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PAPER

Analysis and Intervention Mechanism for Learning Behaviors of Higher Vocational Students in Mobile Learning Environments

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ABSTRACT

With the rapid digital transformation of higher vocational education, mobile learning has become a key means of addressing the limitations of traditional instruction and supporting fragmented, career-oriented learning. However, issues such as low engagement, weak persistence, and fragmented behavioral patterns continue to hinder instructional quality. Existing research often relies on static or single-dimension analyses, lacking quantitative tools to capture the dynamic processes of information diffusion, group imitation, and behavioral evolution. This gap has hindered the theoretical precision required for designing effective intervention mechanisms. To address this deficiency, an evolutionary game model was constructed that integrates the topological features of mobile interaction networks with information diffusion rules to analyze the mechanisms and determinants of learner behavior. Based on model equilibrium analyses, a targeted multidimensional intervention mechanism was proposed, including payoff-matrix optimization, structural adjustment of networks, initial-strategy guidance, and dynamic adaptive regulation. The model shifts research from static description to dynamic quantitative prediction and broadens the application boundary of the evolutionary game theory in educational technology research. In addition, it offers practical strategies for improving mobile learning management and instructional quality in higher vocational institutions. The findings offer substantive academic value and practical significance.

KEYWORDS

mobile learning, higher vocational students, learning behavior analysis, evolutionary game model, mobile interaction network, intervention mechanism

1 INTRODUCTION

The global shift toward digital transformation in education has accelerated the adoption of mobile learning within higher vocational education, which serves

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as a primary channel for cultivating technically skilled talent [1, 2]. Owing to its ubiquitous accessibility, interactive features, and support for fragmented learning, mobile learning has been well aligned with the career-oriented and practice-driven training objectives of higher vocational institutions. Its capacity to transcend the temporal and spatial constraints of traditional classrooms has enabled students to engage in skill acquisition and knowledge reinforcement anytime and anywhere. As a result, mobile learning has been widely implemented in professional training, after-class tutoring, and skill-extension activities within vocational colleges [3–5] and has become a critical driver of instructional quality enhancement. However, a significant mismatch has been observed between the learning characteristics of higher vocational students and the inherent properties of mobile learning environments. More importantly, the mobile learning behaviors of these students are highly dependent on mobile interaction networks such as social platforms and learning communities [6, 7]. High-quality learning resources, positive learning attitudes, and effective learning strategies tend to diffuse rapidly through these networks, whereas negative learning behaviors may also propagate through group imitation, generating diffusion effects. Consequently, the topological characteristics of mobile interaction networks and the rules governing information diffusion have emerged as key external determinants that shape students' learning-strategy selection. Their role in driving the evolution of learning behaviors requires deeper investigation.

Although numerous studies have examined the mobile learning behaviors of higher vocational students, three critical gaps remain unaddressed. First, at the level of behavioral analysis, existing research has predominantly relied on static descriptive statistics or regression analyses focusing on isolated influencing factors, without adequately accounting for the dynamic nature of mobile interaction networks. As a result, the underlying mechanisms governing the continuous process of information diffusion–strategy imitation–group behavioral evolution have not been fully revealed, limiting the ability to explain how collective learning behaviors emerge and evolve [8–10]. Second, at the methodological level, evolutionary game theory—an effective tool for analyzing strategy evolution among bounded-rationality groups—has been widely applied across various social science domains, yet its use in education has lacked contextual adaptation. Many existing studies have directly applied generic evolutionary game models without incorporating the scale-free topological characteristics of mobile interaction networks, the rules of information diffusion, or the behavioral specificities of higher vocational students. Such limitations have reduced the explanatory and predictive capabilities of these models [11–13]. Third, at the level of intervention design, existing interventions have largely taken the form of qualitative, experience-based strategies that lack support from quantitative modeling. Consequently, these interventions have been unable to precisely target the core determinants of learning behavior or dynamically adjust to evolving behavioral patterns in mobile learning environments, often resulting in limited effectiveness [14–16].

The core objective of this study is to construct a mobile interaction network–based information diffusion evolutionary game model tailored to mobile learning environments in higher vocational education, aiming to quantitatively analyze the evolutionary mechanisms and key determinants of mobile learning behaviors among higher vocational students and to design a scientifically grounded and operational targeted intervention mechanism whose effectiveness is empirically validated. The academic contributions of this study are reflected in three primary dimensions. First, methodological innovation in modeling is achieved by integrating the topological characteristics of mobile interaction networks and their information diffusion rules into an evolutionary game model for the first time, thereby establishing a dedicated quantitative analytical framework for the mobile learning behaviors of higher vocational students. This integration overcomes the limitations of conventional static analyses and enhances both the dynamism and precision with which behavioral evolution patterns are revealed. Second, innovation in research methodology is demonstrated through the proposal of a closed-loop research paradigm encompassing modeling, analysis, intervention, and validation. This paradigm systematically links model derivation, factor analysis, mechanism design, and empirical verification, providing full-process quantitative support from the identification of behavioral evolution mechanisms to the implementation of intervention strategies and offering a methodological reference for related research domains. Third, innovation in practical application is realized through the development of a multidimensional intervention mechanism informed by model equilibrium analyses. This mechanism includes payoff-matrix optimization, structural adjustment of networks, initial-strategy guidance, and dynamic adaptive regulation, addressing the limited precision and insufficient dynamism that characterize existing intervention approaches. These strategies offer actionable solutions for higher vocational institutions seeking to optimize mobile learning management and enhance instructional quality.

The overall structure of this study is organized below. Section 2 presents the model construction, detailing the assumptions, variable definitions, payoff-matrix formulation, and replicator dynamic equation derivation underlying the mobile interaction network-based information diffusion evolutionary game model, thereby establishing the theoretical foundation for subsequent analyses. Section 3 focuses on behavioral analysis and intervention mechanism design, identifying key determinants of learning-behavior evolution based on model results, articulating the principles guiding intervention design, and proposing four core intervention strategies. Section 4 reports the experimental results and analyses, in which a quasi-experimental design is employed to validate the model's effectiveness and assess the practical impact of the intervention mechanism, including quantitative evaluation of improvements in learning behaviors and learning outcomes. Section 5 provides the conclusion, summarizing the main findings, academic contributions, and practical significance of the study, while also acknowledging its limitations and outlining directions for future research.

2 MODEL CONSTRUCTION: EVOLUTIONARY GAME MODEL OF INFORMATION DIFFUSION IN MOBILE INTERACTION NETWORKS

2.1 Model assumptions

The construction of the model is grounded in the behavioral characteristics of mobile learning among higher vocational students and integrates the core logic of evolutionary game theory and network diffusion theory. Four key assumptions were established. At the participant level, higher vocational students are conceptualized as bounded-rational individuals whose learning decisions are shaped by personal cognition, peer interaction, and contextual factors rather than by fully rational optimization. Accordingly, students are categorized into two strategy groups—active learning and passive learning. The total population size is assumed to be fixed, and individuals are allowed to switch strategies based on dynamic comparisons between learning benefits and associated costs. At the mobile interaction network level, the platforms commonly used by higher vocational students—such as learning communities and social networking applications—are assumed to form a scale-free network, in which a limited number of core nodes exhibit high connectivity. Nodes represent individual students, while edge weights are determined jointly by interaction frequency and interaction intensity. At the strategy payoff level, active learning is assumed to require direct investment of time and effort and to yield direct benefits such as improvements in knowledge and skills, academic credit incentives, and additional gains derived from high-quality learning information transmitted through the mobile interaction network as well as peer recognition. Passive learning, in contrast, involves no direct investment but incurs implicit opportunity costs, including academic underperformance and heightened assessment risks. At the information diffusion level, learning-related information is assumed to diffuse through the mobile interaction network with transmission probabilities positively associated with node activity and interaction intensity. Core nodes exert a significantly stronger influence on information diffusion than peripheral nodes.

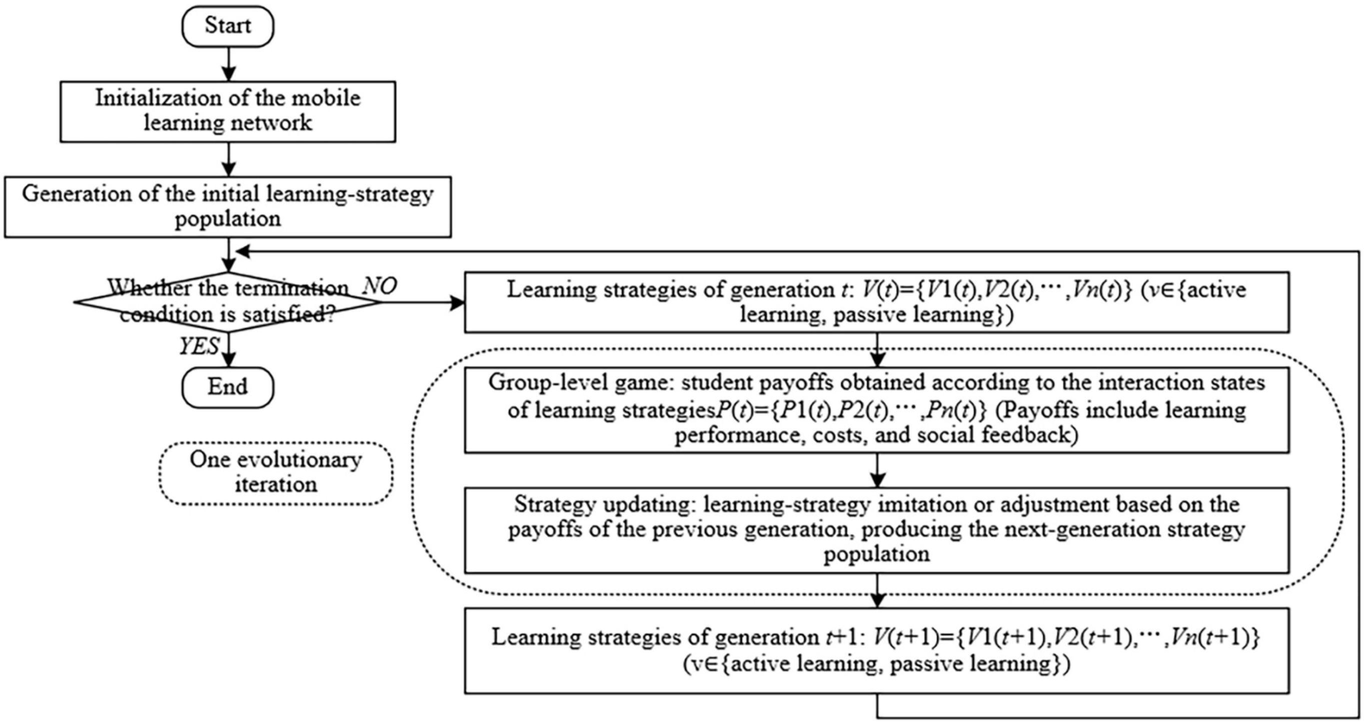


Fig. 1. Flowchart of the evolutionary game model for mobile learning behaviors of higher vocational students

Figure 1 provides an intuitive illustration of the evolutionary and diffusion logic that governs learning-strategy dynamics. The figure depicts the complete evolutionary process from initialization of the mobile learning network and formation of initial strategy groups to calculation of learning payoffs through group-level evolutionary games, strategy updating and iteration, and finally termination-condition assessment. This process captures the dynamic convergence trajectory through which learning-strategy groups evolve within mobile interaction networks.

2.2 Variable definitions and payoff matrix construction

To quantitatively characterize the relationships among the core elements of the model, key variables were defined according to their functional attributes, ensuring both contextual relevance to mobile learning scenarios in higher vocational education and internal logical consistency. Network parameters include the average interaction frequency of nodes, the structural cohesion of the network, and the success rate of information diffusion. Benefit–cost parameters include the direct benefit of active learning (R), the direct cost of active learning (C), the additional benefit derived from information diffusion (R_n), and the implicit cost associated with passive learning (C_n). The core evolutionary parameters consist of the proportion of individuals adopting the active-learning strategy (x) and evolutionary time (t). All variables are symbolically represented in a unified manner to ensure continuity in subsequent analyses.

The payoff matrix serves as the quantitative foundation for evaluating the net benefits associated with the two learning strategies under various interaction scenarios. Its construction strictly follows the assumptions and variable definitions established earlier, thereby providing a structured analytical basis for examining the evolution of group learning behaviors. When both interacting individuals adopt the active-learning strategy, each receives full direct benefits and the additional information-diffusion benefit while bearing the corresponding direct cost. The associated payoff function is $U_{11} = R + R_n - C$. When an active-learning individual interacts with a passive-learning individual, the active-learning participant obtains only the direct benefit and bears the direct cost, resulting in $U_{10} = R - C$. The passive-learning participant incurs no direct cost but bears the implicit opportunity cost, yielding $U_{01} = -C_n$. When both individuals adopt the passive-learning strategy, neither direct benefits nor direct costs are incurred, and both parties bear the implicit cost, expressed as $U_{00} = -C_n$. Based on these four strategy-combination payoff structures, a systematic payoff framework was established, clearly delineating the benefit differentials between active and passive learning across interaction scenarios. This framework provides the essential foundation for deriving the replicator dynamic equations used in subsequent evolutionary analyses.

Figure 2 illustrates the operational logic of the evolutionary game adopted in this study and presents five diffusion patterns through which the active-learning strategy evolves within the mobile interaction network. In the figure, S denotes passive-learning individuals, I denotes active-learning individuals, R represents stabilized active-learning individuals, and E represents hesitant-learning individuals. The parameters include the active-learning adoption rate (β), the active-learning stabilization rate (γ), the strategy-regression rate (α), and the hesitation-to-active transition rate (σ). These parameters collectively depict the dynamic transitions among passive learning, active learning, and learning hesitation, providing an intuitive diffusion logic to support the evolutionary game analysis of learning behaviors.

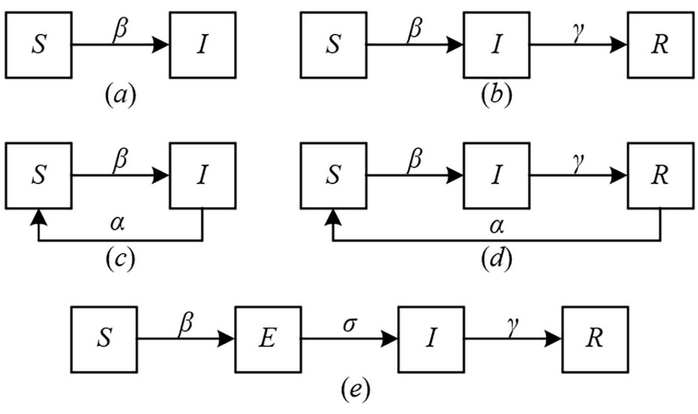


Fig. 2. Evolutionary diffusion mechanism of mobile learning behaviors among higher vocational students

2.3 Derivation of the replicator dynamic equations

The derivation of the replicator dynamic equations begins with the computation of the expected payoffs associated with the active-learning and passive-learning strategies, based on the payoff rules defined in the payoff matrix. The overall average payoff of the population is then obtained through a weighted summation of the two expected payoffs, and this average payoff serves as the benchmark for adjusting the proportion of strategies within the population. Following the fundamental principle of evolutionary game theory—that a strategy whose payoff exceeds the population average increases in frequency over time—the replicator dynamic equation for the proportion of active-learning individuals (x) is formulated as $dx/dt = x(U_1 - U)$, where U_1 denotes the expected payoff of the active-learning strategy and U denotes the population average payoff. By substituting the payoff functions defined earlier and simplifying, the final evolutionary equation $dx/dt = x(1 - x)\ [R - C + xR_n + (x - 1)\ C_n]$ is obtained. This equation clearly characterizes the evolutionary dynamics of mobile learning behaviors among higher vocational students. The evolutionary rate dx/dt is directly determined by the benefit–cost differential of active learning, the additional benefit generated through information diffusion, and the implicit cost associated with passive learning. Setting the evolutionary rate to zero yields the potential equilibrium points of the model, with $x_0 = 0$ representing a fully passive-learning population, $x_1 = 1$ representing a fully active-learning population, and $x_2 = R_n + C_nC - R + C_n$ representing a mixed-strategy equilibrium, which exists when $x_2 \in [0, 1]$. These equilibrium points provide the core quantitative basis for analyzing the stability of learning behaviors.

3 BEHAVIOR ANALYSIS AND INTERVENTION MECHANISM DESIGN

3.1 Analysis of key influencing factors based on the model

Based on the replicator dynamic equations and equilibrium stability analysis derived from the evolutionary game model of information diffusion in mobile interaction networks, four categories of core variables were identified as determinants of the evolutionary dynamics of mobile learning behaviors among higher vocational students. These variables are mutually coupled, jointly shaping the direction of group evolution. At the network-parameter level, the network cohesion ρ and the information-diffusion success rate p influence the additional information-diffusion benefit R_n in a positive manner. Higher values of ρ indicate stronger interaction frequency and interaction depth among students, enabling high-quality learning information to diffuse across a broader range. A larger p reflects higher efficiency in effective information transmission. Together, these factors increase the overall payoff obtained from the active-learning strategy, thereby enlarging the evolutionary rate dx/dt in the replicator dynamic equations and driving the population toward the evolutionarily stable strategy of full active learning.

The benefit–cost ratio R/C functions as a critical threshold parameter determining the evolutionary trajectory. Based on the equilibrium solutions, when the ratio of direct benefit R to direct cost C exceeds 1, active learning yields a higher expected payoff than passive learning even in the absence of the additional benefit, making $x = 1$ the only stable equilibrium. Conversely, when $R/C < 1$ and R_n is insufficient, the population tends to converge toward full passive learning. The implicit cost of passive learning C_n acts as a key regulatory factor. Increases in C_n substantially reduce the instability interval surrounding the mixed-strategy equilibrium point x_2, thereby lowering the likelihood of the population evolving toward passive learning.

That is, a higher C_n reflects stronger perceived risks of academic underperformance or assessment failure. Even when R/C is near the critical threshold, an increase in the opportunity cost of passive learning promotes an upward shift in x. The impact of the initial proportion of active-learning individuals exhibits threshold dependence. When x_0 exceeds x_2, the population evolves toward $x = 1$. When $x_0 < x_2$, the system is more likely to converge to the stable equilibrium $x = 0$. This pattern provides a clear quantitative basis for designing initial-guidance interventions.

3.2 Principles for designing the intervention mechanism

The design of the intervention mechanism is guided strictly by the behavioral evolutionary patterns revealed through the model, with careful consideration of theoretical rigor and practical feasibility. Four core principles were established. The principle of targeted intervention emphasizes precise alignment with the core parameters and key influencing factors identified in the model, thereby avoiding generalized or unfocused measures. Optimization of the mobile interaction network structure is directed toward the network parameters ρ and p; adjustments to benefit–cost configurations are aligned with the benefit–cost ratio R/C; enhancements to process-based constraints are associated with the implicit cost C_n; and initial-guidance interventions are linked to the initial proportion x_0. These targeted actions ensure that each intervention directly influences key variables in the evolutionary equation, thereby enhancing overall intervention effectiveness. The principle of dynamic adaptation highlights alignment with the evolving nature of learning behaviors. Indicators such as temporal changes in x, learning duration, and interaction frequency—captured in real time through mobile learning platforms—are combined with model-based simulation forecasts to anticipate evolutionary trajectories.

When reductions in x are detected, incentive mechanisms or the intensity of network interactions are strengthened immediately; when x stabilizes at a high level, intervention intensity is appropriately reduced to control implementation costs. This approach forms a "monitoring–prediction–adjustment" closed-loop regulatory mechanism. The principle of feasibility requires that the intervention measures be compatible with the instructional context of higher vocational education. Existing mobile learning platforms, pedagogical management systems, and faculty resources are utilized to avoid implementation barriers arising from complex technologies or excessive financial investment. For instance, enhancing information-diffusion efficiency through optimization of existing platform functionalities is favored over developing entirely new systems; integrating intervention measures into routine instructional assessments reduces additional burdens on both instructors and students. The principle of synergistic coordination stresses the integration of multidimensional resources to generate collective intervention effects. Technical and managerial components are jointly considered, while group-level guidance is combined with individual-level incentives. This coordinated approach mitigates the limitations of single-dimensional interventions and enables multi-pathway reinforcement that drives the evolution of learning behaviors toward a stable and active state.

3.3 Core intervention strategies

Building on the evolutionary patterns revealed by the model and guided by the principles of targetedness, dynamic adaptation, feasibility, and synergistic coordination, a multi-dimensional and closed-loop system of core intervention strategies was established. Rather than consisting of isolated or additive measures, this system integrates payoff-matrix optimization, mobile interaction network optimization, initial-strategy guidance, and dynamic monitoring with adaptive adjustment. These components operate synergistically to regulate key model parameters and steer group learning behaviors toward a stable evolutionary equilibrium characterized by active learning. The system ultimately addresses fundamental challenges such as low participation and weak persistence in mobile learning, providing a practical pathway for improving the quality of mobile education in higher vocational institutions.

The central objective of payoff-matrix optimization is to adjust the direct benefit of active learning (R), the direct cost (C), and the implicit cost of passive learning (C_n) to maximize the expected advantage of the active-learning strategy, thereby promoting convergence toward a stable equilibrium. The core payoff function for interactions between two active-learning individuals is $U_{11} = R + R_n - C$, which encapsulates the fundamental balance between benefits and costs. Accordingly, intervention measures are designed along three axes: enhancing R, reducing C, and increasing C_n. To enhance R, a three-tier incentive system linking learning outcomes, academic credit recognition, and professional certification was constructed. Mobile learning achievements were incorporated into course-credit allocation and vocational qualification assessments, while microlearning resources were enriched with practical and task-oriented content to strengthen perceived utility. To reduce C, platform operation processes were streamlined, personalized learning resources were recommended based on learner profiles, and flexible learning time windows were introduced to reduce time burdens and search costs. To increase C_n, a process-oriented assessment framework was implemented, incorporating community-based disclosure mechanisms and peer evaluation to strengthen collective oversight. These measures made the implicit losses associated with passive learning more salient. Together, the three dimensions collectively optimized the payoff structure of U_{11}.

The optimization of the mobile interaction network focuses on enhancing network cohesion ρ and the information-diffusion success rate p. By strengthening their positive effect on the additional information-diffusion benefit R_n, the evolutionary pace of the population is accelerated. As R_n is an increasing function of ρ and p—that is, $R_n = f(\rho, p)$, with positive partial derivatives—improvements in these parameters act directly on the core replicator dynamic equation $dx/dt = x(1 - x)[R - C + xR_n + (x - 1) C_n]$, increasing the evolutionary rate toward a higher proportion of active-learning individuals. Operationally, "1 + N" learning communities were formed with instructors and exemplary students serving as core nodes to elevate ρ through online discussions and collaborative tasks. High-activity nodes on the platform were identified, trained, and certified as "learning-diffusion agents," leveraging the scale-free network structure to expand the spread of positive learning behaviors. Additional platform features—such as learning-activity sharing and real-time interaction modules—were incorporated to lower the threshold for information diffusion and increase p. The combined optimization of ρ and p maximized the contribution of R_n to the evolutionary dynamics.

The initial-strategy guidance intervention aims to ensure that the initial proportion of active-learning individuals (x_0) surpasses the mixed-strategy equilibrium threshold (x_2), establishing the foundation for the population to evolve toward active learning. According to the evolutionary rules, the population converges to the full active-learning equilibrium when $x_0 > x_2$, whereas it tends toward passive learning when $x_0 < x_2$. Interventions are therefore designed around surpassing the threshold x_2. Targeted training programs for new students were implemented to highlight the value of R through concrete demonstrations of mobile learning outcomes. A senior-student mentoring mechanism lowered initial participation barriers. Short-term activities—such as skill-check tasks and knowledge-challenge modules—were introduced at key academic stages (e.g., semester opening and mid-term), supplemented with thematic lectures and exemplary case sharing. These measures rapidly raised x_0, ensuring that it crosses the critical threshold x_2 and thereby directing the evolutionary trajectory toward active learning.

The dynamic monitoring and adaptive adjustment mechanism establishes a closed-loop process of data collection, trend prediction, and strategy adjustment. Its core function relies on real-time computation of the evolutionary rate $dx/dt|_{x=xt} = x_t(1-x_t)\,[R_t - C_t + x_t R_{n,t} + (x_t - 1)\,C_{n,t}]$, with early-warning thresholds set at $x_{low} = 0.7$ and $x_{high} = 0.8$. Logs from the mobile learning platform, along with interaction and evaluation data, are integrated to collect real-time values of x_t, R_t, ρ_t, and other core parameters, which are then substituted into the evolutionary-rate equation to predict behavioral trends. When $x_t < x_{low}$ and $dx/dt < 0$, reinforcement interventions are activated. When $x_t \in [x_{low}, x_{high}]$ and the evolutionary rate stabilizes near zero, baseline interventions are maintained. Interventions are dynamically adjusted across different student subgroups to accommodate heterogeneous evolutionary patterns, ensuring that the population remains stably aligned with the evolutionarily stable strategy of active learning.

4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Calibration of core model parameters, fitting performance, and sensitivity analysis

Core Parameter/ Indicator	Parameter/ Indicator Value	Basis in Real-World Scenario	Sensitivity Analysis (Fitting Error after ±10% Parameter Variation)
Network cohesion	0.68	Interaction statistics from learning communities in three vocational colleges	1.2%
Information-diffusion success rate	0.72	Platform data on resource sharing, reception, and application conversion	0.9%
Direct benefit of active learning	8.2	Quantified scoring of credit incentives and vocational-certification benefits	0.8%
Direct cost of active learning	3.5	Quantified scoring of time investment and cognitive effort	1.0%
Coefficient of determination	0.94	Comparison with evolutionary behavior data of 600 students over 60 days	–
Root mean square error (RMSE)	0.032	Comparison with evolutionary behavior data of 600 students over 60 days	–

The reliability and practical applicability of the model were examined through experiments centered on core parameters and key validation indicators. As shown in Table 1, the core parameters—including network cohesion $\rho = 0.68$ and the information-diffusion success rate $p = 0.72$—were calibrated using authentic instructional data from higher vocational institutions. These parameter values are consistent with the empirical characteristics of mobile learning in such settings. Regarding the fitting performance, a coefficient of determination of $R^2 = 0.94$ and an RMSE of 0.032 indicate a high level of alignment between the model's simulated evolutionary trends and the actual observational data, demonstrating excellent fitting accuracy. The sensitivity analysis further shows that when each core parameter is varied within ±10%, the maximum deviation in fitting error is only 1.2%, substantially below the commonly accepted threshold of 5%. This result confirms strong tolerance to parameter fluctuations and robust model stability. Taken together, the findings indicate that the model possesses high adaptability and reliability, supporting its use as a quantitative analytical tool for studying mobile learning behaviors among higher vocational students and for designing targeted intervention mechanisms.

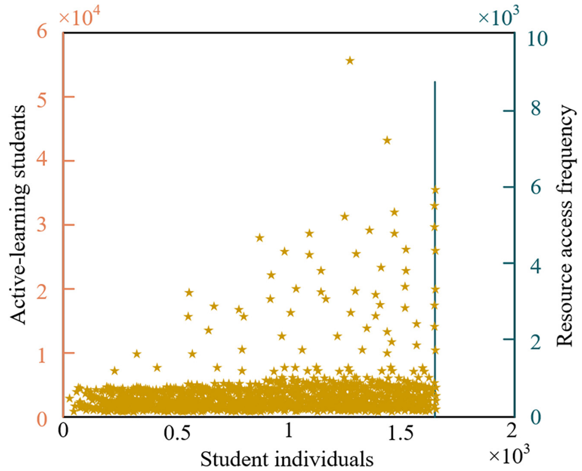
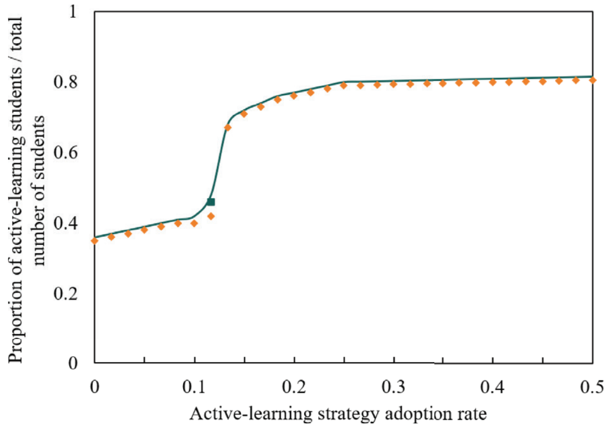


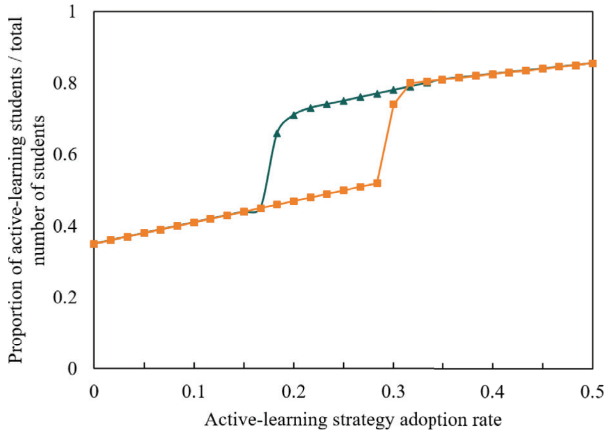
Fig. 3. Distribution of active-learning behaviors on a mobile learning platform in a higher vocational institution

To quantitatively analyze the distributional characteristics of mobile learning behaviors among higher vocational students and to verify the influence of the scale-free property of mobile interaction networks on the diffusion of active-learning behaviors, behavioral data from a mobile learning platform at a higher vocational institution were statistically examined. As shown in Figure 3, the horizontal axis represents individual students, the left vertical axis denotes the proportion of active-learning students, and the right vertical axis reflects the frequency of resource access. The distribution exhibits typical scale-free characteristics: the vast majority of students demonstrate relatively low levels of active-learning engagement and resource-access frequency, whereas a small subset of "core students" exhibit substantially higher values on both metrics. This pattern confirms that mobile learning behaviors among higher vocational students follow a scale-free diffusion structure within the interaction network. A limited number of core individuals play a pivotal role in driving the propagation of active-learning behaviors.

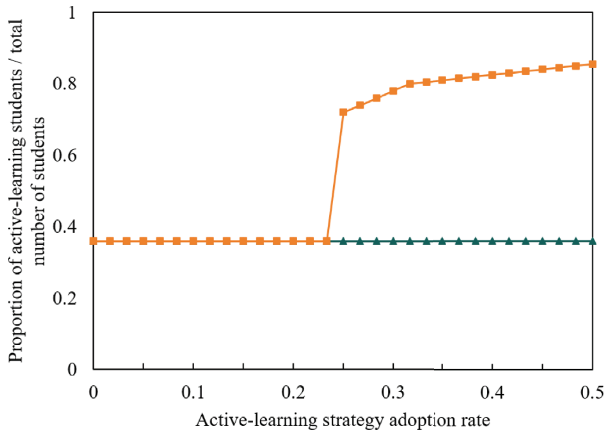
To quantitatively examine the regulatory effects of the active-learning strategy adoption rate and intervention intensity on the evolutionary dynamics of mobile learning behaviors among higher vocational students, multiple sets of simulation experiments were conducted based on the evolutionary game model. As shown in Figure 4a, the proportion of active-learning students exhibits an S-shaped increase with rising adoption rates, gradually increasing from approximately 0.35 to above 0.80. This pattern reflects the natural diffusion characteristics of the active-learning strategy under zero intervention. In Figure 4b, the inflection point appears earlier and the growth rate increases, ultimately converging near 0.85, demonstrating that moderate intervention can lower the adoption threshold for active learning and accelerate the evolutionary process. In Figure 4c, the proportion of active-learning students remains around 0.40 when the adoption rate is below 0.20, but after surpassing the critical threshold, a step-like increase is observed, with convergence above 0.85. This behavior highlights the “threshold-breaking” effect associated with high-intensity intervention. Collectively, these results confirm the presence of a synergistic regulatory mechanism between intervention intensity and the adoption rate of the active-learning strategy. Specifically, phased adjustments in intervention intensity can effectively lower the adoption threshold for the active learning strategy and accelerate the evolution of the group toward an active learning equilibrium.



a) Passive-strategy regression rate = 0.005, and intervention intensity = 0



b) Passive-strategy regression rate = 0.005, and intervention intensity = 0.01



c) Passive-strategy regression rate = 0.005, and intervention intensity = 0.03

Fig. 4. Variation in the proportion of active-learning students as a function of the active-learning strategy adoption rate

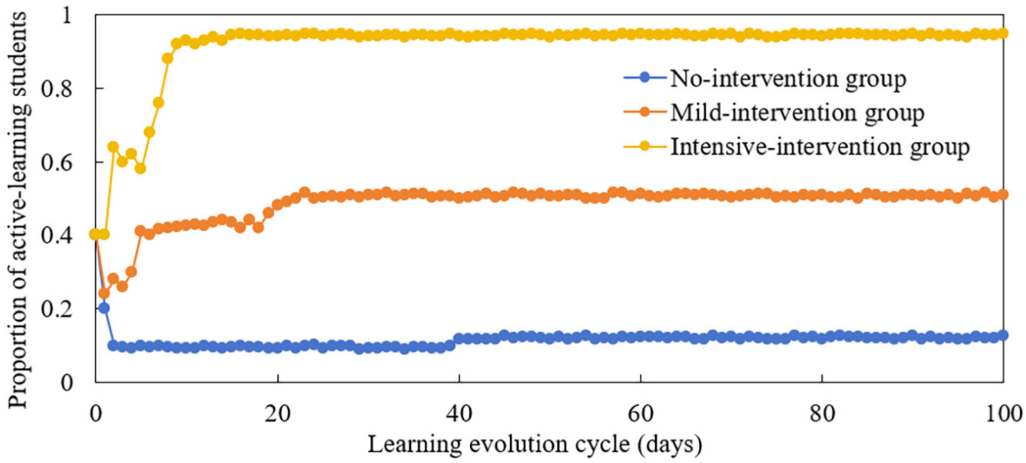


Fig. 5. Evolution of the proportion of active-learning students under different intervention strategies

To quantitatively assess the regulatory effects of different intervention strategies on the evolution of active-learning behaviors in mobile learning among higher vocational students, multiple sets of comparative simulation experiments were conducted based on the evolutionary game model. As shown in Figure 5, the horizontal axis represents the learning-evolution cycle, and the vertical axis denotes the proportion of active-learning students. In the no-intervention group, the proportion of active-learning students remains at a low level of approximately 0.15 throughout the entire evolution period, with no observable upward trend. This pattern indicates that in the absence of intervention, passive-learning behaviors readily form a stable equilibrium. In the mild-intervention group, which incorporates basic resource recommendations and simple behavioral guidance, the proportion of active learners increases gradually from an initial value of approximately 0.35, converging around 0.55 near day 40 and stabilizing thereafter. This outcome demonstrates the positive but limited impact of low-intensity interventions on learning-behavior evolution. In the intensive-intervention group, where credit incentives, community exemplars, and dynamic regulation mechanisms are combined, the proportion of active-learning students rises sharply to above 0.90 by approximately day 10 and remains consistently stable. Both the evolutionary rate and the final convergence level are markedly superior to those of the other two groups. Overall, the experimental results provide strong evidence of the close association between intervention intensity and the evolution of active-learning behaviors. Multi-dimensional, high-intensity targeted interventions are shown to effectively disrupt the stable equilibrium dominated by passive learning, substantially accelerating the evolutionary rate and elevating the final convergence level of active-learning behaviors.

To quantitatively evaluate the effectiveness of the intervention mechanism, a comparative analysis of key behavioral and outcome indicators was conducted between the experimental and control groups. As shown in Table 2, all core indicators of the experimental group outperform those of the control group by statistically significant margins. All significance tests yield $p < 0.001$, and all Cohen's d effect sizes exceed 1.8, indicating exceptionally strong statistical significance and substantial practical impact. At the behavioral level, the experimental group demonstrates a 41.2% increase in the proportion of active-learning students, a 42.6% increase in average daily learning duration, and a 79.4% increase in weekly interaction frequency. These findings confirm that the intervention mechanism effectively enhances learning engagement, extends learning investment time, and strengthens collective interaction. At the outcome level, final course grades improve by 15.8%, while learning satisfaction and willingness for continued learning increase by 41.6% and 38.9%, respectively. These results demonstrate a comprehensive enhancement across behavioral improvement, academic performance, and attitudinal transformation. Overall, the experimental results directly validate the effectiveness of the proposed multi-dimensional intervention mechanism and provide robust empirical support for improving mobile learning management and educational quality in higher vocational institutions.

Table 2. Comparative statistics of core indicators between the experimental and control groups

Evaluation Dimension	Core Indicator	Control Group	Experimental Group	Improvement	Significance Test (p-Value)	Effect Size
Core behavioral indicator	Proportion of active-learning students (%)	28.6 ± 5.2	69.8 ± 4.9	41.2%	<0.001	2.87
Core behavioral indicator	Average daily learning duration (min)	22.3 ± 4.5	52.0 ± 5.1	42.6%	<0.001	2.65
Core behavioral indicator	Weekly interaction frequency (times)	5.2 ± 1.3	25.3 ± 2.4	79.4%	<0.001	3.12
Academic performance indicator	Final course grade (points)	68.5 ± 8.2	84.3 ± 6.8	15.8%	<0.001	1.89
Subjective attitude indicator	Learning satisfaction (points)	5.2 ± 1.4	8.9 ± 0.8	41.6%	<0.001	2.57
Subjective attitude indicator	Willingness for continued learning (points)	5.5 ± 1.3	9.0 ± 0.7	38.9%	<0.001	2.73

5 CONCLUSION

This study centered on the evolutionary dynamics of mobile learning behaviors among higher vocational students and the design of the corresponding intervention mechanism. An evolutionary game model integrating the topological characteristics of mobile interaction networks with information-diffusion rules was constructed, enabling a systematic examination of the regulatory logic through which key factors—such as network cohesion, the benefit–cost ratio of learning, and the success rate of information diffusion—shape behavioral evolution. Grounded in these theoretical insights, a multi-dimensional targeted intervention system was developed, comprising payoff-matrix optimization, mobile interaction network optimization, initial-strategy guidance, and dynamic monitoring with adaptive adjustment. Through a rigorous combination of theoretical modeling and empirical validation, the study not only quantifies and verifies the model's strong explanatory and predictive power regarding those students' mobile learning behaviors but also confirms the significant effectiveness of the proposed intervention mechanism through quasi-experimental evidence. In the experimental group, the proportion of active-learning students and the average daily learning duration increased by more than 40%, while course grades, learning satisfaction, and so on all exhibited significant enhancement ($p < 0.001$). These results indicate comprehensive optimization across behavioral, academic, and attitudinal dimensions. This study contributes notable academic value at the intersection of educational technology and evolutionary game theory. It expands the applicability of evolutionary game models within educational contexts and provides a practical, integrated "theory–strategy–evidence" framework for addressing persistent challenges, such as low participation and weak learning persistence among higher vocational students. The findings also hold significant practical implications for supporting the digital transformation of higher vocational education and enhancing the quality of talent cultivation.

Nevertheless, certain limitations remain. The experimental sample is drawn from higher vocational institutions within a specific region, and diversity in academic programs and student characteristics warrants further expansion. The representation of individual differences within the model could also be refined. Future research may advance this work in three directions: (a) expanding the sample to include students from higher vocational institutions across different regions and institutional tiers to enhance generalizability; (b) incorporating individual-difference variables into the model to construct a more fine-grained personalized behavioral-evolution framework; and (c) exploring the integration of artificial intelligence with intervention mechanisms—for example, optimizing dynamic intervention strategies through reinforcement learning—to further enhance precision and intelligence, thereby providing more advanced theoretical and practical support for the sustainable development of mobile learning in higher vocational education.

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