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iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 18 No. 22 (2024) | OPEN ACCESS

https://doi.org/10.3991/ijim.v18i22.52449

PAPER

Implementation Strategy of Project-Based Learning in Mobile Learning Environments and Its Effects

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ABSTRACT

With the rapid development of mobile learning technologies, mobile learning environments have become an integral part of modern education, offering students flexible learning methods and a wealth of educational resources. In this context, project-based learning (PBL), a student-centered instructional model, has garnered significant attention due to its proven effectiveness in enhancing students' autonomous learning capabilities and problem-solving skills. However, effectively implementing PBL within mobile learning environments still presents numerous challenges. The current study primarily focuses on technical support and infrastructure development and lacks systematic knowledge models, precise knowledge recommendation mechanisms, and effective utilization of expert resources. To address these issues, this study provides new theoretical perspectives and practical approaches in this domain by constructing a knowledge model for PBL within mobile learning environments, designing a knowledge recommendation system, and developing an expert map application. The findings of this study are expected to offer a more targeted and practical strategy for PBL in mobile learning environments, thereby improving educational outcomes.

KEYWORDS

mobile learning environment, project-based learning (PBL), knowledge model, knowledge recommendation, expert map

1 INTRODUCTION

With the rapid advancement of information technology (IT), mobile learning environments have gradually become an integral component of modern education. The widespread adoption of mobile devices and the digitization of learning resources have enabled students to engage in autonomous learning at any time and place [1–4]. Against this backdrop, project-based learning (PBL), a student-centered instructional model, has gained widespread attention and application due to its

Qu, L., Li, L. (2024). Implementation Strategy of Project-Based Learning in Mobile Learning Environments and Its Effects. *International Journal of Interactive Mobile Technologies (iJIM)*, 18(22), pp. 4–18. https://doi.org/10.3991/ijim.v18i22.52449

Article submitted 2024-07-25. Revision uploaded 2024-09-23. Final acceptance 2024-09-26.

effectiveness in enhancing students' autonomous learning abilities and problem-solving skills [5–10]. However, the effective implementation of PBL within mobile learning environments remains a significant challenge in current educational study.

Implementing PBL in a mobile learning environment is not merely an extension of traditional teaching methods but represents a new exploration of learning approaches and experiences. PBL emphasizes the acquisition of knowledge and the development of skills through the execution of real-world projects. When combined with the flexibility and extensive resources offered by mobile learning, it can provide students with a more personalized and interactive learning experience [11–14]. Therefore, investigating how to effectively implement PBL in a mobile learning environment is of both theoretical significance and practical value, contributing to the optimization of current teaching models and the improvement of educational quality.

However, existing research on the integration of mobile learning environments with PBL has primarily focused on technical support and infrastructure development. There has been limited exploration into the construction of systematic knowledge models, the development of precise knowledge recommendation mechanisms, and the utilization of expert maps to support students' practical applications [15–18]. The prevailing research methods often lack systematicity, are insufficiently targeted, and have limited practical applicability, failing to fully meet the personalized needs of students in mobile learning environments [19–21].

The study focuses on an effective PBL strategy in mobile learning environments and its outcomes. It is divided into three parts: first, creating a PBL knowledge model for a systematic framework in mobile settings; second, developing a personalized knowledge recommendation system; and third, creating an expert map application to enhance resource utilization and learning outcomes. This study offers theoretical and practical insights into integrating mobile learning with PBL, making it significant for both academic and practical endeavors.

2 KNOWLEDGE MODEL FOR PBL IN MOBILE LEARNING ENVIRONMENTS

To enhance the precision of knowledge recommendations, a knowledge model for PBL within mobile learning environments was developed in this study. This model constitutes a systematic knowledge architecture that integrates the characteristics of mobile learning with the requirements of PBL, aiming to support students in efficiently acquiring, organizing, and applying knowledge in diverse and flexible mobile learning scenarios. Specifically, this knowledge model includes the categorization of learning content, the modeling of relationships between knowledge points, and the strategy for aligning these with project tasks. The establishment of this knowledge model enabled students to clearly comprehend the knowledge systems they needed to master on their mobile devices and dynamically adjust their learning content according to the progress of their projects. Moreover, this model was designed to incorporate intelligent functionalities, such as analyzing student behavior data to provide personalized knowledge path recommendations, thereby assisting students in autonomously constructing the necessary knowledge networks during project implementation, ultimately enhancing both learning efficiency and the quality of project completion.

a) Knowledge content structure modeling: The knowledge content structure modeling is based on a metadata matrix CS = {*title*, *summary*, *theme*, *category*, *keywords*, *body*, *author*, *post-time*, *references*}, which systematically organizes and structures knowledge texts related to PBL. Initially, the title and summary metadata enable students to quickly grasp the core content of the knowledge. The theme and category metadata can be employed to classify the knowledge texts, ensuring that students can easily locate knowledge resources closely related to their current project tasks on the mobile learning platform. The inclusion of keywords further enhances the precision of knowledge retrieval, allowing students to swiftly locate the necessary knowledge through simple keyword searches. The body of the text provides detailed explanations, and given the fragmented nature of mobile learning, the structure of the body content should be designed to facilitate segmented reading and gradual comprehension on mobile devices. The author information and post-time provide background context, assisting students in assessing the authority and timeliness of the knowledge. References offer further resources for in-depth learning, encouraging students to expand the breadth and depth of their knowledge as they progress with their projects.
b) Knowledge content feature modeling: To address the multidisciplinary and multi-theme knowledge content that may be involved in PBL, the learning platform needs to establish a knowledge classification system, a multi-level theme system, and a keyword database related to professional fields. This system serves as the foundation for knowledge feature modeling, ensuring that students in mobile learning environments can swiftly access knowledge resources closely related to their project tasks. The knowledge classification system encompasses the major fields and disciplines within PBL, ensuring comprehensiveness and systematicity in knowledge classification. The multi-level theme system refines and differentiates various levels of knowledge themes, meeting students' learning needs at different project stages. The keyword database provides data support for subsequent knowledge retrieval and recommendation. During the knowledge content feature modeling process, knowledge texts were first classified using a knowledge classifier, categorizing them into appropriate professional fields or disciplinary categories. Next, a theme recognizer was utilized to mine the themes within the text content, identifying the primary themes covered by the text, which aids students in better understanding the application scenarios of the knowledge. The keyword extraction module then analyzes the knowledge text and automatically generates keyword tags related to the content, assisting students in quickly locating knowledge points relevant to their projects on mobile devices.
c) Knowledge space vector modeling: In the context of PBL, students are required to filter out content from a vast array of knowledge resources that is relevant to their current project tasks. The construction of the knowledge space vector model begins with the identification of keywords within the knowledge texts, which reflect the core content and themes of the knowledge. Subsequently, the importance of each keyword in the knowledge space was determined by calculating its weight within the text. This weight was calculated based on metrics such as term frequency (TF) of keywords in the text and their inverse document frequency (IDF) across the entire knowledge base, thereby forming a vector representation of each knowledge text. Figure 1 illustrates a schematic diagram of the knowledge space vector modeling process.

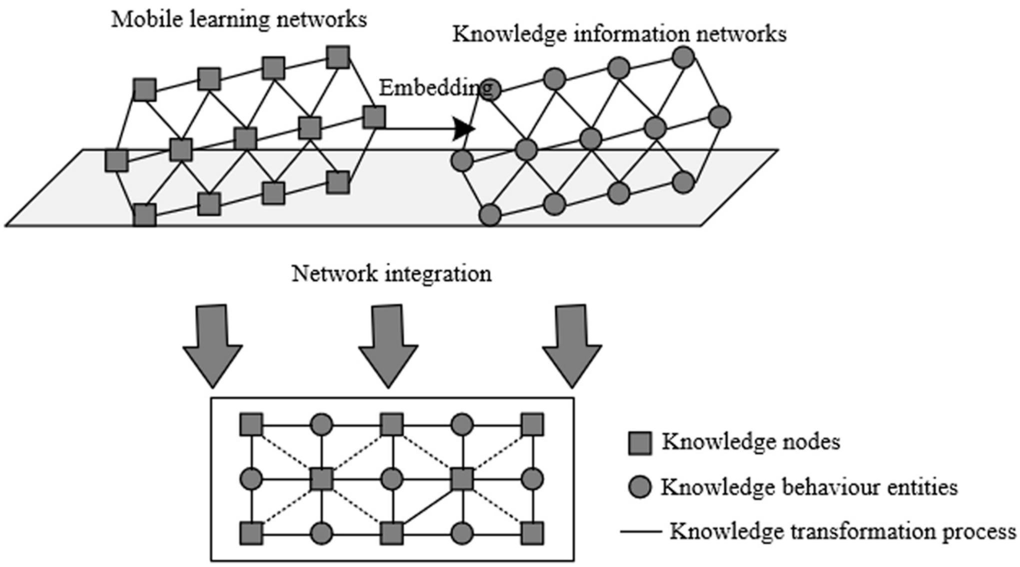

Fig. 1. Schematic diagram of knowledge space vector modeling

Specifically, let the knowledge set in the PBL knowledge base be denoted as $F = \{f_1, f_2, ..., f_u, ..., f_k, ..., f_V\}$, where V represents the total number of knowledge texts in the knowledge base. The set of all words appearing in these texts is denoted as $S = \{f_1, f_2, ..., f_v\}$, where v represents the number of distinct words across all V knowledge texts. The weight of each word in the knowledge text f_u was calculated using the TF-IDF method from information retrieval. Let $TF(s_j, f_u)$ represent the frequency of the j-th word in the text f_u, and let v_j represent the number of texts containing the j-th word across all texts.

$$TF-IDF(s_j, f_u) = TF(s_j, f_u) \cdot \log \frac{V}{v_j} \tag{1}$$

The weight of the j-th word in the knowledge text f_u can be determined using the following formula:

$$q_{uj} = \frac{TF-IDF(s_j, f_u)}{\sqrt{\sum_{t=1}^{|S|} TF-IDF(s_j, f_u)^2}} \tag{2}$$

Finally, the knowledge space vector model for the knowledge text f_u can be expressed as:

$$f_u = \begin{Bmatrix} s_1 & TF-IDF_1 \\ s_2 & TF-IDF_2 \\ \cdots & \cdots \\ s_v & TF-IDF_v \end{Bmatrix} = \{q_{u1}, q_{u2}, \ldots s_{uv}\} \tag{3}$$

3 KNOWLEDGE RECOMMENDATION FOR PBL IN MOBILE LEARNING ENVIRONMENTS

To facilitate knowledge recommendation within the context of PBL in mobile learning environments, a dynamic knowledge popularity model was constructed in this study. This model, by comprehensively considering both the static popularity of the knowledge and student interaction behavior, assists the system in recommending the most popular and relevant knowledge content, thereby meeting the immediate needs of students engaged in project-based learning.

The static popularity of knowledge serves as the foundational component of the dynamic knowledge popularity model, with initial scores assigned based on the inherent attributes of the knowledge. In PBL, two core factors determine static popularity: the knowledge category and the author's identity. The knowledge category determines the thematic domain of the content. If a particular category of knowledge is closely related to the current project, that category can receive a higher static popularity score. Additionally, the authority of the author's identity directly influences the static popularity of the knowledge. Knowledge published by authoritative authors is generally considered to possess higher credibility and value, thereby holding greater weight in the initial popularity score. As students interact more with the knowledge after its publication, the interaction popularity score begins to play a role in the dynamic popularity model. Student interaction behaviors, including the number of clicks, searches, favorites, comments, and shares, represented by *ZN*, *EV*, *ZV*, *FV*, and *TV*, respectively, are indicators of students' actual attention and approval of the knowledge content. These interaction behaviors are factored into the dynamic popularity score through different weights, further adjusting the knowledge's overall popularity. The weight calculation formula is as follows:

$$XQ = \begin{cases} CL \to 1 \\ SE \to 3 \\ SH \to 5 \\ RE \to 8 \\ FA \to 10 \\ \quad \cdots \end{cases} \tag{4}$$

Assuming the adjustment coefficient of a fixed value is denoted by *V* and the student population is represented by *FXI*, the popularity score generated by student interaction can be calculated as follows:

$$\begin{aligned} UG = V \times [XQ(CL) \cdot ZN + XQ(SH) \cdot TV + XQ(RE) \cdot FV \\ + XQ(SH) \cdot EV + XQ(FA) \cdot ZV]/FXI \end{aligned} \tag{5}$$

Furthermore, a time decay factor was employed to account for the changes in knowledge popularity over time. When knowledge is first published, it typically exhibits high popularity due to its novelty. However, as time progresses, this novelty diminishes, leading to a gradual decline in its popularity. The time decay factor ensures that the system does not continually recommend outdated knowledge but rather prioritizes newly published and highly interactive knowledge, thereby maintaining the relevance and timeliness of the recommendations. Assuming the current time is denoted by S_1, the time of knowledge publication by S_0, and the adjustment coefficient of a fixed value by *j*, the time-decayed popularity score can be calculated using the following formula:

$$SX(t) = e^{j \cdot (S_1 - S_0)} \tag{6}$$

The final formula for the popularity algorithm is:

$$FG = (TG + UG)/SX(t) \tag{7}$$

In PBL, knowledge content typically spans a wide range of domains, such as specific technical skills, project management strategies, or case studies. To effectively recommend relevant knowledge to students, the system first needs to construct a vector space model for each knowledge item. This involves converting the knowledge content into a multi-dimensional vector, where each dimension represents a feature such as keywords, themes, or tags. Once the knowledge is represented as a vector space model, the system can recommend content by calculating the similarity between different knowledge items. Specifically, when a student shows interest in a particular knowledge text, f_u, the system calculates the similarity between f_u and other knowledge texts using cosine similarity. Cosine similarity measures the similarity between two vectors by calculating the cosine of the angle between them. The smaller the angle, the closer the cosine value is to 1, indicating greater similarity between the two knowledge contents. The calculation formula is:

$$sim(f_u, f_k) = \frac{\sum_{j=1}^{v} q_{uj} \times q_{dj}}{\sqrt{\sum_{j=1}^{v} (zt_{uj})^2 \times \sum_{j=1}^{v} (zs_{kj})^2}} \tag{8}$$

Assuming the v-th keyword component of knowledge f_u is denoted by q_{uv}, the vector space models for knowledge f_u and f_k are expressed as:

$$f_u = (q_{u1}, q_{u2} \ldots, q_{uv}) \tag{9}$$

$$f_k = (q_{k1}, q_{k2} \ldots, q_{kv}) \tag{10}$$

In mobile learning environments, PBL often involves high levels of collaboration and immediateness, making collaborative filtering algorithms based on student interactions particularly effective in certain scenarios. For example, in a specific project task, multiple learners may encounter similar challenges or problems. By analyzing the knowledge behavior data of these learners, the system can promptly recommend knowledge resources that have been used by other similar learners and proven helpful for the project, thereby enhancing the efficiency and quality of project completion. Specifically, the algorithm first constructs a student-knowledge interaction matrix, which records the interactions of different learners with various types of knowledge. By calculating the similarity between the target learner and other learners, commonly using methods such as Pearson correlation coefficient or cosine similarity, the algorithm can identify the group of students whose knowledge preferences most closely align with those of the target learner. The system then recommends the knowledge content read by these similar student groups to the target learner, helping them discover potentially interesting knowledge that they have not yet encountered.

Assume the student set in the system's student database is denoted as $I = \{i_1, i_2 \ldots i_u \ldots i_k \ldots i_V\}$, and the interest model of student i_u is represented as IT_u. The similarity calculation formula is as follows:

$$sim(IT_u, IT_k) = \frac{|IT_u \cap IT_k|}{\sqrt{|IT_u| \times |IT_k|}} \tag{11}$$

The j students most similar to the target student i_u in the student set are identified, represented by the set $I(i_u, j)$. After extracting the knowledge that students in I are interested in, the knowledge that student i_u has already learned was filtered out, generating a candidate knowledge list. Assume that student i_n belongs to the student set $I(i_u, j)$ and has read knowledge f_k, with the known interest score of student i_n in knowledge f_k denoted as $o(i_n, f_u)$. The following formula calculates the interest score of students i_u for each piece of knowledge f_u in the candidate knowledge list:

$$o(i_u, f_k) = \sum_{i_n \in I(i_u, j) \cap F(f_k)} sim(IT_u, IT_k) \times o(i_n, f_k) \tag{12}$$

Finally, the top-ranked knowledge based on the interest scores is recommended.

4 EXPERT MAP APPLICATION IN PBL WITHIN MOBILE LEARNING ENVIRONMENTS

This study explores the application of an expert map to address the lack of professional guidance that students often experience in mobile learning environments. A core element of PBL is the ability for students to receive guidance and feedback from experts throughout the project process. However, in mobile learning environments, interactions between students and experts are often constrained by time and space, making it challenging for students to obtain timely professional support. By developing an expert map application, students can easily locate and contact experts related to their projects, thereby receiving the necessary guidance and assistance during project implementation. This application not only transcends the traditional spatial and temporal limitations of student-expert interactions but also enhances the quality and effectiveness of PBL through expert involvement. Consequently, it aids students in achieving higher levels of knowledge construction and skill development in a mobile learning environment. Figure 2 illustrates the three-dimensional structural model of the expert map.

In a mobile learning environment, the candidate expert pool may include both external industry experts and internal knowledge contributors. Through qualitative assessment methods, such as resume screening and questionnaire testing, the backgrounds, experiences, and professional capabilities of candidate experts are preliminary evaluated, filtering out those who do not meet the project learning requirements. The objective of this stage is to narrow the candidate pool, thereby reducing the workload of subsequent selection and combination processes. For candidates who pass the initial screening, the system employs an expert discovery algorithm to further evaluate their knowledge level and contributions in specific fields. This process not only focuses on the candidates' knowledge structures and abilities but also considers their adaptability to the mobile learning environment and their willingness to participate. The expert discovery algorithm assesses the potential contribution value of candidates in PBL by analyzing data such as their previous knowledge-sharing records, project involvement, and learner feedback, ultimately selecting the candidates who best meet the requirements of the expert map. The final stage is the combination phase, where the initiators of the learning platform and existing experts rate the filtered candidates across multiple dimensions. The evaluation criteria include not only the experts' knowledge level but also their alignment with the organization's business objectives, the effectiveness and efficiency of their knowledge sharing, and their collaborative capabilities. Based on these comprehensive considerations, the final expert list is compiled, and this information is added to the expert map.

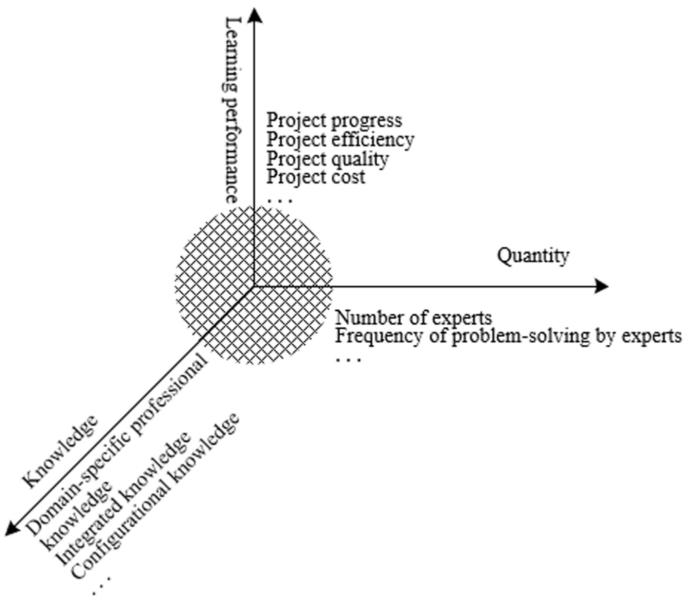

Fig. 2. Three-dimensional structural model of the expert map

In the context of a mobile learning environment, the computational approach to the expert discovery process should include a bidirectional discovery mechanism for both external and internal experts, with a focus on selecting the most suitable experts based on their alignment with the relevant knowledge domains. Initially, in the discovery of external experts, the learning platform must clearly define specific knowledge domains that are typically closely related to the goals of PBL. To identify suitable external experts, organizations can retrieve literature and research findings related to these specific knowledge domains from external knowledge repositories. By analyzing the keywords that appear in these documents, the system can identify expert candidates with extensive experience and academic achievements in these knowledge domains. The core of this computational approach lies in comparing the overlap between the research keywords of the candidate experts and the keywords of the knowledge domains, and assessing the candidates' suitability based on the degree of overlap. Experts with higher overlap are more likely to provide valuable knowledge support in PBL. Figure 3 illustrates the PBL process utilizing the expert map.

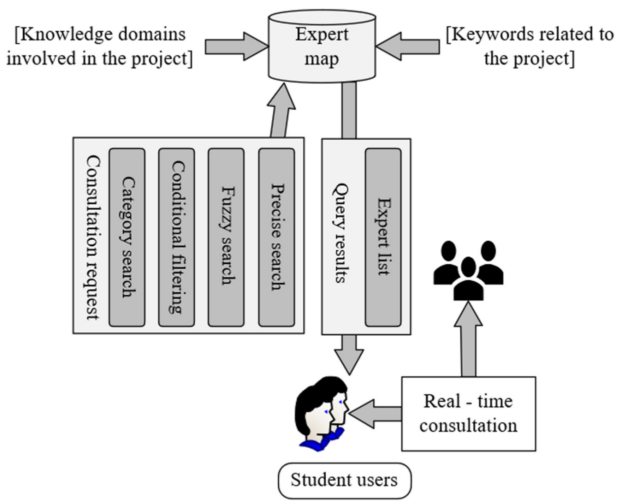

Fig. 3. PBL process utilizing the expert map

Assume the combination of keywords extracted from knowledge u is represented by $JQ(u)$. The following formula provides the expression for the keyword set of the corresponding knowledge category obtained by combining the keywords from v articles:

$$JQ_{dr} = I_{j \in Z_{jx}} \times JQ(u) \tag{13}$$

Assume that expert dr is the author of knowledge article u, and article u mentions expert dr. This situation can be represented by $X(u, dr) = 1$; otherwise, $X(u, dr) = 0$. The formula for calculating the expert-related keyword set is:

$$KW_{fe} = U_{k \in C_{ka}, A(i, fe)=1} \times KW(i) \tag{14}$$

The internal knowledge base records the knowledge contributions, project participation, and relevant professional domains of employees within the organization. Similar to external expert discovery, the system analyzes the keywords of internal candidate experts and compares these keywords with those of the required knowledge domains. By calculating the degree of overlap between these keywords, the system can identify the most suitable candidates to become experts among the internal employees. This approach not only ensures precision in expert selection but also encourages internal employees to actively contribute knowledge, thereby enhancing overall knowledge management. The expertise of an expert in a specific knowledge domain can be represented by the overlap rate between the keywords of the knowledge domain and those of the specific expert and is calculated as follows:

$$SC(dr, jx) = \left| JQ_{dr} \cap JQ_{jx} \right| / \left| JQ_{jx} \right| \tag{15}$$

Ultimately, whether for external or internal expert discovery, the system selects and ranks experts based on their overlap scores. Experts with higher scores are prioritized for inclusion in the expert map for use in PBL. This computational approach ensures that the learning platform can quickly identify the most suitable knowledge experts in response to diverse learning needs, thereby improving the efficiency and effects of project-based learning.

5 VALIDATION OF ALGORITHM EFFECTIVENESS AND EFFECT ANALYSIS OF THE STRATEGY

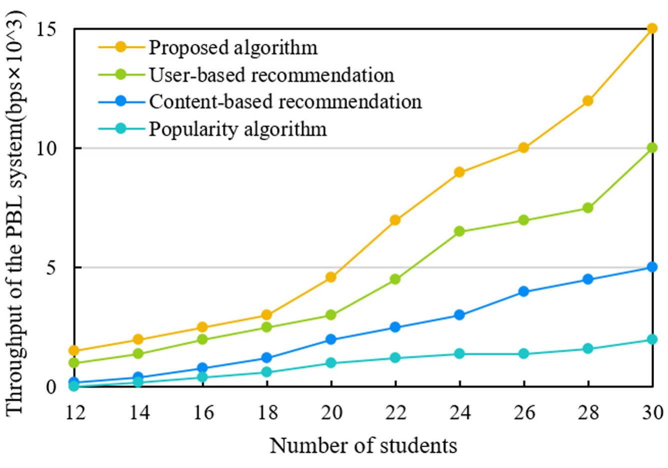

Fig. 4. Throughput of the PBL system in mobile learning environments using the proposed recommendation algorithm

As shown in Figure 4, the system throughput of the proposed algorithm gradually increases as the number of students rises. When the number of students reaches 12, the throughput of the proposed algorithm is 1.5. The throughput escalates to 15 when the number of students increases to 30. This growth trend is more pronounced compared to other algorithms. Although the user-based recommendation algorithm also demonstrates good scalability, its throughput is only 10 when the number of students reaches 30, significantly lower than that of the proposed algorithm. Additionally, the throughput of the content-based recommendation algorithm and the popularity algorithm exhibits only minor growth as the number of students increases, reaching five and two, respectively, when the number of students is 30. Therefore, the proposed algorithm shows superior system throughput performance in handling large-scale student populations, effectively addressing the substantial personalized learning demands. The experimental results indicate that the system throughput of the proposed algorithm significantly improves as the number of students increases, demonstrating its efficiency and reliability in managing large-scale data processing requirements.

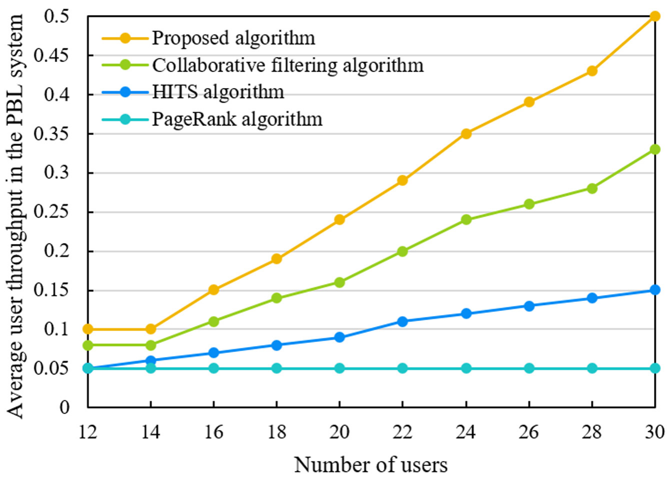

Fig. 5. Average user throughput in a PBL system within mobile learning environments using the proposed expert map algorithm

As shown by the data in Figure 5, the average user throughput of the proposed algorithm steadily increases as the number of students grows, rising from 0.1 with 12 students to 0.5 with 30 students. This indicates that the proposed algorithm effectively enhances average user throughput when facing larger student populations. In contrast, the collaborative filtering algorithm also shows some improvement under the same conditions. However, its growth is slower, with an average user throughput of only 0.33 when the number of students reaches 30. The hyperlink-induced topic search (HITS) and PageRank algorithms perform relatively poorly, particularly the PageRank algorithm, which remains unchanged throughout the experiment, with an average user throughput consistently at 0.05, exhibiting a clear bottleneck effect. This growth trend demonstrates that the proposed expert map algorithm has significant advantages in optimizing resource utilization and meeting personalized learning needs. In comparison, although the collaborative filtering algorithm does exhibit some scalability, its performance in handling large-scale data is inferior to that of the proposed algorithm. The HITS and PageRank algorithms, due to their inherent limitations, show a more pronounced bottleneck when confronted with increasing user demands.

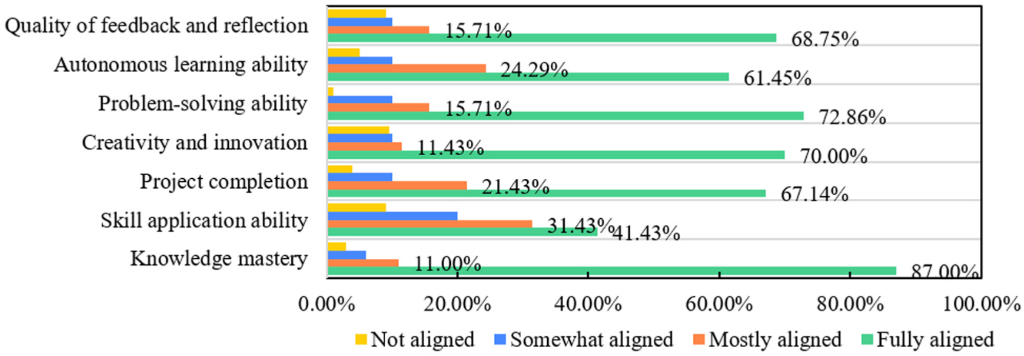

Fig. 6. Quality evaluation results of learning outcomes

Figure 6 shows the detailed quality evaluation results of learning outcomes. For the indicator "knowledge mastery," 87.00% of students are fully aligned with expectations, with an additional 11.00% mostly aligned. In contrast, "skill application ability" shows that only 41.43% of students are fully aligned, 31.43% are mostly aligned, and 9.00% are not aligned. In terms of "project completion," 67.14% of students fully meet expectations, indicating that the majority of students are able to complete projects with high quality. Although the percentages of students fully aligned for "creativity and innovation" and "problem-solving ability" are 70.00% and 72.86%, respectively, the "autonomous learning ability" has a fully aligned rate of only 61.45%, suggesting room for improvement. Additionally, 68.75% of students are fully aligned with expectations for the "quality of feedback and reflection." The analysis of the data indicates that the PBL strategy employed in this study has achieved significant success in improving students' knowledge mastery and project completion, with the vast majority of students excelling in these areas. However, the relatively lower fully aligned rates for skill application and autonomous learning abilities suggest that there is still room for improvement in practical skill application and autonomous learning. The high fully aligned rates for creativity and innovation, as well as problem-solving ability, demonstrate the effectiveness of PBL in fostering innovative thinking and enhancing problem-solving skills among students.

As shown in Figure 7, the evaluation results of learner engagement reveal differences in student performance across various dimensions. In the dimension of "online interaction frequency," 75.71% of students are fully aligned, indicating that the majority of students actively participate in online interactions during the learning process. Additionally, 70.00% of students are fully aligned in "collaborative engagement," reflecting the effectiveness of collaborative efforts within the PBL environment. However, only 48.57% of students are fully aligned in "task completion rate," with 21.43% somewhat aligned, suggesting that task completion performance is less ideal compared to other indicators. Regarding "learning motivation and attitude," 62.80% of students are fully aligned, whereas only 44.29% are fully aligned in "sustained participation time," indicating challenges in maintaining long-term engagement in learning activities. The data suggest that the PBL approach studied in this study effectively enhances students' online interaction frequency and collaborative engagement, highlighting the strategy's success in fostering interaction and cooperation among students. However, the relatively lower fully aligned rates in task completion and sustained participation time indicate that, while students are actively engaged in learning activities in the short term, improvements are still needed in task completion and maintaining long-term learning motivation. The high alignment rate in learning motivation and attitude suggests that PBL can stimulate students' interest and enthusiasm for learning, but the strategy to further improve task completion rates and sustained participation may be key areas for future research and practice.

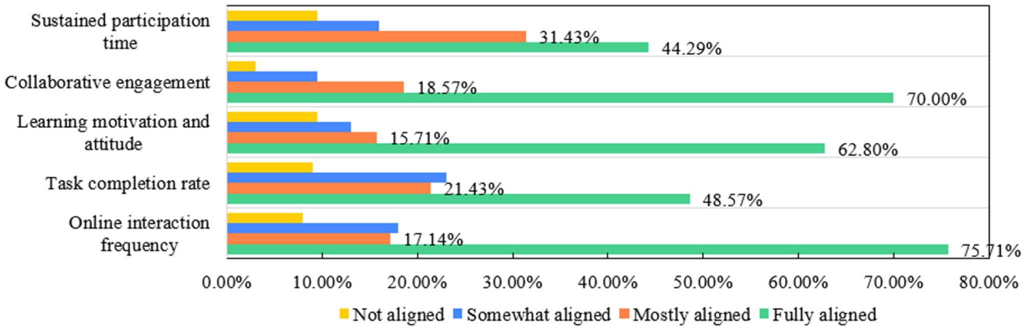

Fig. 7. Evaluation results of learner engagement

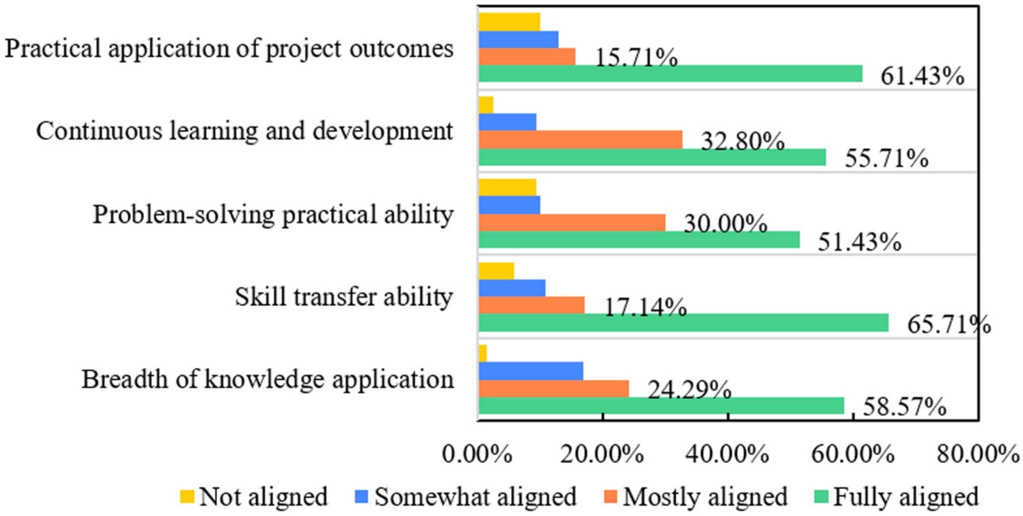

Fig. 8. Evaluation results of learning transfer and application

According to the data in Figure 8, the evaluation results of learning transfer and application show variations in student performance across multiple dimensions. In the dimension of "skill transfer ability," 65.71% of students are fully aligned, indicating that the majority of students can effectively apply the skills they have learned to new contexts. For the dimensions of "breadth of knowledge application" and "practical application of project outcomes," the proportions of students fully aligned are 58.57% and 61.43%, respectively, demonstrating that students are able to broadly apply their acquired knowledge and achieve practical applications within their projects. However, in "problem-solving practical ability" and "continuous learning and development," the fully aligned rates are 51.43% and 55.71%, respectively, suggesting there is room for improvement in these areas. Notably, 9.50% of students are not aligned in "problem-solving practical ability." The data analysis indicates that the PBL strategy employed in this study has achieved significant success in enhancing students' skill transfer ability and breadth of knowledge application, particularly in applying learned skills and knowledge to real projects with exceptional performance of students. However, despite the positive outcomes in skill transfer and knowledge application, there remains substantial room for improvement in the depth and sustainability of problem-solving practical ability and continuous learning and development. These findings suggest that future research and practice could focus on further strengthening students' problem-solving practice and encouraging continuous self-improvement and development after project completion, thereby more comprehensively enhancing learning transfer and application.

6 CONCLUSION

This study comprehensively explored the implementation strategy and actual effects of PBL in a mobile learning environment by constructing a knowledge model, designing a personalized knowledge recommendation system, and developing an expert map application. The findings indicate that the system designed in this study effectively enhances students' learning outcomes, particularly excelling in knowledge mastery and project completion. Additionally, the expert map application significantly improved student engagement and collaboration by integrating expert resources, thereby optimizing learning outcomes. The experimental results demonstrated that the proposed recommendation algorithm exhibited outstanding throughput performance in the PBL system and especially showcased remarkable scalability in handling large-scale student populations. Furthermore, the evaluation results of learning outcomes quality, learner engagement, and learning transfer and application all suggest that the proposed strategy achieved positive effects in enhancing students' skill transfer ability, breadth of knowledge application, and problem-solving ability. However, the results also reveal areas for improvement in task completion rates and sustained learning ability, as some students have not reached the desired level in these dimensions.

The research presented in this study holds significant theoretical and practical implications in the field of mobile learning. By integrating the characteristics of PBL with those of the mobile learning environment, a systematic learning solution was proposed, which helps students better tackle complex learning tasks and improve learning efficiency. However, certain limitations exist in this study. Firstly, the sustained engagement effects of the system over extended periods have not yet been fully validated. Secondly, there remains room for improvement in the performance of some students in actual task completion. Future research could further optimize the system's task management and personalized recommendation features to enhance task completion rates and sustained learning capabilities. Additionally, further exploration is needed on how to better support students' autonomous learning and reflection within the mobile learning environment, thereby improving the practical application outcomes of PBL. Through these improvements and expansions, the PBL system in a mobile learning environment will become more refined and widely applicable in practical teaching.

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