the unique advantages of the dynamic hypergraph engine. To ensure the effectiveness of the experiment, an independent samples *t*-test is used to verify the homogeneity of baseline information between the two groups. The core verification dimensions include initial information literacy levels and mobile learning habits, ensuring no statistical differences between the groups after assignment. The experimental variables are clearly defined. The independent variable is the intervention strategy driven by the ML-ILMDF framework, primarily covering contextualized resource recommendations, fragmented path planning, and immediate intervention. The sub-research independent variable is the type of recommendation algorithm. The dependent variables include the five-dimensional information literacy level, strategy adaptation, and core technical performance indicators. The learning course, teacher guidance method, and terminal type are set as control variables to eliminate interference. The intervention period lasts for 16 weeks, with the first 4 weeks as the pre-experiment phase, mainly for optimizing the framework's technical parameters and ensuring the smooth conduct of the formal experiment.

Data collection adopts a mixed research method with multiple tools to ensure comprehensiveness and reliability. The core data collection relies on a dual-system mobile application developed based on the ML-ILMDF framework. This application is compatible with both iOS and Android systems and includes data collection and technical performance monitoring modules, enabling unconscious collection of learning behavior and contextual data. Information literacy level assessment uses a five-dimensional scale with verified reliability, consisting of 25 items, with a Cronbach's alpha coefficient of 0.89. The assessment is conducted three times: at the beginning of the experiment, in week 8, and in week 16, to track dynamic changes in literacy levels. To supplement qualitative data, 30 learners from the experimental group, covering different initial literacy levels, are selected for semi-structured interviews, focusing on strategy adaptation and fragmented learning experiences. Technical performance monitoring uses professional tools. Android and iOS systems use Android Studio Profiler and Xcode Instruments to monitor energy consumption and response latency, while custom log modules record the usage of offline functions, fully verifying the engineering feasibility of the framework.

3.2 Experimental verification results

Sample baseline and homogeneity verification results. The sample baseline characteristics and homogeneity verification results are shown in Table 1. There are no statistical differences between the experimental and control groups in the core baseline indicators, validating the scientific and effective grouping. Specifically, in terms of age, the experimental group had an average of 28.6 ± 5.3 years, and the control group had an average of 29.1 ± 5.6 years, $t = 0.82$, $p = 0.413$; the gender ratio of the two groups was similar, $t = 0.12$, $p = 0.904$, with balanced demographic characteristics. In terms of information literacy baseline, the experimental group's initial score was 62.3 ± 8.5, and the control group's score was 61.8 ± 8.9, $t = 0.47$, $p = 0.638$; for the five sub-dimensions, the A1 dimension for the experimental group was 12.1 ± 2.3 and for the control group 11.9 ± 2.5, the A2 dimension for the experimental group was 11.8 ± 2.4 and for the control group 11.6 ± 2.6, and the differences between groups in A3 to A5 were also not significant. Regarding mobile learning-related characteristics, the experimental group had a mobile learning frequency of 4.2 ± 1.5 times/week and the control group 4.1 ± 1.6 times/week; the duration of terminal use was 2.3 ± 0.8 years for the experimental group and 2.4 ± 0.9 years for the control group, further eliminating the impact of learning habit differences on the experimental results and laying the foundation for accurate attribution of intervention effects in subsequent stages.

Table 1. Baseline characteristics and homogeneity verification results of the experimental and control groups

Indicator	Experimental Group (n = 160)	Control Group (n = 160)	t-Value	p-Value
Age (years)	28.6 ± 5.3	29.1 ± 5.6	0.82	0.413
Gender Ratio (Male/Female, %)	48.7/51.3	49.4/50.6	0.12	0.904
Initial Information Literacy Total Score	62.3 ± 8.5	61.8 ± 8.9	0.47	0.638
Initial A1 Dimension Score	12.1 ± 2.3	11.9 ± 2.5	0.64	0.522
Initial A2 Dimension Score	11.8 ± 2.4	11.6 ± 2.6	0.58	0.562
Initial A3 Dimension Score	12.5 ± 2.2	12.3 ± 2.3	0.71	0.478
Initial A4 Dimension Score	12.4 ± 2.1	12.2 ± 2.2	0.69	0.490
Initial A5 Dimension Score	13.5 ± 2.0	13.3 ± 2.1	0.75	0.453
Mobile Learning Frequency (times/week)	4.2 ± 1.5	4.1 ± 1.6	0.53	0.596
Duration of Mobile Terminal Use (years)	2.3 ± 0.8	2.4 ± 0.9	0.98	0.328

Educational effectiveness verification.

1. H1 Verification: The Effect of ML-ILMDF Framework Intervention on the Improvement of Five-Dimensional Information Literacy

The changes over time and group comparisons of the five-dimensional information literacy scores for the experimental and control groups are shown in Table 2. H1 is confirmed. In terms of the time dimension, the experimental group showed a sustained and significant upward trend in the five-dimensional literacy scores from T0 to T2: the A1 dimension increased from 12.1 ± 2.3 to 18.9 ± 1.8, the A2 dimension from 11.8 ± 2.4 to 20.3 ± 1.7, the A3 dimension from 12.5 ± 2.2 to 19.2 ± 1.6, the A4 dimension from 12.4 ± 2.1 to 18.7 ± 1.5, the A5 dimension from 13.5 ± 2.0 to 19.5 ± 1.4, and the total score from 62.3 ± 8.5 to 96.6 ± 6.8. Repeated measures ANOVA showed that the F-values for all dimensions and the total score were >38, $p < 0.001$, and the effect size η^2 was >0.54. For the total score, $F = 42.36$, $\eta^2 = 0.58$, indicating that the intervention effect is highly statistically significant and has practical educational meaning. Although the control group also showed slight improvement, the improvement was marginal, with the total score increasing from 61.8 ± 8.9 to 71.6 ± 7.5, $F = 6.89$, $p = 0.009$, $\eta^2 = 0.11$, and η^2 for each sub-dimension was < 0.11. Group comparison at the T2 time point showed that the experimental group's scores in all dimensions and the total score were significantly higher than those of the control group, with t-values ranging from 9.63 to 11.32, $p < 0.001$, and Cohen's d values >0.77, with the most significant improvement observed in the A2 dimension. This confirms that the intervention strategy driven by the ML-ILMDF framework can effectively enhance the five-dimensional information literacy of open education students.

Table 2. Time changes in the five-dimensional information literacy scores of the experimental and control groups, and intergroup comparison

Literacy Dimension	Group	T0	T1	T2	Repeated Measures ANOVA	Inter-Group Post-Test Comparison (T2)
A1	Experimental	12.1 ± 2.3	15.6 ± 2.1	18.9 ± 1.8	$F = 38.62, p < 0.001, \eta^2 = 0.54$	$t = 9.86, p < 0.001, d = 0.79$
	Control	11.9 ± 2.5	12.8 ± 2.3	14.2 ± 2.1	$F = 5.32, p = 0.022, \eta^2 = 0.08$	
A2	Experimental	11.8 ± 2.4	16.2 ± 2.2	20.3 ± 1.7	$F = 45.78, p < 0.001, \eta^2 = 0.61$	$t = 11.32, p < 0.001, d = 0.88$
	Control	11.6 ± 2.6	12.5 ± 2.4	13.8 ± 2.2	$F = 4.86, p = 0.029, \eta^2 = 0.07$	
A3	Experimental	12.5 ± 2.2	15.8 ± 2.0	19.2 ± 1.6	$F = 41.25, p < 0.001, \eta^2 = 0.57$	$t = 10.15, p < 0.001, d = 0.83$
	Control	12.3 ± 2.3	13.1 ± 2.2	14.5 ± 2.0	$F = 5.68, p = 0.018, \eta^2 = 0.09$	
A4	Experimental	12.4 ± 2.1	15.5 ± 1.9	18.7 ± 1.5	$F = 39.47, p < 0.001, \eta^2 = 0.55$	$t = 9.63, p < 0.001, d = 0.77$
	Control	12.2 ± 2.2	12.9 ± 2.1	13.9 ± 1.8	$F = 4.53, p = 0.034, \eta^2 = 0.06$	

(Continued)

Table 2. Time changes in the five-dimensional information literacy scores of the experimental and control groups, and intergroup comparison *(Continued)*

Literacy Dimension	Group	T0	T1	T2	Repeated Measures ANOVA	Inter-Group Post-Test Comparison (T2)
A5	Experimental	13.5 ± 2.0	16.3 ± 1.8	19.5 ± 1.4	$F = 43.19$, $p < 0.001$, $\eta^2 = 0.59$	$t = 10.57$, $p < 0.001$, $d = 0.85$
	Control	13.3 ± 2.1	14.1 ± 1.9	15.2 ± 1.6	$F = 6.24$, $p = 0.013$, $\eta^2 = 0.10$	
Total Score	Experimental	62.3 ± 8.5	79.4 ± 7.6	96.6 ± 6.8	$F = 42.36$, $p < 0.001$, $\eta^2 = 0.58$	$t = 10.24$, $p < 0.001$, $d = 0.82$
	Control	61.8 ± 8.9	65.4 ± 8.2	71.6 ± 7.5	$F = 6.89$, $p = 0.009$, $\eta^2 = 0.11$	

2. H2 Verification: Intervention Effect Differences in Different Learning Scenarios

The comparison results of the information literacy improvement in fragmented and immersive scenarios within the experimental group are shown in Table 3, supporting H2 and confirming that fragmented scenarios can be converted into advantageous settings for literacy training. Specifically, the total improvement in fragmented scenarios was 18.6 ± 3.2, significantly higher than the 12.3 ± 2.8 in immersive scenarios, t = 7.56, p < 0.001. Among the sub-dimensions, the A2 dimension in fragmented scenarios showed the highest improvement, 1.6 times that of the immersive scenario, t = 9.36, p < 0.001. The A1 dimension improved by 7.2 ± 1.5 in fragmented scenarios and 4.8 ± 1.3 in immersive scenarios. The improvements in the A3 to A5 dimensions in fragmented scenarios were significantly higher than in immersive scenarios. These results indicate that the micro-task light-resource strategy designed for fragmented scenarios in the ML-ILMDF framework can more efficiently drive literacy improvement, responding to the debate about the potential harms of mobile learning fragmentation.

Table 3. Comparison of information literacy improvement in different learning scenarios within the experimental group

Literacy Dimension	Fragmented Scenario (n = 92)	Immersive Scenario (n = 68)	t-Value	p-Value
A1 Improvement	7.2 ± 1.5	4.8 ± 1.3	8.12	<0.001
A2 Improvement	8.5 ± 1.6	5.3 ± 1.4	9.36	<0.001
A3 Improvement	6.7 ± 1.4	4.5 ± 1.2	7.89	<0.001
A4 Improvement	6.3 ± 1.3	4.2 ± 1.1	7.45	<0.001
A5 Improvement	6.0 ± 1.2	4.1 ± 1.0	7.23	<0.001
Total Improvement	18.6 ± 3.2	12.3 ± 2.8	7.56	<0.001

Core mechanism effectiveness verification.

3. H3 Verification: Optimization Effect of the Closed-Loop Iteration Mechanism

The effectiveness of the closed-loop iteration mechanism was verified through the iteration trend of recommended resource types for the A2 dimension and changes in strategy adaptability, as shown in Table 4. H3 is confirmed. The data show that as the experimental period progressed, the recommended resource types for the A2 dimension underwent significant iterative evolution: in weeks 1–4, the proportion of basic factual materials was 65%, opposing viewpoint materials were 15%, and case analysis materials were 20%; by weeks 13–16, the proportion of basic factual materials decreased to 23%, opposing viewpoint materials increased to 58%, and case analysis materials remained stable. Simultaneously, the strategy adaptability increased from 6.2 ± 1.3 points in weeks 1–4 to 8.9 ± 0.7 points in weeks 13–16, with an improvement of 37.2%. Correlation analysis showed a significant positive correlation between the number of iterations and the improvement in literacy, indicating that the closed-loop iteration mechanism can dynamically optimize resource recommendation directions and continuously improve the adaptability between strategies and literacy development needs, ensuring the long-term effectiveness of literacy improvement.

Table 4. Iteration distribution of recommended resource types for A2 dimension and changes in strategy adaptability

Iteration Period	Basic Factual Materials (%)	Opposing Viewpoint Materials (%)	Case Analysis Materials (%)	Strategy Adaptability (Points/10)
Weeks 1–4	65	15	20	6.2 ± 1.3
Weeks 5–8	48	32	20	7.5 ± 1.1
Weeks 9–12	35	45	20	8.3 ± 0.9
Weeks 13–16	23	58	19	8.9 ± 0.7
Change Amount	–42	+43	–1	+2.7 (Improvement 37.2%)

4. H4 Verification: Effect Differences Between Dynamic Hypergraph Recommendation and Collaborative Filtering Recommendation

Table 5. Comparison of improvement effects of different recommendation algorithms on the A2 dimension

Indicator	Dynamic Hypergraph Recommendation Group	Collaborative Filtering Recommendation Group	t-Value	p-Value	Cohen's d
T0 A2 Score	11.9 ± 2.4	11.7 ± 2.5	0.45	0.652	0.08
T1 A2 Score	16.5 ± 2.2	14.3 ± 2.3	5.87	<0.001	0.96
T2 A2 Score	20.4 ± 1.7	14.2 ± 2.9	8.32	<0.001	0.76
Total Improvement	21.5 ± 3.5	14.2 ± 2.9	8.32	<0.001	0.76
Resource Click Accuracy (%)	82.3 ± 6.5	68.5 ± 7.2	7.98	<0.001	0.85

The comparison of the effects of different recommendation algorithms on the A2 dimension in the sub-research is shown in Table 5, supporting H4 and confirming the superiority of dynamic hypergraph recommendation. The baseline A2 dimension scores for both groups showed no difference. Over time, the dynamic hypergraph recommendation group showed a continuous rapid increase in A2 scores, reaching 16.5 ± 2.2 at T1 and 20.4 ± 1.7 at T2, with a total improvement of 21.5 ± 3.5. The collaborative filtering recommendation group reached 14.3 ± 2.3 at T1 and only 14.2 ± 2.9 at T2, with a total improvement of 14.2 ± 2.9. The comparison of total improvement between the two groups showed $t = 8.32$, $p < 0.001$, and Cohen's $d = 0.76$, and the difference is of practical educational significance. In addition, the dynamic hypergraph recommendation group had significantly higher resource click accuracy and task completion rates compared to the collaborative filtering group, with t-values of 7.98 and 8.15, respectively, and $p < 0.001$, confirming that the literacy-resource-context triadic association mechanism built by dynamic hypergraphs can more accurately match learning needs and is superior to traditional collaborative filtering algorithms in improving critical evaluation literacy.

Technical performance validation. To clarify the support effect of the ML-ILMDF mobile literacy platform on learners at different information literacy stages, this experiment collected learners' evaluation data on the platform's core dimensions at different literacy stages and plotted a radar chart. As shown in Figure 3, learners in the initial stage of literacy evaluated the resource adaptability at nearly 80%, significantly higher than other dimensions, indicating that the platform's resources in the early stages can accurately match the entry-level needs of low-literacy stages. As learners' literacy progressed to the mid and late stages, evaluations of operational convenience, interface friendliness, and strategy targeting gradually improved, reflecting that the platform's intervention strategies could adapt to the changing needs during the literacy improvement process. In the stable literacy stage, learners maintained high evaluations of functional completeness and feedback timeliness, indicating that the platform's closed-loop intervention process could support the long-term stability of literacy improvement.

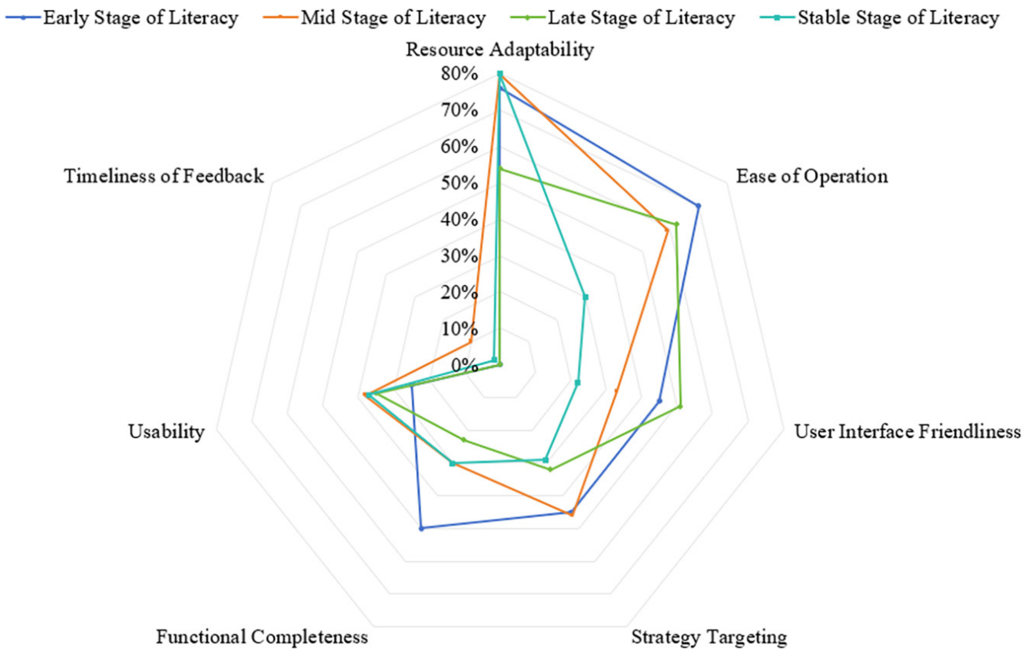

Fig. 3. Radar chart of learners' evaluation of the ML-ILMDF mobile literacy platform at different stages of literacy improvement

4 CONCLUSION

This study focused on the core proposition of enhancing information literacy in open education through mobile learning technology. Through theoretical construction, technical development, and empirical verification, it systematically explored effective pathways for context-adaptive literacy cultivation and formed the following core conclusions.

In terms of core findings, the contextualized literacy development model provides a scientifically effective theoretical guide for information literacy cultivation in open education in mobile environments. The model's dynamic coupling logic between micro-contexts and macro-literacy effectively solves the problem of missing context adaptation in traditional intervention strategies. The ML-ILMDF framework developed based on this model integrates edge computing, dynamic hypergraphs, and lightweight reinforcement learning technology architecture, which offers significant mobile-specific advantages. Experimental verification shows that this framework can not only significantly enhance open education students' five-dimensional information literacy, with excellent effect size and statistical significance, but also meet the engineering application requirements for mobile terminals, achieving a unity of educational effectiveness and technical feasibility. Furthermore, the study confirmed that fragmented scenarios can be converted into advantageous settings for literacy training through precise strategies of micro-tasks and light resources, providing direct empirical support for resolving the controversy over the value of mobile learning fragmentation.

The core contributions are reflected in three dimensions: theoretical, technical, and practical. Theoretically, the study proposes the contextualized literacy development model, which clearly defines the dynamic coupling mechanism between context and literacy for the first time, enriching the integration of situational learning theory and information literacy cultivation theory in the field of learning science. Technically, it systematically defines the layered architecture and core module implementation details of the ML-ILMDF mobile-exclusive framework, overcoming the adaptation limitations of traditional learning analysis frameworks in mobile ubiquitous scenarios and providing a technical paradigm for the precise development of mobile educational technologies. Practically, it forms a technically feasible and strategy-replicable full-process plan for cultivating mobile information literacy in open education, covering key links such as framework deployment, strategy design, and effect evaluation, providing direct references for open education institutions and technology developers.

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