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PAPER

# The Impact of Interactive Mobile Technology on Enhancing Self-Management and Autonomous Learning Abilities in Higher Education

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**ABSTRACT**

In the digital transformation process of vocational education, interactive mobile technology has become a key support for enhancing the autonomous learning abilities of vocational college students. This study, based on situational intelligence theory, social constructivism, and metacognitive theory, constructs a three-dimensional ecological framework comprising situational awareness and adaptation, social regulatory networks, and dynamic metacognitive scaffolding. It systematically reveals the internal mechanisms through which mobile technology empowers self-management and autonomous learning in vocational students. Using a mixed-methods research approach, the study investigates the application effectiveness of a mobile learning system guided by this framework, with a sample of 286 students from three vocational colleges. The results show that the framework significantly improves students' abilities in goal-setting, time management, strategy regulation, and reflective correction. Furthermore, the precise adaptation of situational awareness, the mutual support of social networks, and the personalized guidance of dynamic scaffolding have synergistic effects. The application of technology shows heterogeneity among different student groups based on professional types and learning foundations. The findings provide theoretical foundations and practical references for the development of mobile learning resources in vocational education, the design of intelligent learning platforms, and the innovation of autonomous learning cultivation models.

**KEYWORDS**

interactive mobile technology, vocational education, self-management ability, autonomous learning, situational intelligence, ecological framework

## 1 INTRODUCTION

Vocational education focuses on the cultivation of skilled talents, and self-directed learning and self-management abilities are key competencies for students to adapt to

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the demands of professional positions and achieve lifelong learning [1–3]. Currently, vocational college students generally face issues such as unclear learning goals, weak time planning, and insufficient strategy application [4, 5], which directly constrain their career development potential and the enhancement of sustainable learning abilities. Meanwhile, the continuous iteration of 5G, the Internet of Things, and artificial intelligence technologies is driving mobile learning to upgrade in an interactive and intelligent direction [6, 7], providing core technical support to address the fragmented learning and practical learning needs of vocational students. Interactive mobile technology, with advantages such as multimodal interaction, real-time data collection, and dynamic feedback [8, 9], breaks the spatial and temporal limitations of traditional learning, becoming an important carrier to optimize the self-directed learning process. However, existing research on mobile learning mostly focuses on single-function applications or resource delivery [10], lacking a systematic consideration of the interaction between technology, learners, and learning contexts. A technological empowerment framework that covers the entire self-management process and aligns with the career-oriented and practice-oriented core learning characteristics of vocational students has not yet been formed. Additionally, empirical research on how mobile technology enhances the autonomous learning ability of vocational students through multidimensional synergy is still relatively scarce, which makes it difficult to meet the practical needs of vocational education's digital transformation.

Based on the above background, this study holds significant theoretical and practical implications. On the theoretical level, the study will construct a self-regulated learning ecological framework integrating situational intelligence, enriching the theoretical system of mobile learning and autonomous learning, and systematically revealing the multidimensional mechanisms through which interactive mobile technology empowers self-management in vocational students. This will expand the theoretical research perspective of vocational education's digital transformation. On the practical level, the research findings can provide modular design solutions for the development of mobile learning platforms in vocational education, offer technical tools to support teachers in personalized teaching guidance, and provide operable practical pathways for cultivating vocational students' autonomous learning abilities, thereby contributing to the improvement of vocational education's talent cultivation quality.

The core objective of this study is to construct an interactive mobile technology empowerment framework suitable for vocational education, verify the effectiveness of this framework in enhancing vocational students' self-management and autonomous learning abilities, and clarify the synergistic mechanisms and application boundaries of each subsystem within the framework. To achieve this, the study will focus on answering the following questions: Does the situational intelligence-based three-dimensional ecological framework significantly enhance vocational students' self-management abilities, such as goal setting, time management, strategy regulation, and reflective correction? What are the action pathways and synergistic mechanisms of the situational awareness and adaptation layer, social regulatory network layer, and dynamic metacognitive scaffolding layer in the framework? Are there any differences in the effects of the framework among vocational students with different professional types and learning foundations?

The following chapters of this paper will proceed as follows: first, the theoretical framework construction and research hypotheses will be explained; second, the research design and methods will be detailed, including the selection of research subjects, development of research tools, implementation of the research process, and data analysis plan; then, the research results will be presented, covering sample characteristics, scale reliability and validity tests, between-group and within-group difference analysis, action pathway verification, and moderation effect results; finally, the conclusions will be summarized, theoretical and practical implications will be extracted, and research limitations and future prospects will be discussed.

## 2 THEORETICAL FRAMEWORK AND RESEARCH HYPOTHESES

### 2.1 Construction of the self-regulated learning ecological framework integrating situational intelligence

**Core logic of the framework.**

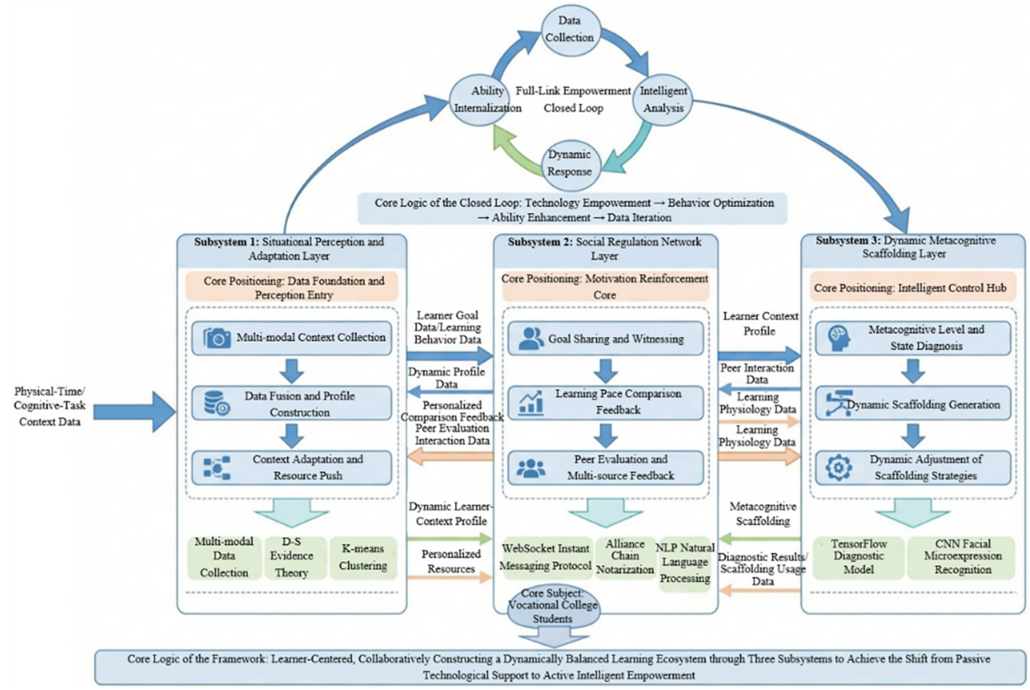


**Fig. 1.** Architecture of the self-regulated learning ecological framework integrating situational intelligence

The framework is learner-centered, capturing learning needs through situational awareness, strengthening learning motivation through social networks, and guiding ability internalization with metacognitive scaffolding, forming a full-link empowerment loop of "data collection—intelligent analysis—dynamic response—ability internalization." The framework deeply relies on multimodal mobile technology, accurately adapting to the career-oriented and practice-oriented learning characteristics of vocational students. Its core goal is to promote the stepwise improvement of autonomous learning ability. The core innovation lies in breaking through the traditional single-dimensional technical application model, emphasizing deep interaction between technology, learners, and learning contexts. Through the synergistic action of three-dimensional subsystems, a dynamically balanced learning ecosystem is constructed, achieving the transformation from passive technical support to active intelligent empowerment. Figure 1 shows the architecture of the self-regulated learning ecological framework integrating situational intelligence.

**Composition, function, and technical realization details of the three-dimensional subsystems.** The situational awareness and adaptation layer, as the data foundation and perception entry of the framework, focuses on multimodal data collection and intelligent matching algorithms [11, 12]. It adopts a "terminal collection-edge preprocessing-cloud fusion" three-level architecture design, effectively reducing data transmission delay and energy consumption and adapting to fragmented learning scenarios such as breaks between classes and training sessions. The data collection process captures both physical-time context and cognitive-task context comprehensively. The physical-time context obtains basic data through the integration of built-in sensors in mobile devices and associates it with calendars and timetables. The cognitive-task context is collected through point tracking technology, OCR text recognition, and speech emotion recognition. Speech emotion recognition is based on the Mel-frequency cepstral coefficients (MFCC) algorithm, with the core computation as follows:

$$C(m)=\sum_{n=0}^{N-1} x(n)\cdot h_m(n)(m = 0,1,..., M-1) \tag{1}$$

where, $C(m)$ is the $m$-th Mel cepstral coefficient, $x(n)$ is the speech signal sample, $h_m(n)$ is the $m$-th filter impulse response of the Mel filter bank, $N$ is the signal sampling length, and $M$ is set to 12 to balance recognition accuracy and computational efficiency. This formula accurately extracts speech features to determine the emotional state of learning. In the data fusion process, weighted $D-S$ evidence theory is used to integrate multi-source heterogeneous data, solving the uncertainty of a single data source. The weighted synthesis formula of the basic trust distribution function is as follows:

$$m(A)=\frac{1}{1-K}\sum\nolimits_{A_1\cap A_2\cap\ldots\cap A_n=A}\prod_{i=1}^{n} w_i\cdot m_i(A_i) \tag{2}$$

where, $m(A)$ is the trust degree of proposition $A$ after synthesis, $K$ is the conflict coefficient, $w_i$ is the weight of the $i$-th data source, and $m_i(A_i)$ is the basic trust degree of the $i$-th data source for proposition $A_i$. Then, based on the K-means clustering algorithm, a dynamic "learner-context" profile is constructed. The clustering objective function is as follows:

$$J=\sum_{K=1}^{K}\sum_{x\in C_k}\left\|x-\mu_k\right\|^2 \tag{3}$$

where, $J$ is the sum of squared clustering errors, $K$ is set to 6 to correspond to the six core dimensions of the profile, $C_k$ is the $k$-th cluster, $x$ is the data sample within the cluster, and $\mu_k$ is the center of the $k$-th cluster. The profile update frequency is dynamically adjusted according to the scenario: fragmented scenarios update every 30 minutes; immersive learning scenarios update every 2 hours. The situational adaptation and resource push use a two-layer matching model. The first layer completes the preliminary matching of scenes and resource types through a rule engine, and the second layer uses collaborative filtering algorithms to push specific resources. Additionally, reinforcement learning algorithms are introduced, with resource completion rate $r$ and answer accuracy $a$ as feedback indicators to construct the reward function:

$$R=\alpha\cdot r+(1-\alpha)\cdot a \tag{4}$$

where, $\alpha$ is set to 0.4, and $R$ is the comprehensive reward value, used to guide the dynamic iteration and optimization of the push strategy.

The social regulatory network layer serves as the core of the framework's motivation reinforcement. Its technical core includes instant messaging protocols, blockchain certification, and semantic analysis. A lightweight social interaction module is constructed based on the WebSocket protocol to ensure the smooth real-time interaction among peers. Blockchain technology is introduced to achieve the immutable certification of learning goals and progress data, reinforcing the network trust mechanism. This layer externalizes and visualizes the learner's self-regulation process through three core functions: goal sharing and witnessing, learning rhythm comparison feedback, and peer evaluation. Goal sharing and witnessing support multimodal goal entry, standardizing information through natural language processing technology, and using the "blockchain certification + peer signature" model to ensure traceability. Learning rhythm comparison feedback stores anonymized peer data in a distributed database, generates personalized comparison results through real-time computation, and visualizes the results. Peer evaluation constructs a dual-dimensional evaluation system for process and result, integrating the BERT semantic analysis model to perform sentiment recognition and keyword extraction from comments. The sentiment tendency probability is calculated and output using the Softmax function:

$$P(y_i|x) = \frac{e^{s_i}}{\sum_{j=1}^{3} e^{s_j}}. \tag{5}$$

where, $P(y_i|x)$ is the probability that the input comment $x$ belongs to the category $y_i$, $s_i$ is the model output score for category $y_i$, $j = 3$ corresponds to the three sentiment labels, and the model automatically generates a comment summary to assist the learner in identifying areas for improvement.

The dynamic metacognitive scaffolding layer serves as the core intelligent regulation hub of the framework. Its technical core includes machine learning diagnosis, rule engines, and adaptive push. It adopts a "real-time diagnosis—dynamic decision—precise push" three-layer technical chain. The diagnostic model is built based on TensorFlow, and a rule engine is used to flexibly adjust the scaffolding strength. Metacognitive level and status diagnosis are performed by constructing a multi-input feature vector, including learning behavior data, situational data, and peer evaluation data. The random forest algorithm is used to train the evaluation model, and the model's decision output formula is as follows:

$$f(x) = arg \max_{y \in Y} \sum_{t=1}^{T} I(h_t(x) = y) \tag{6}$$

where, $f(x)$ is the final classification result, $T$ is the number of decision trees, $h_t(x)$ is the output of the $t$-th decision tree, $I()$ is the indicator function, $Y$ is the set of categories, and the model accuracy is not lower than 85%. At the same time, cognitive load and emotional states are comprehensively judged based on the cognitive load scale and physiological data such as facial micro-expressions and heart rate variability. Based on the diagnostic results, a scaffolding strategy library is constructed. A production rule engine matches the scaffolding type and strength: for low metacognition, high load, or negative emotions, highly structured scaffolding such as step-by-step operation templates and interference application locking programs is pushed; for medium metacognition, moderate load, or neutral emotions, semi-structured scaffolding such as thinking mind map templates is pushed; for high metacognition, low load, or positive emotions, unstructured scaffolding such as open-ended questions is pushed. A dynamic mechanism of "re-diagnosis after completing 2 learning tasks + effect feedback correction" is used to adjust the scaffolding strategy, achieving gradual guidance from external technical support to internal ability internalization.

**Synergistic mechanism among subsystems.** The three-dimensional subsystems achieve efficient data communication and functional collaboration through *RESTful API*, forming a closed-loop ecosystem of "data communication—collaborative decision-making—precise empowerment." The situational awareness and adaptation layer will real-time synchronize the dynamically constructed "learner-context" profiles to the social regulatory network layer and the dynamic metacognitive scaffolding layer, providing an accurate data foundation for subsequent motivation reinforcement and intelligent regulation. The social regulatory network layer will feed back the collected peer interaction data and group comparison data to the situational awareness and adaptation layer, helping to optimize the accuracy of the profile construction. At the same time, this data will be pushed to the dynamic metacognitive scaffolding layer to provide supplementary evidence for diagnosing metacognitive level and status. The dynamic metacognitive scaffolding layer will feed back the diagnostic results and scaffolding usage effectiveness data to the situational awareness and adaptation layer, guiding the optimization and adjustment of resource adaptation and push strategies. The three subsystems mutually support and progress in layers, achieving the organic unity of data flow and functional collaboration, thus ensuring the maximization of the framework's empowerment effect.

## 2.2 Research hypotheses

Based on the self-regulated learning ecological framework integrating situational intelligence constructed in the previous section and combining the research findings of social constructivism [13], metacognitive theory [14], and mobile learning [15], a series of research hypotheses are proposed concerning the mechanisms of action, synergistic effects, and application boundaries of the three-dimensional subsystems. The situational awareness and adaptation layer, through multimodal data collection and intelligent adaptation, provides precise situational support and resource guarantees for self-management of vocational students. Its core function lies in matching learning needs with environmental conditions, helping learners efficiently plan learning time, integrate learning resources reasonably, and clarify learning goals. Based on this, hypothesis H1 is proposed: The application of the situational awareness and adaptation layer has a significant positive impact on the self-management ability of vocational students. The social regulatory network layer, relying on social interaction and trust mechanisms, externalizes the self-regulation process to the peer network. Through goal witnessing, rhythm comparison, and peer evaluation, it strengthens learning persistence, promotes learners to optimize learning strategies, and conducts deep reflection. Based on this, hypothesis H2 is proposed: The application of the social regulatory network layer has a significant positive impact on the self-management ability of vocational students. The dynamic metacognitive scaffolding layer, through machine learning diagnosis and adaptive support, directly acts on the learners' metacognitive processes, guiding them to master scientific learning strategies and enhance learning initiative, ultimately promoting the core enhancement of autonomous learning ability. Based on this, hypothesis H3 is proposed: The application of the dynamic metacognitive scaffolding layer has a significant positive impact on the autonomous learning ability of vocational students.

The three-dimensional subsystems do not function in isolation but instead achieve data communication and functional collaboration through *RESTful API*, forming a closed-loop empowerment chain of "data collection—motivation reinforcement—intelligent regulation." The precise profiles provided by the situational awareness and adaptation layer lay the foundation for the personalized interaction of the social regulatory network layer and the precise diagnosis of the dynamic metacognitive scaffolding layer. The interaction data of the social regulatory network layer then feeds back to optimize the profile and scaffolding adaptation, while the diagnostic results of the dynamic metacognitive scaffolding layer further guide the adjustment of resource push strategies. The synergistic effect of the three should produce an empowerment effect that exceeds that of a single subsystem. Therefore, hypothesis H4 is proposed: There is a synergistic effect among the situational awareness and adaptation layer, the social regulatory network layer, and the dynamic metacognitive scaffolding layer, jointly promoting the improvement of self-management and autonomous learning abilities in vocational students.

Considering the heterogeneity of vocational students based on professional types and learning foundations, there are differences in the learning needs and ability gaps across different groups, which may lead to differentiated effects in the application of the framework. Engineering students rely more on situational data collection in practical training scenarios, while liberal arts students may gain more benefits from social interaction. Students with lower learning foundations have a more urgent need for dynamic metacognitive scaffolding, while students with higher learning foundations may benefit more from situational adaptation functions in autonomous resource integration. This group difference suggests that professional types and learning foundations may moderate the effects of the framework's application. Based on this, hypothesis H5 is proposed: Professional types and learning foundations have a significant moderating effect on the application effect of the framework.

## 3 RESEARCH DESIGN AND METHODS

This study adopts a multi-stage sampling method to select research subjects, covering three vocational colleges with engineering, liberal arts, and arts majors. A total of 286 students were included and divided into an experimental group and a control group, with 143 students in each group. The experimental group used a mobile learning system developed based on the three-dimensional ecological framework constructed earlier, while the control group used a traditional mobile learning platform that only provided basic resource pushing and simple interaction functions. To control the interference of irrelevant variables on the experimental results, pre-tests were conducted to ensure no significant differences between the two groups of students in terms of core demographic variables such as gender, major type, and learning foundation, thus establishing baseline conditions for the subsequent intervention effect comparison.

The research tools used in this study include three core components: an interactive mobile learning system developed based on the three-dimensional ecological framework, which integrates the three core modules of situational awareness, social interaction, and dynamic metacognitive scaffolding to realize a functional loop of multimodal data collection, social interaction support, and adaptive scaffolding push; a series of measurement scales that have been revised and validated, including a self-management ability scale that was revised based on existing mature scales and adapted to the learning characteristics of vocational students, covering four dimensions—goal setting, time management, resource integration, and reflective correction—with a total of 16 items; an autonomous learning ability scale that includes three dimensions—metacognitive level, strategy application, and learning initiative—with a total of 12 items; and a system usability experience scale used to collect feedback on the use of various modules of the system from experimental group students, with a total of 8 items. Auxiliary data collection tools include learning behavior logs that record key information such as learning duration, resource type selection, and interaction frequency in real time, and semi-structured interview outlines designed for experimental group students and teaching faculty, used to collect qualitative research data.

# 4 RESEARCH RESULTS

## 4.1 Basic sample characteristics

A total of 286 vocational students were included in this study, with 143 students in the experimental group and 143 students in the control group. The distribution of demographic characteristics was balanced between the two groups, with no significant differences, ensuring the validity of the intervention effect comparison. Specific sample characteristics are shown in Table 1.

**Table 1.** Descriptive statistics of sample demographic characteristics (N = 286)

| Feature Dimension | Category | Experimental Group (n = 143) | Control Group (n = 143) | $\chi^2$ Value | p-Value |
|---|---|---|---|---|---|
| Gender | Male | 82 (57.3%) | 80 (55.9%) | 0.08 | 0.77 |
| | Female | 61 (42.7%) | 63 (44.1%) | | |
| Major Type | Engineering | 65 (45.5%) | 63 (44.1%) | 0.32 | 0.85 |
| | Liberal Arts | 48 (33.6%) | 50 (35.0%) | | |
| | Arts | 30 (21.0%) | 30 (21.0%) | | |
| Learning Foundation | High | 36 (25.2%) | 34 (23.8%) | 0.25 | 0.88 |
| | Medium | 72 (50.3%) | 75 (52.4%) | | |
| | Low | 35 (24.5%) | 34 (23.8%) | | |

The results in Table 1 show that there are no statistical differences between the experimental and control groups in terms of gender, major type, or learning foundation, indicating that the baseline conditions of the two groups are consistent. This ensures that demographic variables do not interfere with the subsequent intervention effects, providing a foundation for the effectiveness of the experiment.

## 4.2 Scale reliability and validity test results

The self-management ability scale and the autonomous learning ability scale used in this study both demonstrated good reliability and validity, in accordance with academic research standards. Specific reliability and validity indicators are shown in Table 2.

The results in Table 2 show that the Cronbach's α coefficients for all dimensions and total scales are greater than 0.83, and the composite reliability (CR) values are higher than 0.88, indicating good internal consistency reliability of the scales. The average variance extracted (AVE) values for each dimension are all greater than 0.64, meeting the criteria for convergent validity. Additionally, the results of confirmatory factor analysis show that the fit indices for the self-management ability scale are $\chi^2/df = 2.31$, RMSEA = 0.06, GFI = 0.92, and CFI = 0.95, and the fit indices for the autonomous learning ability scale are $\chi^2/df = 2.25$, RMSEA = 0.05, GFI = 0.93, and CFI = 0.96, all of which reach ideal fit levels, indicating good structural validity of the scales. These scales can be used for the formal data collection and analysis of this study.

**Table 2.** Reliability and validity test results of scales

| Scale Name | Dimension | Number of Items | Cronbach's α | Composite Reliability (CR) | Average Variance Extracted (AVE) |
|---|---|---|---|---|---|
| Self-Management Ability Scale | Goal Setting | 4 | 0.86 | 0.90 | 0.68 |
| | Time Management | 4 | 0.84 | 0.89 | 0.65 |
| | Resource Integration | 4 | 0.85 | 0.89 | 0.66 |
| | Reflective Correction | 4 | 0.87 | 0.91 | 0.70 |
| | Total Scale | – | 0.92 | 0.94 | 0.72 |
| Autonomous Learning Ability Scale | Metacognitive Level | 4 | 0.85 | 0.89 | 0.67 |
| | Strategy Application | 4 | 0.83 | 0.88 | 0.64 |
| | Learning Initiative | 4 | 0.86 | 0.90 | 0.69 |
| | Total Scale | – | 0.91 | 0.93 | 0.71 |

## 4.3 Analysis of ability differences before and after intervention

The results of within-group differences in self-management ability and autonomous learning ability for the experimental group and control group before and after the intervention are shown in Figure 2.

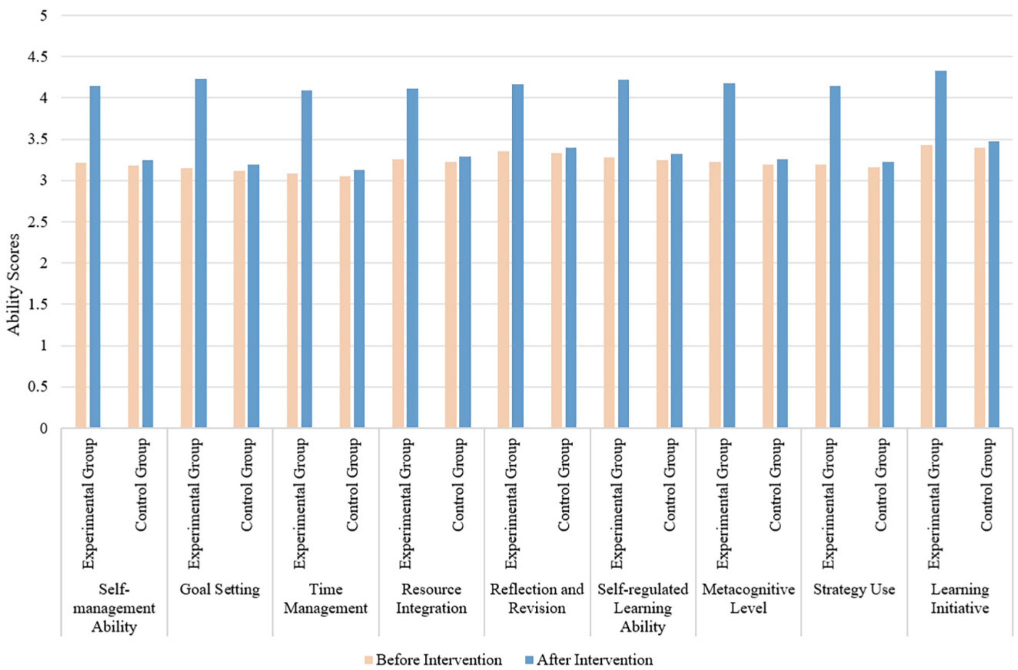


**Fig. 2.** Within-group ability score differences before and after intervention

The results in Figure 2 show that after the intervention, the experimental group significantly improved in self-management ability and in the scores of each dimension of goal setting, time management, resource integration, and reflective correction, as well as in autonomous learning ability and in the scores of metacognitive levels, strategy application, and learning initiative, all of which had statistically significant differences compared to before the intervention. The control group showed no significant differences in the scores of these dimensions before and after the intervention. This indicates that the mobile learning system based on the three-dimensional ecological framework of situational intelligence can effectively improve vocational students' self-management and autonomous learning abilities, while the traditional mobile learning platform has no significant effect on students' ability improvement.

The results of between-group differences in self-management ability and autonomous learning ability after the intervention are shown in Table 3.

**Table 3.** Between-group ability score differences after intervention (M ± SD)

| Ability Dimension | Experimental Group | Control Group | t Value | p Value | Effect Size d |
|---|---|---|---|---|---|
| Self-management Ability | 4.15 ± 0.46 | 3.25 ± 0.54 | 16.89 | <0.001 | 1.82 |
| Goal Setting | 4.23 ± 0.45 | 3.19 ± 0.57 | 17.32 | <0.001 | 1.90 |
| Time Management | 4.09 ± 0.48 | 3.13 ± 0.60 | 15.67 | <0.001 | 1.68 |
| Resource Integration | 4.11 ± 0.47 | 3.29 ± 0.55 | 15.98 | <0.001 | 1.72 |
| Reflective Correction | 4.17 ± 0.44 | 3.40 ± 0.52 | 14.89 | <0.001 | 1.56 |
| Autonomous Learning Ability | 4.22 ± 0.45 | 3.32 ± 0.53 | 17.95 | <0.001 | 1.96 |
| Metacognitive Level | 4.18 ± 0.46 | 3.26 ± 0.56 | 16.54 | <0.001 | 1.78 |
| Strategy Application | 4.15 ± 0.47 | 3.23 ± 0.57 | 16.11 | <0.001 | 1.72 |
| Learning Initiative | 4.33 ± 0.43 | 3.47 ± 0.51 | 18.23 | <0.001 | 2.01 |

The results in Table 3 show that after the intervention, the experimental group had significantly higher scores than the control group in self-management ability and in each dimension of autonomous learning ability. The differences were all statistically significant, with effect sizes (d) greater than 1.56, indicating large effect sizes. This further confirms the effectiveness of the mobile learning system based on the three-dimensional ecological framework of situational intelligence, which significantly outperforms the traditional mobile learning platform in improving vocational students' self-management and autonomous learning abilities.

## 4.4 Testing of the effect paths and synergistic effects of subsystems

To test the effect paths of the three-dimensional subsystems on self-management and autonomous learning abilities, a structural equation model (SEM) was constructed, and fit tests were conducted. The results are shown in Table 4.

**Table 4.** SEM fit indices

| Fit Indices | Standard Value | This Study Model | Fit Results |
|---|---|---|---|
| $\chi^2/df$ | <3.00 | 2.18 | Good |
| *RMSEA* | <0.08 | 0.057 | Good |
| *GFI* | >0.90 | 0.93 | Good |
| *CFI* | >0.90 | 0.96 | Good |
| *NFI* | >0.90 | 0.94 | Good |
| *IFI* | >0.90 | 0.96 | Good |

The results in Table 4 show that all fit indices of the SEM reached the ideal standards. Specifically, $\chi^2$/df = 2.18, RMSEA = 0.057, GFI = 0.93, and CFI = 0.96, indicating that the overall model fits well. This suggests that the model can be used for subsequent testing of effect paths and synergistic effects.

The direct effects and synergistic effects of each subsystem on self-management ability and autonomous learning ability are shown in Table 5.

**Table 5.** Impact paths and synergistic effect test results of subsystems

| Impact Path | Standardized Coefficient β | Standard Error | t Value | p Value |
|---|---|---|---|---|
| Situational Perception and Adaptation Layer → Self-management Ability | 0.32 | 0.04 | 8.01 | <0.001 |
| Social Regulation Network Layer → Self-management Ability | 0.28 | 0.04 | 7.03 | <0.001 |
| Dynamic Metacognitive Scaffolding Layer → Autonomous Learning Ability | 0.41 | 0.04 | 10.25 | <0.001 |
| Situational Perception and Adaptation Layer × Social Regulation Network Layer → Autonomous Learning Ability | 0.12 | 0.05 | 2.43 | <0.05 |
| Situational Perception and Adaptation Layer × Dynamic Metacognitive Scaffolding Layer → Autonomous Learning Ability | 0.15 | 0.05 | 3.02 | <0.01 |
| Social Regulation Network Layer × Dynamic Metacognitive Scaffolding Layer → Autonomous Learning Ability | 0.13 | 0.05 | 2.67 | <0.01 |
| Three-Factor Interaction → Autonomous Learning Ability | 0.19 | 0.06 | 3.18 | <0.01 |

The results in Table 5 show that the Situational Perception and Adaptation Layer and Social Regulation Network Layer have a significant positive direct impact on self-management ability, with $\beta = 0.32$ and 0.28, $p < 0.001$. The Dynamic Metacognitive Scaffolding Layer has a significant positive direct impact on autonomous learning ability, with $\beta = 0.41$, $p < 0.001$. The test results for synergistic effects show that the interaction between any two subsystems has a significant positive impact on autonomous learning ability, and the three-subsystem interaction has an even more significant positive impact, with $\beta = 0.19$, $p < 0.01$. This indicates that the three-dimensional subsystems do not work in isolation but have a significant synergistic effect, collectively promoting the improvement of vocational students' self-management and autonomous learning abilities.

### 4.5 Moderating effect analysis results

The moderating effect test results of professional type and learning foundation on the framework application effect are shown in Table 6.

**Table 6.** Moderating effect test results

| Moderating Variable | Impact Path | Standardized Coefficient β | Standard Error | t Value | p Value |
|---|---|---|---|---|---|
| Professional Type | Situational Perception and Adaptation Layer → Self-management Ability | 0.18 | 0.06 | 3.05 | <0.01 |
| | Social Regulation Network Layer → Self-management Ability | –0.16 | 0.06 | –2.71 | <0.01 |
| Learning Foundation | Overall Framework → Self-management Ability | –0.22 | 0.06 | –3.75 | <0.001 |
| | Overall Framework → Autonomous Learning Ability | –0.20 | 0.06 | –3.38 | <0.001 |

The results in Table 6 show that professional type has a significant moderating effect on the impact paths of the Situational Perception and Adaptation Layer and the Social Regulation Network Layer: students in engineering majors benefit more from the Situational Perception and Adaptation Layer ($\beta = 0.18$, $p < 0.01$), while students in liberal arts majors have more notable improvements in the Social Regulation Network Layer ($\beta = –0.16$, $p < 0.01$). Learning foundation has a significant negative moderating effect on the overall framework's application effect, with $\beta = –0.22$ and –0.20, $p < 0.001$, meaning that students with medium or low learning foundations show a significantly greater improvement in their abilities than students with high learning foundations. This indicates that the framework application effect has group heterogeneity and requires personalized adaptation based on students' professional type and learning foundation.

### 4.6 Qualitative research results

Content coding of semi-structured interview data from 20 experimental group students and 5 teachers identified three core themes. Student feedback revealed that the situational adaptation module accurately matches fragmented learning needs, effectively addressing issues such as "lack of appropriate resources during practical training breaks" and "chaotic learning time planning." The social interaction module enhanced learning motivation through peer goal witnessing and pace comparison, with most students stating, "seeing peers' progress increases the sense of urgency" and "peer feedback helped me identify shortcomings." The dynamic scaffolding module's layered support promoted independent thinking, with lower-level students feeling "step-by-step guidance reduces learning difficulty," and higher-level students appreciating "open-ended questions guiding deep reflection." Teacher feedback indicated that the framework supports personalized teaching by providing data to help teachers precisely grasp students' learning status, optimize teaching strategies, and enhance teaching relevance. The qualitative results complement the quantitative findings, further verifying the practical value of the three-dimensional ecological framework.

## 5 CONCLUSION

This study, based on the digital transformation needs of vocational education and supported by situational intelligence theory, social constructivism, and metacognitive theory, systematically constructs the three-dimensional ecological framework of situational perception and adaptation, social regulation network, and dynamic metacognitive scaffolding. It aims to reveal the intrinsic mechanisms of interactive mobile technology in empowering vocational students' self-management and autonomous learning abilities. Through a 12-week empirical study, combining both quantitative and qualitative analysis methods, the effectiveness and applicability of this framework were validated. The key conclusions are as follows:

First, the three-dimensional ecological framework significantly improves vocational students' self-management and autonomous learning abilities. Empirical results show that the mobile learning system developed based on this framework effectively improves students' performance in core self-management dimensions, such as goal setting, time management, resource integration, and reflective correction, while also significantly enhancing their metacognitive level, strategy application, and learning initiative. This finding confirms the scientific logic of the framework's "data collection—intelligent analysis—dynamic response—ability internalization" closed-loop empowerment, breaking through the limitations of traditional mobile learning platforms with a single functional support.

Second, there is significant group heterogeneity in the framework's application effects. Professional type and learning foundation moderate the framework's empowerment effect: engineering students benefit more from the Situational Perception and Adaptation Layer, while liberal arts students show more improvement in the Social Regulation Network Layer; students with medium or low learning foundations experience significantly greater improvements than those with high learning foundations. This result highlights the core value of personalized adaptation in technology-enabled education, providing clear directions for the precise application of the framework.

Finally, this study provides both theoretical and practical support for the digital transformation of vocational education and the cultivation of autonomous learning abilities. Theoretically, the constructed three-dimensional ecological framework enriches the theoretical system of mobile learning and autonomous learning, extending research perspectives on situational intelligence and social interaction collaborative empowerment. Practically, the research results offer operable reference solutions for modular development of mobile learning platforms, formulation of personalized teaching strategies, and innovation in student autonomous learning models, contributing to the systematic improvement of vocational education talent training quality and laying the technological and theoretical foundation for the cultivation of core competencies for vocational students in a lifelong learning system.

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