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iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 20 No. 8 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijim.v20i08.61249

PAPER

Virtualized and Personalized Financial Management Education Enabled by Mobile Interactive Technologies

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ABSTRACT

Against the backdrop of the deep integration of mobile technologies and educational digitalization, financial management education has been constrained by insufficient levels of virtualization, limited adaptability to individual learners, and inadequate real-time interactive experiences. Existing educational frameworks have struggled to reconcile the computational constraints of mobile devices with the demands of immersive learning environments. To address these challenges, an intelligent education framework centered on mobile devices and organized around a collaborative three-layer architecture was proposed, with the objective of transcending the limitations of traditional instructional models and enabling deeply virtualized and personalized financial management education tailored to the lightweight and ubiquitous characteristics of mobile technologies. Through the coordinated operation of a mobile interactive terminal layer, an edge intelligence layer, and a cloud-based intelligent hub layer, the proposed framework emphasizes innovations in intelligent mobile interaction design, dynamic allocation of edge–cloud computational resources, and multimodal data-driven personalized adaptation. A closed-loop, collaborative, personalized learning ecosystem is thereby constructed. Prototype system evaluations demonstrate that the proposed framework effectively enhances learning immersion, personalization, and learning efficiency in mobile learning scenarios, providing a novel technological paradigm for the deployment of mobile intelligent education in professional disciplines.

KEYWORDS

mobile interactive technology, financial management education, virtualized learning, personalized learning, three-layer collaborative architecture, edge–cloud collaboration

1 INTRODUCTION

With the continuous advancement of educational digital transformation, financial management—characterized by the integration of theoretical foundations and practical applications [1, 2]—has exhibited an increasingly urgent demand for virtualized training environments and personalized instructional approaches [3].

Li, L. (2026). Virtualized and Personalized Financial Management Education Enabled by Mobile Interactive Technologies. *International Journal of Interactive Mobile Technologies (iJIM)*, 20(8), pp. 103–117. https://doi.org/10.3991/ijim.v20i08.61249

Article submitted 2026-01-10. Revision uploaded 2026-02-24. Final acceptance 2026-02-27.

The widespread adoption of mobile devices has provided essential hardware support for fragmented and context-aware learning modalities [4, 5]. However, existing educational solutions remain subject to notable limitations. Conventional approaches have largely relied on personal computer-based virtual reality/augmented reality systems, which are constrained by limited portability and high deployment costs [6, 7]. In contrast, mobile-oriented solutions have predominantly involved the direct migration of instructional content, resulting in insufficient immersion and limited real-time interactivity while failing to resolve the fundamental tension between constrained mobile computational resources and the generation of personalized learning content [8, 9]. Moreover, existing three-layer architectures have not established mobile terminals as the architectural core, leading to suboptimal allocation of data flows and computational flows and rendering them inadequate for the specific requirements of financial management training scenarios. Recent advances in mobile graphics processing unit performance, the proliferation of multimodal sensors, and the maturation of edge-cloud collaboration technologies [10, 11] have created favorable conditions for overcoming these constraints. Under this technological backdrop, the construction of an intelligent financial management education framework specifically adapted to mobile learning scenarios has emerged as a critical pathway for addressing the aforementioned challenges.

Despite growing interest, significant gaps remain in both international and domestic research. Existing international studies have primarily focused on lightweight interaction design for mobile terminals and the application of edge computing, with an emphasis on generalized educational scenarios and personalized content delivery. However, domain-specific virtualized architectures tailored to financial management education have been largely overlooked, and the advantages of multimodal data acquisition and local rendering capabilities on mobile terminals have not been fully exploited [12, 13]. In contrast, domestic research has concentrated on cloud-based content development and the mobile adaptation of traditional educational systems. Notable deficiencies persist in end–edge–cloud collaborative optimization, immersive rendering for financial management training scenarios, and the precision of personalized learning path planning [14]. Overall, existing studies have yet to establish a three-layer collaborative architecture centered on mobile terminals. The inherent conflict between limited mobile computational capacity and immersive learning requirements has not been effectively resolved, nor has a multimodal data-driven solution for personalized and virtualized financial management education been systematically developed. This unresolved research gap provides a clear direction for the present study.

This study is structured around the application of mobile interactive technologies to the virtualization and personalization of financial management education. The core components include the systematic specification of a three-layer collaborative architecture and its bidirectional closed-loop coordination mechanisms; the design of multimodal interaction and lightweight rendering strategies for mobile terminals; the implementation of real-time computational offloading and millisecond-level feedback within the edge intelligence layer; the construction of cloud-based personalized decision-making and artificial intelligence-generated content modules; and the development of a prototype system followed by comprehensive multidimensional testing and validation. A standardized technical pathway—comprising framework design, core module implementation, prototype development, testing and optimization, and outcome-oriented evaluation—is adopted to clarify the key objectives at each research stage. Through this structured progression, a complete and closed research loop is established, ensuring methodological coherence and technical rigor.

The contributions of this study are articulated across three dimensions. From a theoretical perspective, the integration framework of mobile intelligent education and virtualized financial management training is extended, enriching existing architectural design paradigms. From a technological perspective, a deployable system architecture and a set of core technical solutions are proposed, addressing critical challenges. From a practical perspective, a prototype system is developed and empirically validated, providing a standardized and cost-effective solution for the mobile, personalized, and virtualized transformation of financial management education, as well as actionable guidance for educational institutions and enterprise-level financial training.

2 OVERALL DESIGN OF THE INTELLIGENT EDUCATION FRAMEWORK

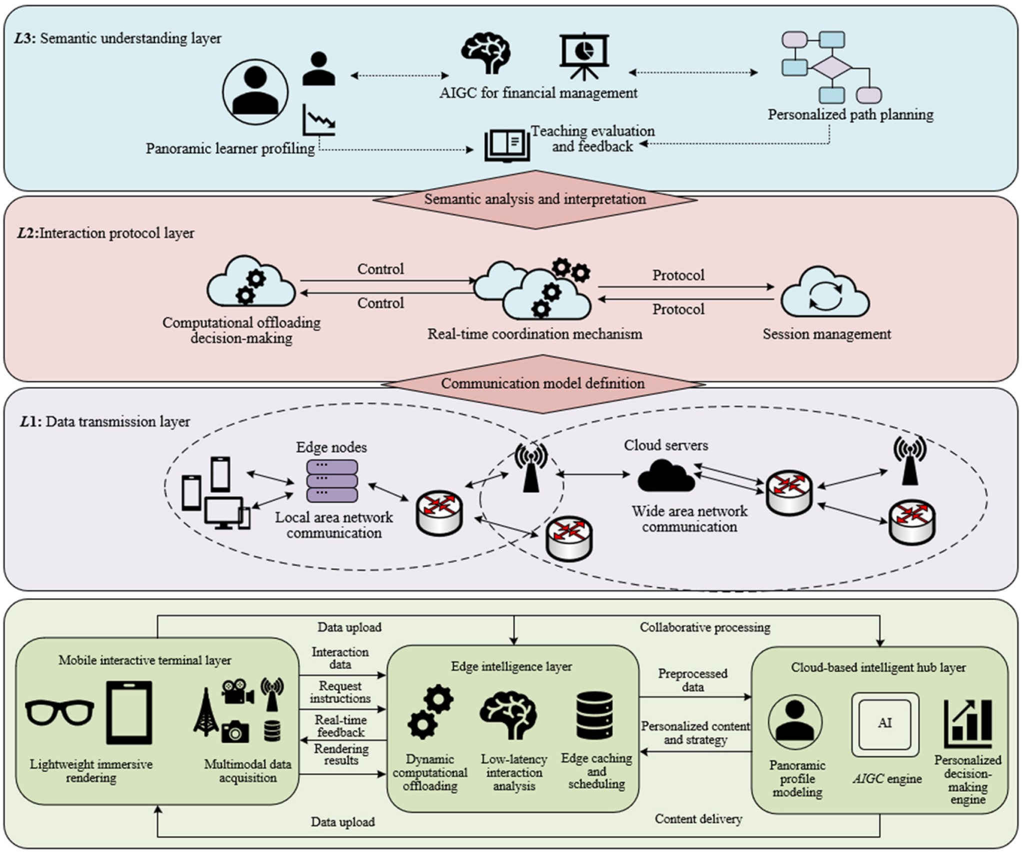

Fig. 1. Overall end–edge–cloud three-layer architecture of the intelligent financial management education system

Figure 1 illustrates the overall "end–edge–cloud" three-layer architecture of the intelligent financial management education system. The framework adopts a collaborative architecture composed of a mobile interactive terminal layer, an edge intelligence layer, and a cloud-based intelligent hub layer. Targeted innovations are incorporated at each layer and within their coordination mechanisms, forming a synergistic ecosystem through bidirectional closed-loop interactions of data flows and control instructions. The mobile interactive terminal layer integrates a lightweight immersive rendering engine and multimodal data acquisition modules. By employing a level-of-detail dynamic precision optimization algorithm and graphics processing unit-based parallel rendering techniques, lightweight local rendering of virtual financial scenarios is achieved. Simultaneously, interaction data are structured and labeled through a micro artificial intelligence agent, thereby mitigating the challenges of limited mobile computational capacity and fragmented data acquisition. The edge intelligence layer is designed with a dynamic computational offloading decision module. A model is constructed based on terminal computational capacity, network bandwidth, and task complexity. The core decision function is expressed as $U = \alpha \cdot (C_e/C_t) + \beta \cdot (B/T) - \gamma \cdot (T/C_t)$, where U denotes the offloading decision factor, C_e and C_t represent the computational capacities of the edge node and the mobile terminal, respectively, B denotes network bandwidth, T denotes task complexity, and α, β, and γ are weighting coefficients satisfying $\alpha + \beta + \gamma = 1$. Through this formulation, complex tasks are dynamically allocated, enabling millisecond-level feedback.

At the cloud-based intelligent hub layer, panoramic learner profiling and artificial intelligence-generated content modules for financial management education are constructed. Leveraging multimodal data and a financial knowledge graph, federated learning is employed to achieve privacy-preserving profile fusion and modeling, thereby overcoming the dimensional limitations of traditional learner profiling approaches. The closed-loop interaction logic across the three layers is defined as follows: data are uploaded from the terminal layer to the edge layer; preprocessing and task scheduling are performed at the edge layer and synchronized with the cloud layer; personalized decisions and content are generated at the cloud layer and cached at the edge layer; and the results are ultimately delivered to the mobile terminals. This mechanism substantially enhances system efficiency and adaptation accuracy.

3 CORE MODULE DESIGN AND TECHNICAL IMPLEMENTATION OF EACH FRAMEWORK LAYER

3.1 Design and implementation of the mobile interactive terminal layer

The mobile interactive terminal layer is positioned as the sole user interface and the primary carrier of system interaction. Guided by the principles of experience prioritization and computational offloading, this layer is responsible for multimodal data acquisition, lightweight immersive rendering, real-time interactive response, and personalized content presentation. It serves as the central hub for enabling mobile and virtualized learning in financial management education. A hardware–software co-designed architecture is adopted. At the hardware level, mobile graphics processing units supporting Open Graphics Library for Embedded Systems 3.2 or higher are selected, and high-frame-rate cameras, six-axis gyroscopes, and other multimodal sensors are integrated to balance computational capability and portability. At the software level, a low-coupling, lightweight modular architecture is constructed, in which four core modules are integrated and interconnected through an internal high-speed bus to enable efficient data exchange and to support ubiquitous mobile learning scenarios.

The lightweight immersive rendering engine and the multimodal data acquisition module constitute the core components of the terminal layer. The lightweight rendering engine eliminates redundant modules commonly found in conventional heavy-weight engines and optimizes the rendering pipeline specifically for mobile graphics processing units. A streamlined Open Graphics Library for Embedded

Systems graphical interface is integrated, and a level-of-detail dynamic precision adjustment algorithm is employed to partition financial models into three levels of geometric fidelity. When combined with frame-buffer preloading techniques, rendering latency is maintained within 100 ms. Through this approach, two-dimensional financial data are transformed into three-dimensional interactive models, supporting natural gesture-based interaction and touch-pressure sensing. The multimodal data acquisition module is implemented through the integration of multi-sensor fusion and simultaneous localization and mapping techniques. Coordinated operation between the camera and simultaneous localization and mapping enables augmented reality scene localization and map construction, with positioning error controlled within 5 mm. Fine-grained user interaction data are captured through multi-sensor collaboration, while a lightweight speech recognition model is embedded within the microphone subsystem. Data acquisition frequency is optimized to 10 Hz, and a sliding-window filtering algorithm is applied for noise reduction, thereby achieving a balanced trade-off between data fidelity and terminal energy consumption.

Terminal-layer performance is further enhanced through the integration of a real-time response agent, a micro artificial intelligence agent, and a dynamic computational offloading strategy. The micro artificial intelligence agent is implemented using a lightweight neural network model with a footprint of less than 100 MB, through which interaction data are standardized, labeled, and preprocessed in real time, thereby providing normalized inputs for cloud-based panoramic learner profiling. The real-time response agent adopts a hybrid communication protocol by combining the transmission control protocol with the user datagram protocol, in which instruction streams are transmitted via the user datagram protocol to guarantee millisecond-level delivery, while data streams are transmitted via the transmission control protocol to ensure transmission reliability. When combined with an incremental data synchronization mechanism, inter-layer interaction latency is maintained below 15 ms. The dynamic computational offloading strategy is realized through a hybrid decision-making algorithm that integrates rule-based logic with machine learning. The core equation is defined as $D = \omega_1 \cdot (CPU_{util}/CPU_{max}) + \omega_2 \cdot (B/100) + \omega_3 \cdot (T/10)$, where D denotes the offloading decision value, CPU_{util} and CPU_{max} represent the real-time and maximum central processing unit utilization of the mobile terminal, respectively, B denotes available network bandwidth, T denotes task complexity score, and ω_1, ω_2, and ω_3 are weighting coefficients satisfying $\omega_1 + \omega_2 + \omega_3 = 1$. Based on real-time evaluation of this equation, task offloading priorities are dynamically determined. Computationally intensive workloads, including complex three-dimensional rendering and deep multimodal data analysis, are offloaded to the edge intelligence layer, whereas lightweight workloads—such as simple interaction responses and local data caching—are retained at the terminal layer. Through this allocation mechanism, a dynamic balance between terminal computational consumption and interaction smoothness is achieved, enabling maximal utilization of local mobile computing resources.

3.2 Design and implementation of the edge intelligence layer

The edge intelligence layer functions as an intermediate buffer and accelerator between the terminal layer and the cloud-based layer. Core responsibilities include real-time rendering computation offloading, low-latency interactive analysis and feedback, and coordinated data forwarding, thereby serving as a critical hub for ensuring immersion and real-time responsiveness in virtualized financial management training. This layer is composed of edge servers and gateway devices and integrates four core modules within a low-coupling, lightweight architectural design. Module collaboration is enabled through an internal high-speed bus, achieving a balance between computational efficiency and deployment convenience, while accommodating the dynamic interaction requirements of mobile financial training scenarios.

Real-time rendering computation offloading and low-latency interaction analysis constitute the principal technical highlights of this layer. To address the limited rendering capability of mobile terminals, a distributed task decomposition strategy is implemented within the real-time rendering offloading module. Only viewpoint parameters, interaction instructions, and simplified model data are transmitted from the terminal layer, while high-precision rendering is performed in parallel at the edge layer. The compression ratio is defined as $CR = V_{original}/V_{compressed}$, where CR denotes the compression ratio, $V_{original}$ represents the original data volume, and $V_{compressed}$ represents the compressed data volume. A compression ratio of at least 80% is ensured. In addition, the H.265 video compression standard is applied to the rendered video streams, by which transmission latency is strictly constrained within 50 ms, effectively overcoming the rendering performance bottleneck of mobile terminals. The low-latency interaction analysis module employs a lightweight convolutional neural network–long short-term memory hybrid network with model parameters not exceeding 500 MB. By integrating financial scenario–specific interaction rules, intent recognition accuracy is maintained at or above 95%. The feedback generation module incorporates lightweight financial visualization components, with response latency controlled within 10 ms, thereby satisfying the immediacy requirements of practical training scenarios.

The edge–terminal–cloud data collaboration module further optimizes the least recently used caching algorithm. High-frequency access content, including commonly used virtual training scenarios and generic financial knowledge, is preferentially cached. Cache hit rate is defined as $H = N_{hit}/N_{total} \times 100\%$, where H denotes the cache hit rate, N_{hit} denotes the number of cache hits, and N_{total} denotes the total number of access requests. A cache hit rate of at least 90% is maintained. An incremental data synchronization protocol is designed to transmit only differential data between the edge and cloud layers, reducing data transmission volume by more than 60%. In addition, a bidirectional hash verification mechanism is established to ensure the consistency and integrity of learner profiles and interaction data. Through these mechanisms, real-time data linkage across the three layers is achieved, providing reliable support for the collaborative learning ecosystem.

3.3 Design and implementation of the cloud-based intelligent hub layer

The cloud-based intelligent hub layer functions as the central decision-making and orchestration core of the system. Responsibilities include global data aggregation, deep modeling, content generation, and system-wide scheduling. By moving beyond the limitations of conventional cloud layers, this layer is designed with a focus on precision, personalization, and security. Through the coordinated operation of four core modules, an intelligent decision-support service system is established, providing global support for the three-layer architecture. A modular collaborative architecture is adopted, in which the four core modules are interconnected via a high-speed data bus. Targeting the specific requirements of financial management education, long-standing challenges related to delayed cloud-side decision-making, content homogenization, and insufficient data security are effectively addressed.

The panoramic learner profiling module and the artificial intelligence content engine constitute the primary technical highlights of this layer. The panoramic learner profiling module integrates multimodal interaction data with structured educational data. Privacy preservation is ensured through federated learning, while learner profiles are modeled using Transformer-based architectures. A three-dimensional indicator system encompassing knowledge, cognition, and behavior is constructed. Profiling accuracy is defined as $P = N_c/N_t \times 100\%$, where P denotes profiling accuracy, N_c represents the number of accurately labeled profile samples, and N_t denotes the total number of profile samples. A profiling accuracy of at least 96% is maintained. In addition, a minute-level dynamic update mechanism is designed to synchronize learner profiles with real-time learning states. The artificial intelligence content engine integrates a fine-grained financial knowledge graph with a lightweight, artificial intelligence-generated content large model. Content generation throughput reaches one item per second. By leveraging learner profiles, personalized training content is automatically generated and subsequently assembled into adaptive learning packages through a content composition algorithm, enabling precise alignment.

System-level scheduling capability and service availability are further enhanced through the personalized decision engine and the virtual environment data service module. The personalized decision engine adopts a hybrid algorithm combining reinforcement learning with pedagogical rules. A reward function is constructed as $R = \lambda \cdot K - \mu \cdot T$, where R denotes the reward value, λ and μ are weighting coefficients, K represents the knowledge improvement rate, and T denotes learning time consumption. Through optimization of this reward function, decision strategies are continuously refined, with learning path adjustment latency constrained to within 1 second, thereby enabling individualized scheduling at scale. The virtual environment and data service module employs a modularized virtual scenario repository that supports flexible composition. A distributed database architecture is adopted to optimize multimodal data storage, maintaining access latency within 20 ms. In addition, a data visualization module enables real-time visualization of data, providing robust analytical support for framework optimization and instructional evaluation.

3.4 Implementation of the three-layer collaborative mechanism

The core innovation of the three-layer collaborative mechanism lies in the construction of a bidirectional, real-time closed-loop interaction framework. By overcoming the limitations of conventional three-layer architectures characterized by unidirectional transmission of data flows and control instructions, efficient coordination among the mobile interactive terminal layer, the edge intelligence layer, and the cloud-based intelligent hub layer is achieved. Through explicit definition of interaction pathways and optimization of transmission protocols, robust support is provided for system-level real-time responsiveness and interaction smoothness. Both data flows and control instruction flows are designed with bidirectional interaction mechanisms. Multimodal interaction data are collected at the terminal layer and forwarded to the edge intelligence layer for preprocessing, after which the processed data are transmitted to the cloud-based intelligent hub layer for deep modeling and analytical processing. Personalized content and learner profile updates generated at the cloud layer are subsequently cached and optimized at the edge layer before being delivered to the terminal layer for presentation. In parallel, control instruction flows originate from the cloud-based decision engine, where commands related to content delivery and computational offloading are generated. These instructions are forwarded and synchronously executed by the edge layer, while interaction commands and computational state information from the terminal layer are aggregated at the edge layer and fed back to the cloud layer, enabling dynamic adjustment of decision strategies.

To enhance transmission performance, the message queuing telemetry transport protocol is adopted. Message transmission success rate is defined as $P_{trans} = N_{succ}/N_{total} \times 100\%$, where P_{trans} denotes the transmission success rate, N_{succ} represents the number of successfully transmitted messages, and N_{total} represents the total number of transmitted messages. A transmission success rate of at least 99.9% is ensured. In addition, message fragmentation and priority-based scheduling mechanisms are employed to constrain instruction flow transmission latency within 10 ms and data flow transmission latency within 50 ms, thereby guaranteeing the real-time performance and reliability of the closed-loop interaction system. Figure 2 illustrates the global collaborative scheduling framework and the bidirectional closed-loop interaction mechanism based on multidimensional state awareness.

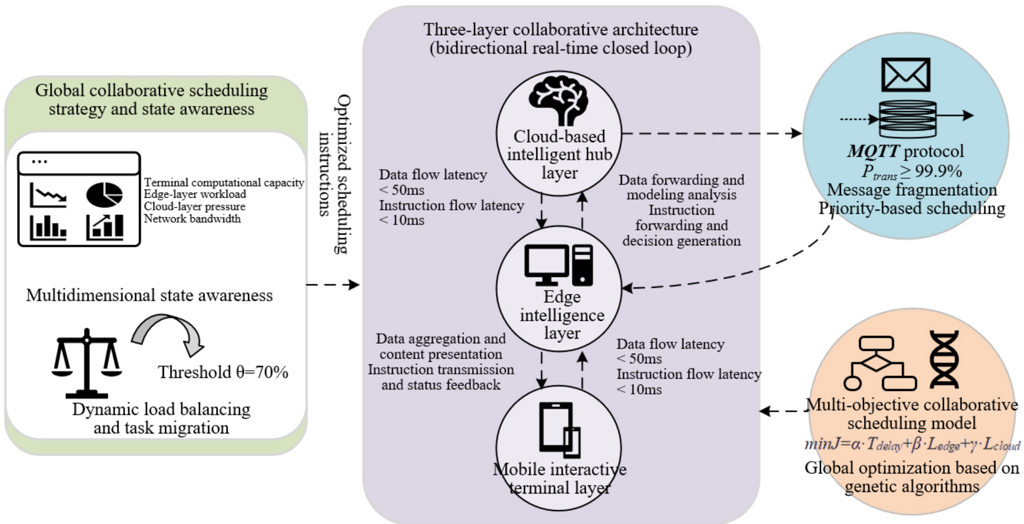

Fig. 2. Global collaborative scheduling and bidirectional closed-loop interaction mechanism based on multidimensional state awareness

The innovation of the global collaborative scheduling strategy lies in the realization of dynamic task allocation and load balancing under multidimensional state awareness. By transcending the limitations of traditional localized scheduling approaches, a balanced optimization of system real-time responsiveness, smoothness, and computational resource consumption is achieved. A comprehensive system state monitoring framework is established, within which key parameters—including terminal computational utilization, edge node workload, cloud server pressure, and network bandwidth—are continuously collected in real time. Based on these inputs, a multi-objective collaborative scheduling model is constructed. Genetic algorithms are employed to perform global optimization of task allocation and data transmission paths. The scheduling objective function is defined as $minJ = \alpha \cdot T_{delay} + \beta \cdot L_{edge} + \gamma \cdot L_{cloud}$, where J denotes the scheduling cost and α, β, and γ are weighting coefficients satisfying $\alpha+\beta+\gamma=1$, T_{delay} represents transmission latency, and L_{edge} and L_{cloud} denote the load rates of the edge and cloud layers, respectively. A dynamic load balancing mechanism is further designed, in which an edge node load threshold of $\theta = 70\%$ is predefined. When the workload of an edge node exceeds this threshold, computationally intensive tasks—such as rendering computation and data processing—are automatically migrated to idle edge nodes or to the cloud-based intelligent hub layer, thereby preventing single-node overload. Simultaneously, data transmission paths are dynamically adjusted, with priority given to links characterized by higher bandwidth and lower latency. Through these mechanisms, stable system operation is ensured, and optimal matching between computational resources and task allocation across the three-layer architecture is achieved.

4 PROTOTYPE SYSTEM DEVELOPMENT AND EXPERIMENTAL EVALUATION

A full-stack development environment was established for the prototype system in accordance with the three-layer architecture, and the technical stack was systematically selected to balance computational support and scenario adaptability. At the mobile interactive terminal layer, Android and iOS platforms were adopted, and smartphones equipped with Adreno 730 or higher graphics processing units were selected. The edge intelligence layer was deployed on edge servers configured with Intel Xeon E3 central processing units and 16 GB of memory, while the cloud-based intelligent hub layer was implemented on Alibaba Cloud Elastic Compute Service (ECS) instances equipped with Intel Xeon Platinum 8375C central processing units and 64 GB of memory. These configurations were selected to match the differentiated computational demands of each architectural layer. Technology selection was tightly aligned with the proposed innovative functionalities. At the mobile terminal layer, Unity3D was combined with Open Graphics Library for Embedded Systems to enable lightweight immersive rendering, while TensorFlow Lite was employed for the deployment of micro artificial intelligence agents. At the edge intelligence layer, Python was adopted as the primary development language, TensorRT was utilized to accelerate model inference, and Docker was applied to support modularized deployment. At the cloud-based intelligent hub layer, modeling frameworks were constructed using Python and PyTorch, with MySQL employed for structured data storage and Redis used for high-frequency data caching. At the communication layer, the message queuing telemetry transport protocol and transmission control protocol/user datagram protocol were integrated to ensure reliable bidirectional interaction. ARCore and VR SDKs were adopted to develop financial management–specific virtual environments.

5 RESULTS AND ANALYSIS

A series of systematic experiments was conducted to evaluate the effectiveness of the proposed mobile-terminal–centered, three-layer collaborative intelligent education framework across multiple dimensions. Experimental assessments focused on five key aspects: core system performance and network adaptability, mobile device compatibility, effectiveness of personalized strategies, long-term operational stability and data security, and comparative learning outcomes. Standardized testing environments and rigorously controlled comparative experimental designs were adopted. All experiments were repeated three times, and mean values were reported as final results to ensure data reliability and experimental rigor.

The core performance and network environment adaptability evaluation was conducted to validate the fundamental technical performance of the framework and its adaptability to mobile networking conditions. A comparative analysis was performed between the proposed framework and a representative existing mobile education framework. Experiments were carried out under four commonly encountered mobile network environments, including 5G, 4G, Wi-Fi, and weak network conditions. The simplified key results are presented in Figure 3 and Table 1.

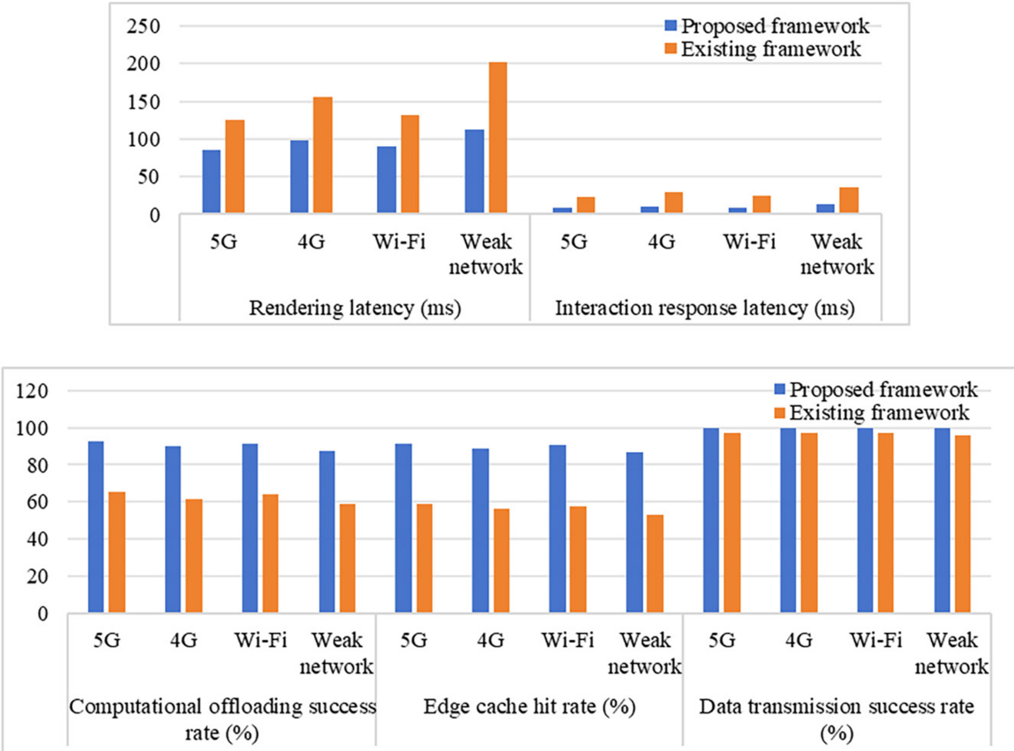

Fig. 3. Core performance and network environment adaptability test results

Table 1. Test results of network switching stalling duration and data interruption rate

Test Metric	Unit	Network Environment	Proposed Framework	Existing Framework	Performance Improvement
Network switching stalling duration	ms	5G → 4G	35.6 ± 4.2	89.7 ± 7.5	59.2%
		4G → weak network	48.9 ± 5.3	112.4 ± 8.6	56.5%
		Wi-Fi → 5G	28.7 ± 3.8	76.5 ± 6.9	62.5%
Data interruption rate	%	All switching scenarios	0.3 ± 0.1	2.8 ± 0.4	89.3%

As indicated by Figure 3 and Table 1, the proposed framework consistently outperformed the existing framework across all evaluated network environments. For key user-experience indicators, rendering latency and interaction response latency under 5G conditions were reduced to 85.3 ms and 8.2 ms, respectively. Although performance degradation was observed under weak network conditions, rendering latency and interaction response latency remained constrained to 112.5 ms and 13.7 ms, respectively, substantially outperforming the existing framework. Across all network environments, critical performance indicators—including computational offloading success rate and edge cache hit rate—were maintained above 86%, with the highest relative improvement reaching 63.8% under weak network conditions. In terms of network adaptability, the average network switching stalling duration of the proposed framework was limited to 37.7 ms, while the data interruption rate was reduced to 0.3%. Data transmission success rate consistently exceeded 99.5% across all scenarios. These results collectively demonstrate the effectiveness of the three-layer collaborative mechanism and the dynamic computational offloading strategy. By effectively mitigating the constraints imposed by mobile device computational limitations and network fluctuations, smooth interactive performance under mobile learning scenarios was ensured.

Mobile device compatibility evaluation was conducted using three representative categories of mobile terminals—low-end, mid-range, and high-end—to assess framework adaptability, performance characteristics, and operational stability across heterogeneous hardware configurations. The test results are summarized in Table 2.

Table 2. Compatibility test results across different mobile device configurations

Test Metric	Unit	Low-End Device (Adreno 610)	Mid-Range Device (Adreno 660)	High-End Device (Adreno 730)	Inter-Device Performance Difference Coefficient
Adaptation success rate	%	96.0 ± 1.2	98.0 ± 0.8	100.0 ± 0.0	2.1%
Rendering latency	ms	118.7 ± 6.5	92.4 ± 4.8	85.3 ± 4.2	15.8%
Interaction response latency	ms	12.5 ± 1.7	9.8 ± 1.4	8.2 ± 1.3	22.4%
Computational offloading success rate	%	86.8 ± 2.2	90.5 ± 1.7	92.3 ± 1.5	6.3%
Edge cache hit rate	%	87.6 ± 1.8	90.2 ± 1.6	91.4 ± 1.4	4.3%
Crash rate during 24 hr continuous operation	%	1.2 ± 0.4	0.5 ± 0.2	0.2 ± 0.1	83.3%
Functional anomaly rate	%	1.8 ± 0.5	0.8 ± 0.3	0.3 ± 0.1	83.3%
Average terminal central processing unit utilization	%	28.7 ± 2.3	25.4 ± 2.1	22.8 ± 1.9	25.9%
Average terminal graphics processing unit utilization	%	35.6 ± 2.8	30.2 ± 2.5	26.5 ± 2.2	34.3%
Average terminal memory utilization	%	32.4 ± 2.5	29.8 ± 2.3	27.6 ± 2.1	17.4%
Multimodal interaction success rate	%	95.7 ± 1.6	97.8 ± 1.2	99.2 ± 0.8	3.6%

As indicated by Table 2, robust compatibility was demonstrated across all three categories of mobile devices, with adaptation success rates exceeding 96% and inter-device performance differences maintained within a reasonable range. On low-end devices, average rendering latency and interaction response latency were measured at 118.7 ms and 12.5 ms, respectively, satisfying the baseline requirements for immersive learning scenarios. On high-end devices, optimal performance was achieved, with rendering latency and interaction response latency reduced to 85.3 ms and 8.2 ms, respectively, while both computational offloading success rate and edge cache hit rate exceeded 90%. As for all device categories, crash rates during continuous 24-hour operation remained below 1.5%, and functional anomaly rates were constrained below 2.0%. Terminal resource utilization decreased progressively with increasing device capability. Even on low-end devices, average central processing unit, graphics processing unit, and memory utilization rates were controlled below 36%, and no resource saturation events were observed.

Multimodal interaction success rates exceeded 95% across all device types, thereby validating the effectiveness of the device-adaptive logic embedded within the lightweight rendering engine and multimodal data acquisition modules. Collectively, these results confirm that the design objectives of experience prioritization and computational offloading were effectively achieved, highlighting the strong universality of the proposed framework across heterogeneous mobile device environments.

The effectiveness of the personalized strategies was evaluated through a controlled comparative experiment, in which the contributions of the cloud-based personalized decision engine and the artificial intelligence-generated content module were independently examined. Interference from other technical factors was eliminated. The test results are summarized in Table 3.

Table 3. Independent validation results of personalized strategy effectiveness

Test Metric	Unit	Personalized Strategy Enabled (Experimental Group)	Personalized Strategy Disabled (Control Group)	Improvement
Personalized path adaptation accuracy	%	94.7 ± 1.3	62.3 ± 2.4	52.0%
Knowledge point mastery rate	%	92.5 ± 1.5	73.6 ± 2.2	25.7%
Practical training operation accuracy	%	90.3 ± 1.7	71.2 ± 2.5	26.8%
Average learning efficiency	Knowledge points/hr	4.8 ± 0.5	2.9 ± 0.4	65.5%
Artificial intelligence-generated content professionalism score	Points	8.8 ± 0.4	–	–
Artificial intelligence-generated content adaptability score	Points	8.9 ± 0.3	–	–
Learning path adjustment rationality score	Points	9.0 ± 0.2	5.2 ± 0.6	73.1%
Precise identification rate of knowledge weaknesses	%	93.8 ± 1.4	68.5 ± 2.3	36.9%

As indicated in Table 3, the experimental group with personalized strategies enabled consistently outperformed the control group across all evaluated metrics. Personalized path adaptation accuracy reached 94.7%, representing a 52.0% improvement over the control group, indicating that the reinforcement learning–based algorithm embedded in the personalized decision engine effectively aligned learning paths with individual knowledge foundations and cognitive characteristics. The knowledge point mastery rate and practical training operation accuracy in the experimental group reached 92.5% and 90.3%, respectively, corresponding to improvements exceeding 25% relative to the control group. Average learning efficiency increased to 4.8 knowledge points per hour, reflecting a 65.5% improvement, thereby confirming the substantial contribution of personalized learning paths to both learning effectiveness and efficiency. The professionalism and adaptability scores of artificial intelligence-generated content approached 9 points, demonstrating strong alignment between the content generation module and professional financial management scenarios. Furthermore, the precise identification rate of knowledge weaknesses reached 93.8%, representing a 36.9% improvement over the control group. This result further validates the synergistic effectiveness of panoramic learner profiling and the personalized decision engine, highlighting the practical value of personalization as a core innovation of the proposed framework.

Long-term operational stability and data security were evaluated through continuous, uninterrupted system operation over an eight-week period to assess engineering usability and data protection capabilities. The experimental results are summarized in Table 4.

Table 4. Long-term operational stability and data security test results

Test Metric	Unit	Week 1	Week 4	Week 8	Performance Degradation
System crash rate	%	0.2 ± 0.1	0.3 ± 0.1	0.5 ± 0.2	150.0%
Rendering latency	ms	85.3 ± 4.2	88.6 ± 4.5	92.8 ± 4.8	8.8%
Interaction response latency	ms	8.2 ± 1.3	8.7 ± 1.4	9.3 ± 1.5	13.4%
Data synchronization accuracy	%	99.9 ± 0.1	99.8 ± 0.1	99.7 ± 0.2	0.2%
Encrypted transmission rate	%	100.0 ± 0.0	100.0 ± 0.0	100.0 ± 0.0	0.0%
Data anonymization compliance rate	%	100.0 ± 0.0	100.0 ± 0.0	100.0 ± 0.0	0.0%
Privacy leakage risk (penetration testing)	Level	No risk	No risk	No risk	0.0%
Average mobile terminal central processing unit utilization	%	22.8 ± 1.9	23.5 ± 2.0	24.2 ± 2.1	6.1%
Average mobile terminal graphics processing unit utilization	%	26.5 ± 2.2	27.3 ± 2.3	28.1 ± 2.4	6.0%
Average edge server central processing unit utilization	%	38.7 ± 2.5	39.5 ± 2.6	40.3 ± 2.7	4.1%
Average cloud server central processing unit utilization	%	42.3 ± 2.8	43.1 ± 2.9	43.8 ± 3.0	3.5%

As demonstrated in Table 4, strong long-term operational stability was maintained throughout the eight-week continuous runtime. After eight weeks of operation, the system crash rate remained limited to 0.5%, while rendering latency and interaction response latency increased modestly to 92.8 ms and 9.3 ms, respectively. Performance degradation across these indicators remained below 15%, indicating the absence of significant performance deterioration. Data synchronization accuracy was consistently maintained above 99.7%, while encrypted data transmission and data anonymization compliance rates remained at 100% throughout the evaluation period. Penetration testing revealed no identifiable privacy leakage risks, thereby validating the effectiveness of the federated learning framework and data encryption mechanisms in safeguarding user interaction data and learner profile information. Resource utilization across system nodes exhibited gradual increases over time; however, after eight weeks of continuous operation, average central processing unit utilization at the mobile terminal, edge server, and cloud server levels remained below 45%, and no resource saturation events were observed. These results collectively demonstrate that the proposed framework possesses robust engineering usability, supporting its suitability for long-term deployment in real-world mobile intelligent education applications.

6 CONCLUSION

This study focuses on the application of mobile interactive technologies to the virtualization and personalization of financial management education. A mobile-device–centered intelligent education framework based on a collaborative three-layer architecture was proposed and implemented. Technical design and development were completed for the mobile interactive terminal layer, the edge intelligence layer, and the cloud-based intelligent hub layer. A prototype system was successfully constructed, and its effectiveness was validated through comprehensive multidimensional experimental evaluations. The results demonstrate that, through the coordinated integration of multimodal interaction and lightweight rendering technologies at the mobile terminal layer, real-time computational offloading strategies at the edge intelligence layer, and panoramic learner profiling together with artificial intelligence-generated personalized content at the cloud-based intelligent hub layer, key challenges in mobile virtualized financial management education—including insufficient immersion, limited personalization, and constrained mobile computational resources—were effectively addressed. As a result, deep virtualization and precise personalization of financial management education were achieved, leading to significant improvements in learning outcomes and user experience in mobile learning scenarios. The core innovations embodied in the proposed framework—namely the three-layer collaborative architecture, dynamic computational offloading mechanisms, and multimodal data-driven personalized decision-making—were experimentally verified to exhibit strong feasibility and technological advancement. By overcoming the inherent limitations of traditional mobile education frameworks, a new paradigm is provided for the practical deployment of mobile intelligent education in professional domains. In addition, the theoretical and technical foundations underlying the integration of mobile intelligent education and financial management digitalization are further enriched.

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