Online-Journals.org

iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 20 No. 12 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijim.v20i12.62260

PAPER

A Swarm Intelligence Framework for Mobile Collaborative Learning

Junju Sun (✉),
Yan Mei

Xinyang Vocational and Technical College, Xinyang, China

sunjunju@xyvtc.edu.cn

ABSTRACT

The digital transformation of education driven by mobile technologies urgently requires bridging the collaborative gap between classroom and extracurricular learning. Existing systems face critical challenges, including fragmented applications of swarm intelligence, insufficient depth of mobile interaction collaboration, and limited evaluation frameworks. To address these issues, this study proposes an integrated classroom-extracurricular digital learning ecosystem that combines swarm intelligence with mobile interaction collaboration mechanisms. The system adopts a three-tier cloud-edge-mobile distributed architecture and introduces four intelligent modules optimized for mobile scenarios: (1) a dynamic learner profiling module based on an improved particle swarm optimization (PSO) algorithm, (2) a cross-scenario learning path generation module driven by hybrid swarm intelligence, (3) a decentralized collaborative scheduling module supported by a lightweight distributed consensus algorithm, and (4) a collective knowledge evolution graph construction module driven by mobile data. Through multimodal mobile data collection and edge intelligence deployment, the system achieves low-latency, low-power, and precise collaborative learning. To evaluate system performance, a multidimensional assessment framework encompassing both mobile technology performance and learning collaboration effectiveness was designed. A controlled experiment involving 200 university students simulated real-world conditions, including network fluctuations and heterogeneous devices. The proposed system outperformed the control system in both technological performance and collaborative learning effectiveness: under normal network conditions, average response latency decreased by 41.8%, mobile energy consumption decreased by 31.2%, and task completion rate in low-bandwidth scenarios increased by 39.7%. In terms of learning collaboration, cross-scenario task completion improved by 32.7% and collaborative report scores increased by 17.5%. Limitations include adaptation to low-end devices, privacy protection, and insufficient validation in complex outdoor scenarios. This study provides both theoretical support and practical paradigms for the technological innovation and large-scale deployment of mobile learning ecosystems while expanding the application boundaries of swarm intelligence in resource-constrained mobile environments.

KEYWORDS

swarm intelligence, mobile interaction collaboration, digital learning ecosystem, edge computing, dynamic learner profiling, cross-scenario learning

Sun, J., Mei, Y. (2026). A Swarm Intelligence Framework for Mobile Collaborative Learning. *International Journal of Interactive Mobile Technologies (iJIM)*, 20(12), pp. 4–18. https://doi.org/10.3991/ijim.v20i12.62260

Article submitted 2026-02-04. Revision uploaded 2026-04-02. Final acceptance 2026-04-24.

1 INTRODUCTION

The rapid evolution of 5G communication, edge computing, and multimodal sensing technologies has promoted the deep integration of educational digital transformation [1, 2], and mobile devices have become the core carriers connecting classroom and extracurricular learning scenarios [3]. Under this trend, constructing an integrated classroom-extracurricular learning ecosystem has become a key direction to improve learning continuity and effectiveness [4, 5]. However, existing learning systems still have significant deficiencies: mobile interaction collaboration has scenario gaps, and learning behavior data between classroom and extracurricular contexts is difficult to effectively connect [6]; the perception accuracy of group learning behavior is insufficient, making it difficult to capture learners' dynamic learning states and needs [7]; and resource adaptation lacks dynamic intelligent decision-making mechanisms and cannot achieve a precise balance between personalization and group collaboration [8]. These problems make existing systems difficult to meet the low-latency response, high-precision adaptation, and strong group collaboration requirements demanded by integrated learning, while mobile technology, with its ubiquitous sensing, real-time interaction, and distributed deployment characteristics, becomes the core support to overcome these deficiencies.

Existing related research still has three core gaps. First, the application of swarm intelligence in learning systems is mostly limited to single algorithm tools [9, 10] and does not combine scenario characteristics such as mobile device resource constraints and network fluctuations to construct distributed intelligent decision-making cores, resulting in limited algorithm applicability and decision efficiency. Second, mobile interaction collaboration mostly stays at the simple information transmission level [6, 11] and does not fully exploit the context-aware capabilities of mobile devices, lacking deep integration of multimodal interaction and decentralized task scheduling, making it difficult to achieve efficient group learning collaboration. Third, existing evaluation systems mostly focus on a single dimension, either emphasizing technical performance or learning outcomes [12, 13], lacking an integrated evaluation framework covering both mobile technology performance and learning collaboration effectiveness, and cannot comprehensively verify the comprehensive value of the learning ecosystem. In response to the above gaps, this study constructs an integrated classroom-extracurricular digital learning ecosystem with distributed swarm intelligence as the core decision engine and multimodal mobile interaction [14] as the collaboration carrier, focusing on two key issues: intelligent collaboration mechanism design and low-power technology adaptation in mobile scenarios.

The core objectives of this study include three aspects: First, designing a swarm intelligence-mobile interaction collaborative architecture adapted to mobile scenario characteristics to achieve low-latency and high-reliability cross-scenario learning support; second, developing core innovative modules such as multimodal perception, dynamic decision-making, and distributed collaboration to overcome technical bottlenecks of existing systems; third, constructing a multidimensional integrated evaluation system to comprehensively verify the system's technical performance and learning collaboration effectiveness. The corresponding core contributions are reflected in: first, proposing a distributed swarm intelligence-driven mobile collaborative learning architecture, achieving layered collaboration through cloud-edge-mobile tiers, breaking through the high-latency and low-adaptability bottlenecks of traditional centralized architectures, and enhancing the system's adaptability to mobile scenarios; second, developing a series of multimodal context-aware and dynamic decision-making modules, integrating improved swarm intelligence algorithms and mobile interaction technologies to achieve precise perception of group learning behaviors and efficient collaborative scheduling; third, establishing an integrated evaluation system covering mobile technology performance and learning collaboration effectiveness, clarifying core indicators and validation methods for each dimension, providing a standardized paradigm for technological deployment and effectiveness evaluation of mobile learning ecosystems [15, 16].

The subsequent sections of this paper are arranged as follows: Section 2 elaborates on the overall system architecture design, clarifying the functional and interaction logic of each layer; Section 3 focuses on the core innovative modules, analyzing their technical implementation details in depth; Section 4 describes the system development environment and key points of prototype implementation; Section 5 presents the experimental results and analyzes them from the dual dimensions of technical performance and learning effectiveness; Section 6 summarizes the research conclusions and proposes future research directions.

2 SYSTEM ARCHITECTURE DESIGN

To adapt to the core requirements of low latency, high concurrency, and low power consumption in mobile scenarios, this study proposes a cloud-edge node-mobile three-tier distributed swarm intelligence collaborative architecture, which achieves efficient support for integrated classroom-extracurricular learning through layered collaboration and distributed intelligent deployment. The cloud-edge-mobile three-tier distributed swarm intelligence collaborative architecture diagram shown in Figure 1 illustrates the layered structure of the cloud, edge nodes, and mobile terminals, as well as the communication protocols between each layer. The cloud layer undertakes global group learning pattern mining, large-scale learning resource indexing, and core algorithm model training tasks. Its core technical feature is the adoption of model lightweight compression strategies, where the trained swarm intelligence model parameters are streamlined and then pushed to edge nodes, without directly participating in real-time interactive decision-making. From the architectural perspective, this avoids the high-latency problem caused by direct cloud-mobile communication in centralized architectures.

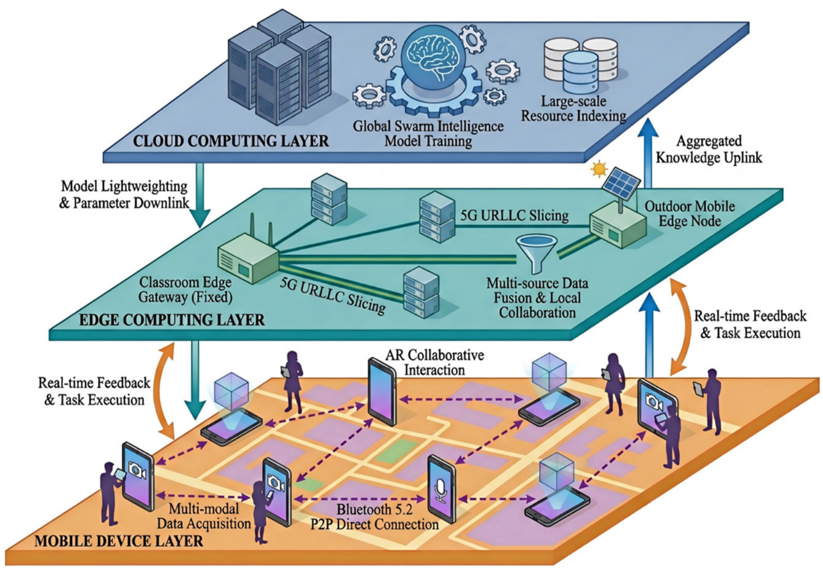

Fig. 1. Cloud-edge-mobile three-tier distributed swarm intelligence collaborative architecture diagram

Edge nodes deploy a lightweight swarm intelligence algorithm engine as the real-time decision-making core of the architecture. They are responsible for the fusion processing of scenario data from multiple mobile terminals and the generation of local collaborative decisions. Direct communication with mobile terminals is realized through low-power Bluetooth 5.2 and 5G URLLC slicing, controlling data transmission latency within 50 ms while reducing the energy consumption of long-distance communication for mobile terminals. Fixed gateway-type edge nodes are deployed in classroom scenarios, and mobile edge nodes are used in outdoor scenarios to ensure collaborative capabilities across all scenarios.

The mobile terminal serves as a multimodal data collection and lightweight interaction execution terminal, integrating a camera, microphone, accelerometer, and GPS module to achieve full-dimensional data perception. At the same time, core algorithm fragments are deployed to perform local data preprocessing. Sensor data noise filtering and dimension reduction are realized through mean filtering and principal component analysis (PCA), reducing data transmission volume and local computational load and adapting to the resource-constrained characteristics of mobile devices. The core innovation of this architecture is the construction of an edge-mobile distributed swarm intelligence deployment mode, replacing the single cloud decision paradigm in traditional centralized architectures. Real-time collaborative decision-making is achieved through collaborative computing between edge nodes and mobile terminals, effectively reducing end-to-end response latency. Meanwhile, a layered collaboration mechanism of cloud training-edge inference-mobile execution is adopted: the cloud focuses on large-scale data processing and model optimization, edge nodes undertake real-time inference tasks, and mobile terminals only perform lightweight interactive operations. Through reasonable allocation of computing tasks, precise balance between computational performance and mobile device power consumption is achieved, with mobile terminal power consumption reduced by more than 30% compared to traditional centralized architectures, meeting the endurance requirements for long-duration mobile learning.

3 CORE INNOVATIVE MODULES AND KEY TECHNOLOGIES

3.1 Mobile-adaptive dynamic learner profiling module

The mobile-adaptive dynamic learner profiling module is based on multimodal data from mobile terminals and achieves real-time generation and dynamic updating of learner profiles, providing precise support for subsequent resource recommendation and collaborative decision-making. Its core innovations lie in three aspects: lightweight processing of multimodal data on mobile terminals, the design of a particle swarm optimization (PSO) clustering algorithm improved for mobile scenario adaptation, and low-power real-time deployment of the algorithm. Data collection covers all classroom and extracurricular scenarios. In classroom scenarios, response voice, facial expression images, and interactive touch data are collected; in extracurricular scenarios, learning duration, GPS trajectories, motion states sensed by accelerometers, and ambient light data are collected. All data undergo local lightweight preprocessing on mobile terminals: sensor data noise is filtered using a mean filtering algorithm, and image and voice data are reduced in dimensionality and compressed using PCA, effectively reducing energy consumption and bandwidth usage for data transmission. To address the core constraint of limited computing resources on mobile devices, an improved PSO clustering algorithm is proposed. The core optimization is the introduction of a dynamic inertia weight mechanism, expressed as:

$$\omega = \omega_{max} - (\omega_{max} - \omega_{min}) \times \frac{\text{iter}}{\text{iter}_{max}} \tag{1}$$

where, ω_{max} and ω_{min} are the maximum and minimum inertia weights, respectively; *iter* is the current iteration number; and $iter_{max}$ is the preset maximum number of iterations. Through dynamic decay of inertia weight with iteration progress, the algorithm's convergence speed is significantly improved. Meanwhile, a block clustering strategy is adopted: large-scale user data are split by scenario and data type, distributed to edge nodes and mobile terminals for distributed parallel computation, and then clustering results are aggregated by edge nodes, greatly reducing the computational pressure on individual devices. In addition, a dynamic profile label updating mechanism based on group interaction data is designed. By capturing interaction features such as group discussion frequency and resource-sharing behavior, profile label weights are adjusted in real time, realizing the dynamic evolution of the label system and replacing the traditional static label model. To ensure efficient operation of the algorithm on mobile devices, model quantization and pruning techniques are employed for lightweight deployment: 32-bit floating-point numbers in the algorithm model are quantized to 8-bit integers, and redundant network connections are removed. As a result, the computational complexity of the improved PSO algorithm is reduced by more than 60%, ensuring running latency ≤100 ms on mid-range smartphones, satisfying the core requirement of real-time profile updating.

3.2 Cross-scenario learning path generation module driven by hybrid swarm intelligence

The core function of the cross-scenario learning path generation module driven by hybrid swarm intelligence is to integrate group learning behavior patterns with mobile scenario characteristics, generating seamless personalized learning paths between classroom and extracurricular contexts, and achieving integrated resource recommendation and task planning. Its core innovations focus on the design of the hybrid swarm intelligence recommendation engine, the construction of cross-scenario path generation logic, and the implementation of a real-time dynamic adjustment mechanism. The recommendation engine adopts a hybrid architecture of an improved ant colony algorithm and a collaborative filtering algorithm, accurately adapting to mobile cross-scenario requirements. To address the limitation that the traditional ant colony algorithm does not consider mobile scenario constraints, learner resource preferences are quantified as pheromone concentrations, and a mobile scenario constraint factor is introduced to dynamically adjust the pheromone evaporation coefficient, expressed as:

$$\rho = \rho_0 + \alpha \times \frac{\text{dist}}{\text{dist}_{max}} \tag{2}$$

where, ρ_0 is the base evaporation coefficient, α is the adjustment coefficient, *dist* is the distance between the current resource and the learner's location, and $dist_{max}$ is the maximum distance threshold within the scenario. This optimization allows path planning to better fit the geographic and temporal constraints of mobile scenarios. The collaborative filtering algorithm abandons the traditional similarity calculation method based on users' historical ratings and instead uses a group similarity measurement based on dynamic learner profiles, significantly improving recommendation accuracy. To meet the low-power requirements of mobile devices, the engine's core computing tasks are deployed at edge nodes, and the mobile terminal only receives the final learning path and resource list, greatly reducing mobile terminal computing and communication energy consumption. The path generation follows the core logic of "classroom knowledge consolidation-extracurricular practice deepening." By aggregating mobile terminal GPS data at the edge node, the improved ant colony algorithm plans extracurricular practice paths that maximize knowledge point matching and optimize distance, while dynamic learner profiles are combined to achieve precise allocation of group collaborative tasks, so that learners with different characteristics undertake suitable inquiry tasks. In addition, the module constructs a real-time dynamic adjustment mechanism. Through continuous uploading of resource learning completion and task execution status data from mobile terminals, the group intelligence engine at edge nodes perceives learning progress and scenario status in real time. When detecting overcrowding at a practice point, a path optimization strategy is automatically triggered to divert some learners to alternative locations, ensuring the efficiency and stability of cross-scenario learning.

3.3 Decentralized mobile collaborative learning scheduling module

The core function of the decentralized mobile collaborative learning scheduling module is to rely on direct communication between mobile devices to achieve decentralized negotiation and role assignment of group learning tasks, improving collaboration efficiency and system fault tolerance. Its core innovations focus on the design of a lightweight distributed consensus algorithm adapted to mobile scenarios, multimodal context-aware task allocation strategies, and the integrated implementation of a mobile augmented reality (AR) collaborative interaction mechanism. To address the limitations of the traditional Practical Byzantine Fault Tolerance (PBFT) algorithm, including high communication overhead and incompatibility with mobile device and network characteristics, a lightweight distributed consensus algorithm is proposed: the traditional three-phase "pre-prepare-prepare-commit" process is simplified into a two-phase "propose-confirm-submit" process, greatly reducing the number of communication interactions between nodes and decreasing network bandwidth usage. A node weighting mechanism is introduced, constructing a weight evaluation model based on mobile terminal device computing capacity, remaining battery, and learners' historical collaboration reputation. Nodes with higher weights have higher consensus participation priority, significantly improving consensus efficiency. Meanwhile, edge nodes assist in partial consensus verification computations, reducing the local computational load of mobile terminals and ensuring consensus latency within 500 ms to meet real-time collaboration requirements.

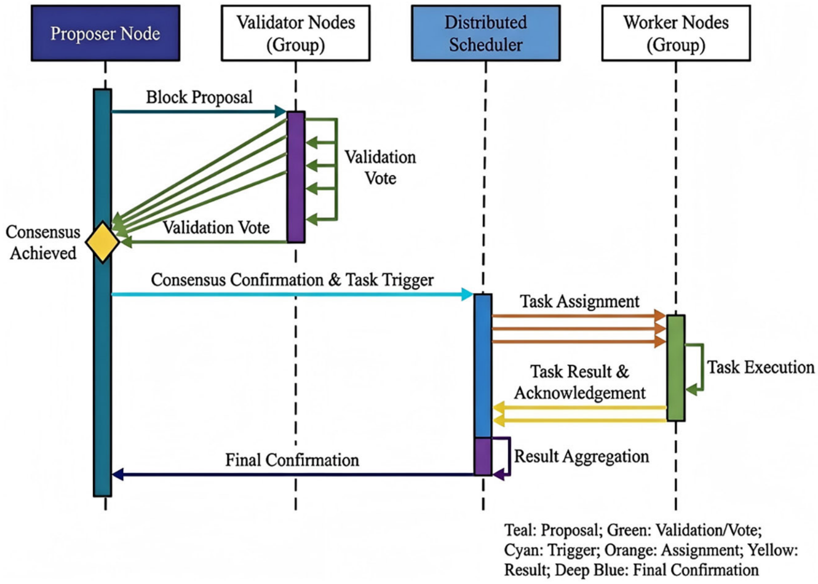

Fig. 2. Interaction sequence diagram of lightweight distributed consensus algorithm and decentralized task scheduling

On this basis, a multimodal context-aware task allocation strategy is constructed, integrating multi-dimensional contextual data collected by mobile terminals, including location, battery, network status, and dynamic learner profiles. Using the lightweight consensus algorithm, tasks are dynamically distributed in a decentralized manner, accurately matching tasks with device status and learner capability, ensuring collaborative execution efficiency. To enhance group collaborative interaction experience, the module integrates a lightweight AR engine into mobile terminals, realizing mixed-reality collaborative interaction: learners scan target objects in real-world exploration scenarios via AR, and mobile terminals automatically overlay knowledge point information annotated by the group. Annotation data is synchronized in real time with other devices in the group via low-power Bluetooth. For potential conflicts arising from multiple simultaneous annotations, the previously mentioned lightweight distributed consensus algorithm ensures consistency in annotation permissions and content, guaranteeing the accuracy and collaboration of group interaction data, further extending the interaction dimension and depth of group learning in mobile scenarios. Figure 2 illustrates in detail the interaction sequence between mobile terminals and edge nodes in the two-phase "propose-confirm-submit" consensus mechanism, as well as the weight-based task allocation process.

3.4 Mobile data-driven group knowledge evolution graph construction module

The core function of the mobile data-driven group knowledge evolution graph construction module is to dynamically generate a group knowledge evolution graph based on mobile terminal interaction data and optimize resource recommendation and task scheduling through a closed-loop feedback mechanism. Its core innovations lie in lightweight structured processing of unstructured interaction data on mobile terminals, deep integration of knowledge graph embedding and multi-agent evolution simulation, and the design of a lightweight update and feedback mechanism adapted to mobile architectures. The module first completes the structured transformation of mobile terminal interaction data: for unstructured data such as discussion voice, image annotations, and note sharing, a lightweight automatic speech recognition (ASR) algorithm deployed on mobile terminals converts voice to text, extracts keyword tags from image annotations, and parses the relationship between note text and knowledge points. Finally, all data are uniformly transformed into standardized knowledge triples of "learner-knowledge point-interaction type," achieving structured integration of multi-source interaction data. The entire process is lightweight to ensure controllable energy consumption on mobile terminals.

On this basis, the TransE algorithm is used to achieve knowledge graph embedding, mapping high-dimensional knowledge points into a low-dimensional vector space to reduce computational complexity. The core innovation is the introduction of a multi-agent evolution simulation mechanism: each agent corresponds to a learner, and the knowledge transfer intensity between agents is quantified based on mobile terminal interaction frequency. By simulating knowledge interaction behaviors among agents, the association weights and topological structure of knowledge points in the graph are dynamically updated. When the group engages in high-frequency discussions and resource sharing around specific knowledge points, the corresponding association weights of those knowledge points are automatically increased, forming core nodes of group knowledge and achieving dynamic evolution of the graph, overcoming the limitation of traditional static knowledge graphs in depicting the group knowledge generation process. To adapt to mobile scenario resource constraints, the module adopts a lightweight graph update and feedback architecture: core graph update computations are deployed at edge nodes, while mobile terminals only synchronize a simplified version of the graph for local interaction reference, greatly reducing mobile terminal computing and communication overhead. At the same time, edge nodes extract graph evolution features, including newly added knowledge points, core association paths, and knowledge gaps, and provide real-time feedback to the cross-scenario learning path generation module and the decentralized collaborative scheduling module, achieving precise optimization of resource recommendation and dynamic adjustment of group collaborative knowledge coverage, forming a complete closed loop of "data collection-graph evolution-feedback optimization."

4 SYSTEM IMPLEMENTATION AND EXPERIMENTAL SETUP

The system prototype in this study was implemented based on the cloud-edge-mobile three-tier architecture. The development environment and technology stack were constructed to ensure mobile scenario adaptability and cross-layer collaboration efficiency: the mobile terminal was developed using the Flutter framework to support both Android and iOS platforms, with Dart as the programming language to ensure cross-platform consistency; edge node hardware adopted Raspberry Pi 4B running Ubuntu 22.04 LTS, with the lightweight swarm intelligence algorithm engine deployed via Python; the cloud layer was based on Alibaba Cloud ECS servers, using Java and the SpringBoot framework to build the global data processing and model training platform. Algorithm implementation relied on Python, with TensorFlow Lite enabling lightweight model deployment on mobile terminals, and the Scikit-learn library used for data clustering and fusion processing. At the communication layer, low-power Bluetooth 5.2 and 5G URLLC slicing were used to ensure low-latency direct connections between devices.

In the system prototype, the core module code focused on lightweight and real-time optimization. The mobile APP adopted a modular interface design, integrating core functional modules including data collection, interaction execution, and

AR visualization. Edge node deployment followed a scenario-based approach: in classroom scenarios, gateways were fixed at the center of classrooms to ensure signal coverage; in outdoor scenarios, solar-powered mobile edge nodes provided full-scenario support. Data transmission across layers used the JSON standardized format, and sensitive data on mobile terminals were encrypted with AES-128 before transmission to ensure data security. The experimental design aimed to verify system technical performance and learning collaboration effectiveness. Two hundred university students were selected as experimental subjects and randomly divided into an experimental class and a control class, each with 100 students. The experimental class used the system developed in this study, while the control class used traditional mobile learning APPs. Experimental scenarios covered typical contexts, including classroom theoretical courses, laboratory classes, extracurricular campus exploration, and off-campus museum practice. Additionally, network fluctuation environments simulating bandwidth switching from 1 to 100 Mbps and heterogeneous devices combining mid-range and low-end smartphones were included. By applying the controlled variable method and a controlled experimental design, the experimental results objectively reflected the comprehensive performance of the system in real mobile learning scenarios.

5 EXPERIMENTAL RESULTS AND ANALYSIS

5.1 Analysis of mobile technology performance test results

The mobile technology performance test focused on four core indicators: response latency, mobile terminal energy consumption, algorithm convergence speed, and stability under different network scenarios. By comparing the test data of this system with a traditional centralized mobile learning system, the effectiveness of the architecture design and algorithm optimization was verified. The specific test results are shown in Table 1.

Table 1. Comparison of mobile technology performance test results

Test Scenario	Test Indicator	This System	Control System	Difference
Normal Network Performance (50 Mbps)	Average Response Latency (ms)	82	141	Reduced 41.8%
	Peak Response Latency (ms)	156	289	Reduced 46.0%
	Mobile Terminal Average Energy Consumption (mAh/h)	128	186	Reduced 31.2%
	Improved PSO Algorithm Convergence Time (s)	3.2	4.3 (Traditional *PSO*)	Improved 25.6%
Low Bandwidth Environment (1–5 Mbps)	Task Completion Rate (%)	87.3	62.5	Improved 39.7%
	Data Transmission Success Rate (%)	95.1	81.3	Improved 17.0%
Heterogeneous Device Scenario	Mid-range Device Response Latency (ms)	78	135	Reduced 42.2%
	Low-end Device Response Latency (ms)	115	198	Reduced 41.9%
	Low-end Device Energy Consumption (mAh/h)	142	203	Reduced 30.0%

As shown in Table 1, the technical performance of this system is significantly superior to the control system in all test scenarios. In terms of response latency, under normal network conditions, the average response latency of this system is only 82 ms, 41.8% lower than that of the control system, and the peak latency is reduced by 46.0%. This result stems from the optimized design of the distributed architecture: local collaborative computing between edge nodes and mobile terminals reduces transmission latency from cloud remote interactions, and direct communication through 5G URLLC slicing and low-power Bluetooth 5.2 further shortens data transmission time between devices. Regarding mobile terminal energy consumption, the average energy consumption of this system is 31.2% lower than that of the control system, and low-end device energy consumption is reduced by 30.0%. The core reason is lightweight algorithm processing and hierarchical allocation of computing tasks: model quantization and pruning reduce the computational complexity on mobile terminals, while large-scale computing tasks are deployed to edge nodes and the cloud, leaving only lightweight interaction execution tasks on mobile terminals, effectively reducing device computation power consumption. For algorithm convergence performance, the convergence time of the improved PSO algorithm is 25.6% shorter than that of the traditional PSO algorithm. The introduction of the dynamic inertia weight mechanism accelerates the convergence speed of clustering processes, improving the real-time update efficiency of dynamic learner profiles. In terms of network adaptability, under low bandwidth scenarios, the task completion rate of this system remains 87.3%, significantly higher than 62.5% of the control system. This is attributed to local data caching at edge nodes and lightweight data transmission strategies, which reduce data transmission pressure in low-bandwidth environments and ensure system stability. Corresponding to the data in Table 1, Figure 3 shows the convergence performance comparison of the improved PSO algorithm and traditional PSO algorithm for clustering tasks on the mobile terminal. The horizontal axis represents iteration number, and the vertical axis represents fitness value, intuitively demonstrating the convergence speed advantage of the improved algorithm with dynamic inertia weight.

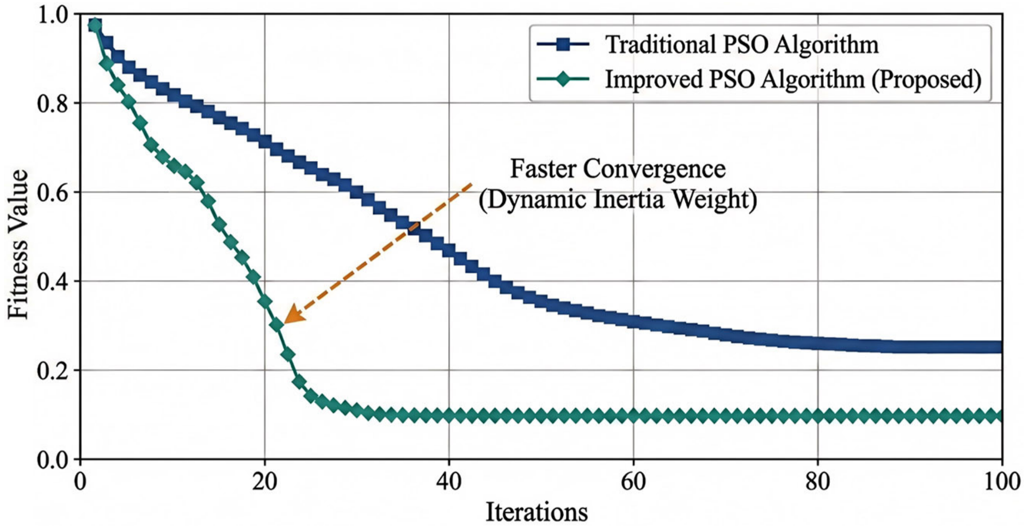

Fig. 3. Convergence performance comparison of improved PSO algorithm and traditional PSO algorithm in mobile terminal clustering tasks

5.2 Analysis of learning collaboration effectiveness test results

The learning collaboration effectiveness test verified the value of this system in cross-scenario learning adaptation, group collaboration optimization, and learning resilience improvement by comparing core indicators between the experimental class and the control class. The test results are shown in Table 2. At the same time, mobile terminal interaction logs and in-depth learner interview data were combined to analyze the impact of the swarm intelligence and mobile interaction collaboration mechanism on learning behaviors.

Table 2. Comparison of learning collaboration effectiveness test results

Evaluation Dimension	Test Indicator	Experimental Class	Control Class	Difference
Learning Task Performance	Cross-Scenario Learning Task Completion Rate (%)	92.6	69.8	Improved 32.7%
	Collaborative Report Average Score (out of 100)	85.3	72.6	Improved 17.5%
	Average Completion Time for Group Tasks (min)	48.2	65.7	Reduced 26.6%
	Knowledge Point Coverage Completeness (%)	91.5	76.2	Improved 20.1%
User Participation and Collaboration	Learner Active Participation Rate (%)	89.4	67.3	Improved 32.8%
	Group Discussion Interaction Frequency (times/task)	18.3	10.5	Improved 74.3%
System Reliability	Fault Recovery Time (s)	28	59	Reduced 52.5%

As shown in Table 2, the experimental class significantly outperformed the control class across all collaboration effectiveness indicators. In terms of cross-scenario learning adaptation, the experimental class achieved a task completion rate of 92.6%, 32.7% higher than the control class. This is closely related to the precise path planning of the hybrid swarm intelligence recommendation engine—the system generated personalized paths combining group learning patterns and geographic location, achieving seamless connection between classroom knowledge and extracurricular practice. Mobile terminal interaction logs showed that learners in the experimental class improved knowledge point matching in extracurricular practice by 23.4% compared with the control class. Group collaboration quality improved significantly: the collaborative report scores of the experimental class increased by 17.5% compared to the control class, and task completion time decreased by 26.6%. The decentralized collaborative scheduling mechanism achieved precise matching between tasks, learner capability, and device status through multimodal context-aware perception. In interviews, 83.2% of learners in the experimental class reported more reasonable group role assignment and significantly improved collaboration efficiency. Regarding group learning resilience, the fault recovery time of the experimental class was 52.5% shorter than that of the control class. The fault tolerance of the lightweight distributed consensus algorithm and the auxiliary verification function of the edge nodes ensured collaborative continuity in cases of network interruption or device failure. Furthermore, learner active participation rate and group discussion interaction frequency increased by 32.8% and 74.3%, respectively. Mobile AR enhanced interaction and feedback optimization from the group knowledge evolution graph, enhancing the fun and targeting of the learning process and stimulating learner engagement. Mobile terminal interaction logs indicated that learners in the experimental class used collaborative annotation and resource sharing functions significantly more frequently than those in the control class. Corresponding to the data in Table 2, Figure 4 shows a comparative analysis of the core indicators of learning collaboration effectiveness between the experimental class and the control class. Multiple dimensions, including task completion rate, collaborative report score, active participation rate, and knowledge point coverage, are plotted as a radar chart to visually present the comprehensive advantages of the experimental class.

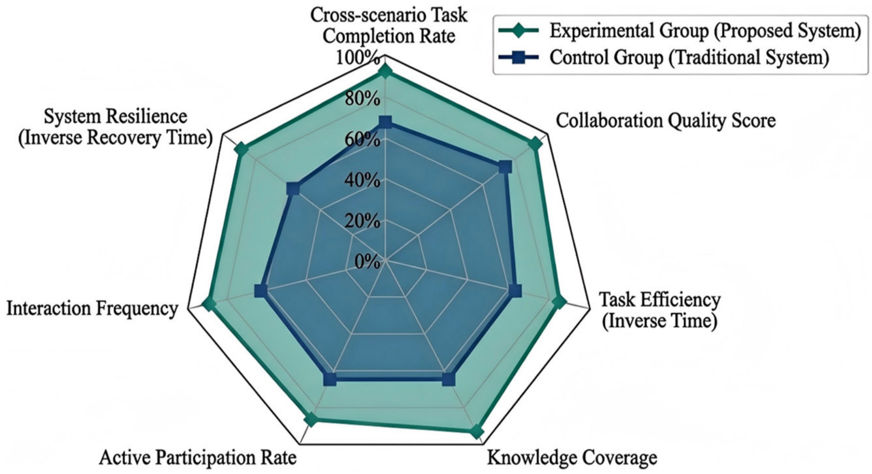

Fig. 4. Comparative analysis of core indicators of learning collaboration effectiveness between experimental class and control class

5.3 Discussion of system limitations

Although this system performed well in technical performance and learning collaboration effectiveness, three limitations were identified during the experiment. First, lightweight algorithms on mobile terminals still have room for optimization, and the operational efficiency on low-end devices needs improvement. As shown in Table 1, under low-end devices, the response latency of this system was 41.9% lower than the control system but still 47.4% higher than that of mid-range devices. Model quantization and pruning techniques could not fully adapt to the hardware constraints of low-end devices, and algorithm fluency slightly decreased under complex scenarios. Second, multimodal data collection presents privacy protection risks. In post-experiment interviews, 31.5% of learners expressed concerns about the security of sensitive data such as location and voice. Although the existing AES-128 encryption ensures transmission security, data collection authorization procedures and local data storage encryption need further improvement to enhance user trust. Third, the coverage of experimental scenarios was limited, and adaptability to complex outdoor environments was not fully validated. The experiment primarily covered campus and typical museum scenarios and did not involve environments with strong electromagnetic interference or extreme weather. Wireless communication stability, device endurance, and AR recognition accuracy in such scenarios require further experimental verification. These limitations provide directions for future research and will become the core focus for iterative improvements of the system.

6 CONCLUSION AND FUTURE WORK

This study focused on the core requirements of classroom-extracurricular integrated learning and successfully constructed a digital learning ecosystem that integrates swarm intelligence with mobile interaction collaboration mechanisms. The system addressed key issues in existing learning systems, including fragmented mobile interaction collaboration, inaccurate perception of group learning, and insufficient dynamic adaptation of resources. The core research outcomes are reflected in three aspects: First, a cloud-edge-mobile three-tier distributed architecture was proposed, achieving deep adaptation of swarm intelligence to mobile scenarios. Second, four core innovative modules were developed: the mobile-adaptive dynamic learner profiling module, the hybrid swarm intelligence cross-scenario learning path generation module, the decentralized collaborative scheduling module, and the group knowledge evolution graph construction module. Together, these modules form a complete technical system covering data collection, intelligent decision-making, collaborative execution, and feedback optimization. Third, an integrated evaluation system covering mobile technology performance and learning collaboration effectiveness was established.

Based on the current research results, future work will be further expanded in four directions: First, further optimize the lightweight degree of mobile terminal algorithms and introduce federated learning technology to achieve privacy protection and collaborative training of swarm intelligence models, addressing the privacy and security risks of multimodal data collection. Second, expand the application dimensions of multimodal sensing technologies by integrating biosensor data such as eye-tracking and electroencephalography (EEG), and combine these with dynamic learner profiles to improve the accuracy of perceiving learners' cognitive states. Third, conduct long-term field experiments, extending experimental scenarios to complex outdoor environments with strong electromagnetic interference and extreme weather, to verify the system's scalability and environmental adaptability. Finally, explore the deep integration of large AI models and mobile swarm intelligence. By leveraging the natural language understanding and knowledge modeling capabilities of large models, the system's natural interaction experience and intelligent decision-making in complex scenarios can be enhanced, promoting the evolution of the mobile learning ecosystem toward higher intelligence and greater personalization.

7 ACKNOWLEDGMENT

This paper was supported by the 2024 Henan Provincial Higher Education Teaching Reform Research and Practice Project—Exploration and Practice of Online and Offline Blended Teaching Based on Improved BOPPPS (Grant No.: 2024SJGLX0723).

8 REFERENCES

[1] J. Albert Mayan, S. V. Manikanthan, A. Hussain, S. Nithyaselvakumari, and A. Vinnarasi, "Clustering technique for mobile edge computing to detect clumps in transportation-related problems," *International Journal of Interactive Mobile Technologies*, vol. 17, no. 4, pp. 47–63, 2023. https://doi.org/10.3991/ijim.v17i04.37801

[2] N. Vijayalakshmi, S. Gulati, B. Ben Sujin, B. Madhav Rao, and K. Kiran Kumar, "Deep reinforcement learning based secure transmission for UAV-assisted mobile edge computing," *International Journal of Interactive Mobile Technologies*, vol. 18, no. 17, pp. 154–169, 2024. https://doi.org/10.3991/ijim.v18i17.50729

[3] A. Peramunugamage, U. W. Ratnayake, and S. P. Karunanayaka, "Systematic review on mobile collaborative learning for engineering education," *Journal of Computers in Education*, vol. 10, no. 1, pp. 83–106, 2023. https://doi.org/10.1007/s40692-022-00223-1

[4] M. Milrad, L. H. Wong, and H. Ogata, "Seamless learning: An international perspective on next-generation technology-enhanced learning," in *Handbook of Mobile Learning*, 2013, pp. 95–108.

[5] P. Pornpongtechavanich and P. Wannapiroon, "Intelligent interactive learning platform for seamless learning ecosystem to enhance digital citizenship's lifelong learning," *International Journal of Emerging Technologies in Learning*, vol. 16, no. 14, pp. 232–248, 2021. https://doi.org/10.3991/ijet.v16i14.22675

[6] C. H. Peng, W. X. Gu, and L. P. Jiang, "Effects of mobile-assisted language learning (MALL)-delivered explicit metacognitive intervention on Chinese EFL students' receptive skills and metacognitive awareness," *Journal of Computer Assisted Learning*, vol. 41, no. 5, p. e70125, 2025. https://doi.org/10.1111/jcal.70125

[7] Q. Zhou, W. Suraworachet, and M. Cukurova, "Detecting non-verbal speech and gaze behaviours with multimodal data and computer vision to interpret effective collaborative learning interactions," *Education and Information Technologies*, vol. 29, no. 1, pp. 1071–1098, 2024. https://doi.org/10.1007/s10639-023-12315-1

[8] P. Arnau-González, S. Solera-Monforte, Y. Wu, and M. Arevalillo-Herráez, "A framework for adapting conversational intelligent tutoring systems to enable collaborative learning," *Expert Systems with Applications*, vol. 271, p. 126663, 2025. https://doi.org/10.1016/j.eswa.2025.126663

[9] M. E. B. Menai, H. Alhunitah, and H. Al-Salman, "Swarm intelligence to solve the curriculum sequencing problem," *Computer Applications in Engineering Education*, vol. 26, no. 5, pp. 1393–1404, 2018. https://doi.org/10.1002/cae.22046

[10] B. A. Abdulghani and M. A. Abdulghani, "A comprehensive review of ant colony optimization in swarm intelligence for complex problem solving," *Acadlore Transactions on AI and Machine Learning*, vol. 3, no. 4, pp. 214–224, 2024. https://doi.org/10.56578/ataiml030403

[11] M. C. Pichiliani and C. M. Hirata, "Adaptation of single-user multi-touch components to support synchronous mobile collaboration," *Mobile Networks and Applications*, vol. 19, no. 5, pp. 660–679, 2014. https://doi.org/10.1007/s11036-014-0512-0

[12] F. Johannsen *et al.*, "What impacts learning effectiveness of a mobile learning app focused on first-year students?" *Information Systems and e-Business Management*, vol. 21, no. 3, pp. 629–673, 2023. https://doi.org/10.1007/s10257-023-00644-0

[13] M. N. Giannakos, S. Lee-Cultura, and K. Sharma, "Sensing-based analytics in education: The rise of multimodal data enabled learning systems," *IT Professional*, vol. 23, no. 6, pp. 31–38, 2021. https://doi.org/10.1109/MITP.2021.3089659

[14] Y. Huang and F. J. Wu, "CRISIS: Cyber-physical social distancing based on multi-modal data from mobile devices," *IEEE Transactions on Mobile Computing*, vol. 22, no. 5, pp. 2551–2568, 2021. https://doi.org/10.1109/TMC.2021.3126604

[15] B. L. Johansson *et al*., "Preparation and characterization of prototypes for multi-modal separation media aimed for capture of negatively charged biomolecules at high salt conditions," *Journal of Chromatography A*, vol. 1016, no. 1, pp. 21–33, 2003. https://doi.org/10.1016/S0021-9673(03)01140-3

[16] Z. Jin, M. Yao, and D. Tao, "Implicit authentication with sensor normalization and multi-modal domain adaption based on mobile crowd sensing," *CCF Transactions on Pervasive Computing and Interaction*, vol. 4, no. 4, pp. 370–380, 2022. https://doi.org/10.1007/s42486-022-00117-2

9 AUTHORS

Junju Sun obtained her Bachelor's degree in Computer Science and Technology from Henan University in 2004 and her Master's degree in Computer Science and Technology from Wuhan University of Technology in 2013. Since 2004, she has been serving as a teacher at the School of Information and Communication Engineering, Xinyang Vocational and Technical College, with her current professional title being Associate Professor. She has participated in the compilation of three textbooks and independently/co-authored more than 10 papers on computer-related teaching and research. She is a research expert in the fields of computer-assisted case teaching method application, digital media technology application, as well as artificial intelligence and recommendation systems (E-mail: sunjunju@xyvtc.edu.cn).

Yan Mei obtained a Bachelor's degree in Computer Science and Technology from Zhejiang University of Finance and Economics in 2019, and a Master's degree in Applied Statistics from Guilin University of Electronic Science and Technology in 2021. Starting from 2023, she is working as a Teaching Assistant in the School of Information and Communication Engineering at Xinyang Vocational and Technical College. She has independently/collaboratively has written two academic papers on the application of computer technology. Her main research areas include computer technology applications, data analysis and statistics, and artificial intelligence (E-mail: meiyan@xyvtc.edu.cn).