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PAPER

Impact of Recommended Resources in a Mobile Learning Environment on Self-Regulated Learning Abilities among Higher Education Students

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ABSTRACT

With the rapid development of mobile technology, mobile learning has increasingly become a significant trend in higher education. Offering flexibility in time and space, online learning introduces new opportunities and challenges for student education. Particularly, the potential of mobile learning to foster students' self-regulated learning (SRL) abilities remains largely untapped. SRL abilities refer to students' capacity to proactively set goals, manage resources, monitor progress, and evaluate outcomes during the learning process, which is crucial for learning effectiveness. Although existing research has started to examine the impact of mobile learning on students' self-regulation abilities, there is still a significant lack of quantitative analysis of students' learning resource preferences and the development of personalized recommendation methods based on the preferences. This study aims to quantitatively analyze the learning resource preferences of higher education students and propose a novel, preference-based equitable recommendation method for mobile learning to support their SRL. The anticipated results are expected to provide theoretical and methodological support for higher education practices, enhance students' SRL abilities, and offer new strategies for the effective utilization of mobile learning resources.

KEYWORDS

mobile learning, self-regulated learning (SRL) abilities, learning resource preferences, personalized recommendations, higher education

1 INTRODUCTION

In today's rapidly changing era of information technology, mobile learning has emerged as an important trend in the field of education, particularly in higher education. Its flexibility and convenience offer students unprecedented learning opportunities [1–10]. With the widespread use of smartphones and tablets, students can access a vast array of educational resources anytime and anywhere, thus

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breaking the temporal and spatial constraints of traditional classroom learning [11–14]. However, this new mode of learning presents new challenges to students' SRL abilities, which are crucial for effective learning outcomes [15, 16]. Students' SRL abilities encompass their capacity to establish learning goals, manage learning resources, self-monitor their learning process, and self-evaluate their learning outcomes. Therefore, exploring the impact of mobile learning on SRL abilities among higher education students is of significant importance for enhancing student learning outcomes and personal development.

Although the application of mobile learning in higher education has received increasing attention, research on how mobile learning affects students' SRL abilities is relatively scarce and limited in terms of research methods and perspectives [17–20]. Current studies primarily focus on descriptive research, lacking in-depth analysis of students' resource preferences and learning strategy choices in a mobile learning environment. Moreover, how to effectively recommend learning resources based on students' preferences for learning resources to support their SRL process is an area that existing research rarely addresses [21–23]. Thus, a deeper exploration of this topic is crucial for optimizing the mobile learning environment and enhancing students' SRL abilities.

Previous studies have primarily utilized qualitative methods such as questionnaires and case studies. While these methods offer initial insights, they have constraints in quantitative analysis and widespread implementation [24, 25]. In particular, there is a lack of research quantitatively analyzing the learning resource preferences of higher education students in a mobile learning environment and methodological research on personalized learning resource recommendations based on these preferences [26]. This gap limits educators' and researchers' ability to deeply understand and effectively utilize mobile learning resources to foster students' SRL potential.

Given this, this paper aims to address the aforementioned research gaps by enhancing the understanding of the issue and investigating strategies through two main research components. Firstly, the paper will employ a quantitative research method to analyze the degree of learning resource preferences among higher education students based on mobile learning information. Secondly, a new equitable recommendation method for mobile learning is proposed based on the grouping of learning resource preferences. The aim is to offer more personalized and effective learning resources for student groups with varying preferences. This research is expected to provide theoretical and methodological support for higher education practices and to have practical value in enhancing students' SRL abilities. Through in-depth exploration and application of the potential of mobile learning resources, this paper aims to offer new perspectives and solutions to teaching reforms and student capability development in higher education.

2 QUANTIFYING THE DEGREE OF LEARNING RESOURCE PREFERENCES IN HIGHER EDUCATION BASED ON MOBILE LEARNING INFORMATION

Exploring the impact of mobile learning on the SRL abilities of higher education students begins with a quantitative study on the extent of learning resource preferences related to mobile learning information. Such research can provide data support and a theoretical basis for subsequent personalized learning resource recommendations. Through quantitative analysis, the extent of students' preferences for various learning resources in a mobile learning environment can be objectively uncovered, thus enhancing the comprehension of students' learning behaviors and requirements. Quantifying these preferences not only helps identify key factors affecting students' SRL abilities but also provides accurate guidance for designing mobile learning strategies and tools that better meet students' personalized needs. By analyzing students' preferences for video tutorials, e-books, interactive discussions, and other resources, educators can optimize the allocation of learning resources. This enables them to formulate more effective learning plans, thereby promoting active participation and enhancing capabilities in students' self-directed learning processes.

In the quantitative study of learning resource preferences in higher education based on mobile learning information, learning behavior data undoubtedly becomes a crucial data source for gaining insight into students' preferences. For example, by analyzing students' access frequency, learning duration, and interaction level with specific learning resources, we can assess the attractiveness and suitability of those resources. This approach aims to quantify the differences in students' preferences for various learning resources, with the goal of using these data on learning behaviors as key indicators to calculate the degree of learning resource preferences. Figure 1 illustrates the process of quantifying the extent of learning resource preferences in higher education.

The recommendation system in this paper needs to calculate students' preferences for evaluating learning resources. The input of this research model includes the student, the learning resource, and the group of learning resources that the student has historically rated highly. The output is the student's evaluation of a specific learning resource in terms of its learning attractiveness. This model includes two submodules: one for calculating the attractiveness score of learning resources and another for integrating multiple scoring dimensions to form the student's overall preference score for a specific learning resource.

Regarding the computation module for the attractiveness of learning resources, each input is a single entity, including the student themselves, a specific learning resource, and each resource from the collection of resources that the student has rated highly in the past. These entities are individually inputted into the module to calculate their respective attractiveness scores for the student. Through this method, the research can accurately quantify and comprehend the extent of student preferences for various learning resources. This provides data support for optimizing the mobile learning environment and recommendation systems. Assuming the average score given by all students is represented by $\bar{e}$, the average score given by student k by $\bar{e}(k)$, and the ratio of student k's scoring to the general scoring habit of students by $\bar{e}(k)/\bar{e}$, the operation of this module can be represented by the following formula.

$$e'_q(u) = \frac{\sum_{k \in E'_u} r(k,u) \Big/ \frac{\bar{e}(k)}{\bar{e}}}{\left|E'_u\right|} \tag{1}$$

In quantifying the degree of preferences for mobile learning resources among higher education students, the method adopted involves analyzing students' behavioral data on specific learning resources, such as visit frequency, interaction number, and learning duration, and comparing it with the students' general learning behavior patterns. The specific calculation method involves normalizing the sum of the student's behavioral data for a specific learning resource based on the student's typical learning behavior habits to mitigate the impact of individual differences on the evaluation results. The score obtained through calculation reflects the degree of student preference for that resource, and comparing this score with the student's ratings for other resources can provide a relative measure. By averaging these relative measures, the final preference degree scores for different learning resources are obtained. Specifically, suppose the highest score among the ratings of student i is represented by $eMAX$, the historical average rating of the student by $\bar{e}(i)$, and the weight parameters by x and y. After completing the calculation of the attractiveness of student i, learning resource s, and the collection of learning resources that i has rated highly, i's rating for s can be calculated using the following formula:

$$e'_q(i,s) = eMAX - x * \left|e'_q(i) - e'_q(s)\right| - y * \frac{\sum_{u \in E_i} e(i,u) * \left|e'_q(i) - e'_q(s)\right|}{\left|R_u \times \bar{r}(u)\right|} \tag{2}$$

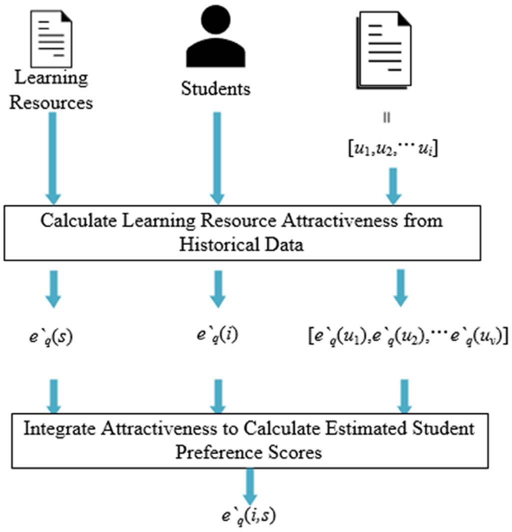

Fig. 1. Quantification process for learning resource preference degree in higher education

In specific studies, evaluating students' degree of preference for particular learning resources involves a detailed and reciprocal evaluation process. The specific method involves traversing the collection of learning resources E_i that student i has highly rated, which includes frequently used or highly interacted with learning resources. By calculating the preference differences of students for these resources, resources that students prefer more are given higher weight. This process not only reflects the students' clear preferences for certain types of content in learning resources but also ensures that students tend to highly rate those resources that meet their learning needs and interests. After completing the preference evaluation $e'_q(i,s)$ for a resource, the universal attractiveness appeal of resources $e'_q(s,u)$ can be further analyzed, allowing for an assessment of how well learning resources can meet the diverse needs of students. This bidirectional evaluation mechanism not only highlights the personalized preferences of students for learning resources but also evaluates the adaptability and popularity of learning resources in the overall teaching environment. This provides important data support and analytical perspectives for optimizing mobile learning resource allocation and recommendation strategies.

3 EQUITABLE RECOMMENDATION METHOD FOR MOBILE LEARNING BASED ON GROUPING BY LEARNING RESOURCE PREFERENCES

In the research process of this paper, after quantifying learning resource preferences, conducting further research on an equitable recommendation method for mobile learning based on grouping by learning resource preferences plays a decisive role in achieving research objectives. By using detailed grouping based on learning resource preferences, this research can design and implement personalized learning resource recommendation strategies for the specific needs of different student groups. This strategy not only optimizes resource allocation, ensuring that each student can access resources that match their preferences and learning goals, but also provides a uniform and personalized learning experience. This further stimulates students' learning motivation and enhances their SRL abilities. Moreover, the equitable recommendation method ensures the diversity and breadth of recommended resources, helping students broaden their knowledge horizons and improve their problem-solving capabilities. This, in turn, deepens the understanding of the role of mobile learning in enhancing the SRL abilities of higher education students. Figure 2 illustrates the principle of the equitable mobile learning recommendation system.

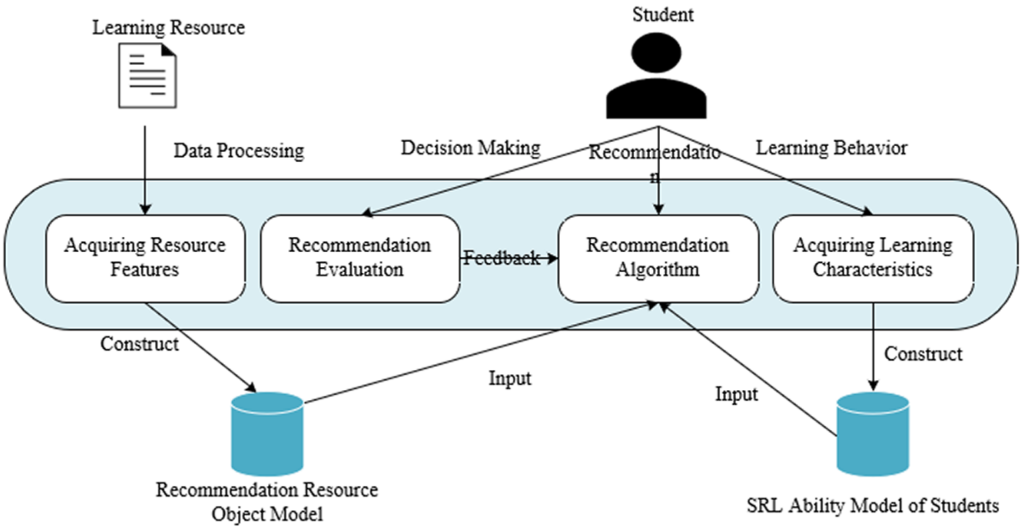

Fig. 2. Principle of the equitable mobile learning recommendation system

In the equitable recommendation method for mobile learning based on grouping by learning resource preferences, the parameter definitions are as follows: Parameter L represents the collection of all learning resources; I_i' represents the collection of learning resources associated with a specific student i, i.e., all resources that student i can access; I_i represents the group of learning resources that match student i's preferences, defined based on the student's historical learning behavior and preferences; $E_i' \subseteq I_i'$ represents the collection of learning resources that student i has already rated; $E_i' \subseteq I_i'$ represents the collection of learning resources that have been helpful to student i, determined based on the student's feedback or improvement in grades; $e(i,s)$ represents the actual rating score of student i for learning resource s; $e_y'(i)$ may represent the resource preference score based on the analysis of student i's academic performance or learning behavior, mainly used for grouping; $e_x'(i,s)$ represents the predicted. The rating score of students i for learning resource s is calculated based on traditional recommendation algorithms focused on accuracy. Here, $e'(i,s)$ represents the final calculated overall predicted rating score of student s for learning resource t.

The overall algorithm model includes five submodules: the grouping module, the accuracy module, the student fairness module, the resource fairness module, and the hybrid module. The purpose of the grouping module is to use information such as academic performance and engagement to group students into communities with similar learning preferences, usually based on their feedback on resources or improvement in grades. The accuracy module uses traditional methods to calculate the predicted satisfaction scores of students for learning resources and can inversely calculate the predicted scores of resources in meeting students' needs. The student fairness module aims to evaluate the fairness of recommending a certain learning resource to a specific student, ensuring that each student can access resources that suit their learning style and capabilities. The resource fairness module evaluates the fairness of recommending learning resources to different students, ensuring that high-quality resources can be evenly distributed among different students. The hybrid module integrates the results of the first four modules to form the final recommendation results. Figure 3 illustrates the recommendation model process.

In the recommendation method, the grouping module plays a crucial role, as its design directly influences the effectiveness of the recommendation results. Excessively detailed grouping may diminish the consistency of recommendation results, resulting in a concentration of the types of resources students encounter; conversely, overly broad grouping may lessen the variety of recommendations, impacting students' chances to explore new resources. Only when both uniformity and diversity reach a high level can the fairness of the recommendation system be best demonstrated. In this study, learning preferences are chosen as the criterion for grouping: that is, students with similar learning preferences and behaviors are grouped together.

From a technical implementation perspective, grouping methods can be divided into dynamic grouping and static grouping, as illustrated in Figure 4. Dynamic grouping adjusts based on real-time changes in students' learning behaviors and preferences, while static grouping is based on criteria set at the beginning and does not change with the changes in students' behaviors. This paper adopts dynamic grouping for improved outcomes. The basic principle of dynamic grouping is to generate corresponding groups dynamically based on students' behaviors and preferences during the learning process. First, students' learning preferences are comprehensively assessed by analyzing their levels of interaction with various learning resources, including visit frequency, study duration, and homework completion. Then, these preference scores are compared with those of other students in the same learning domain, and students with similar learning preferences are grouped together. In the process of dynamic grouping, a range of similarities and learning preferences can be used as the criterion for grouping, or the number of students after grouping can be used as the basis for grouping. Grouping students based on a range of learning preferences allows them to be placed in the same group as long as the variation in their learning preference scores falls within a specified range. This method allows for possibly uneven group sizes but can more accurately reflect students' actual learning needs and interests. Suppose the set differentiation range is represented by *EDI*. The specific grouping process is given by the following formula:

$$Ut(i,s) = \begin{cases} 1, \left| e'_y(u) - e'_y(s) \right| \leq eDI \\ 0, \left| e'_y(u) - e'_y(s) \right| > eDI \end{cases} \tag{3}$$

Suppose the attractiveness ranking of student *I* in the student set is represented by $ufa(i)$, and the maximum ranking difference required for students i and s to be in the same group is represented by *ufaDI*. The final judgment formula is as follows:

$$Ut(i,s) = \begin{cases} 1, \left| uda(i) - ufa(s) \right| \leq ufaDI \\ 0, \left| uda(i) - ufa(s) \right| > ufaDI \end{cases} \tag{4}$$

The fairness recommendation module aims to ensure the fairness of recommending learning resources to specific students, specifically in two aspects: uniformity and diversity. This module primarily calculates several aspects of uniformity: the uniformity of learning resources being recommended on a global scale, the uniformity of learning resources being recommended within specific student preference groups, and the uniformity of learning resource recommendations received by students. By making such calculations, the aim is to achieve two goals: ensuring that every learning resource has equal opportunities to be utilized and explored, and ensuring that each student can access a broad and balanced range of learning resources to meet their personalized learning needs and promote learning efficiency. This consideration of fairness focuses not only on ensuring the broad distribution of resources but also on the equality of students receiving recommendations. This approach promotes a more efficient and personalized learning environment that helps enhance students' SRL abilities.

1. The so-called global uniformity of learning resource recommendations involves measuring the frequency of a specific learning resource being recommended in the entire system and comparing it with the recommendation frequencies of other learning resources. By this means, the uniformity of the recommended resource can be assessed, ensuring all resources have equal opportunities to be recommended and utilized. This helps avoid situations where some resources are overly concentrated or neglected, promoting the comprehensive use of educational resources. Suppose the set of students for whom "*s*" is a recommended learning resource is represented by "I_s," and the global recommendation count for provider "*u*" is represented by "$O_{AL}(u)$". The specific calculation method is as follows:

$$d_{AL}(s) = \frac{\frac{1}{|I_s| - 1} \sum_{u \in I_s, u \neq s} O_{AL}(u) + 1}{O_{AL}(u) + 1} \tag{5}$$

2. Calculating global uniformity alone might result in recommendation results being influenced by the frequency of students accessing the recommendation system, potentially leading to a bias towards recommending a specific class of resources. Therefore, another key indicator in the equitable recommendation method for mobile learning, based on grouping by learning resource preferences, is the uniformity of learning resources being recommended within specific student preference groups. By assessing the balance of resource recommendations within specific preference groups, this indicator ensures that all types of resources have the opportunity to be recommended within the range of students' specific preferences. This approach maintains recommendation diversity and meets personalized needs. The calculation method is shown below:

$$d_{GF}(H_i, s) = \frac{\frac{1}{|I_s| - 1} \sum_{u \in I_s, u \neq s} O(H_i, u) + 1}{d_{GF}(H_i, t) + 1} \tag{6}$$

To calculate the uniformity with which "s" is recommended to the student group "H_i," it is necessary to traverse "I_s" and calculate the number of times each learning resource is recommended to "H_i." Then, calculate the $O_{GR}(H_i, u)$, find its average, and divide by the number of times "*s*" is recommended to "H_i." The larger the value of d_{GF}, the lower the relative frequency with which "*s*" is recommended to H_i, and thus the higher the recommendation score.

3. Based on the assumption that recommended resources should help enhance students' SRL abilities, the recommendation algorithm also considers student diversity. Since the frequency with which students receive recommendations is subjectively determined, consumer uniformity is defined as the opportunity for students to access different types or levels of learning resources being equal. This implies that, irrespective of the student group and their learning preferences, the allocation of learning resources in the recommendation system should be equitable. This ensures that all students have equal access to a diverse array of learning materials, fosters knowledge exploration, and enhances learning efficiency. Suppose the frequency with which "*s*" is recommended to "*i*" is represented by $O(i, u)$, its calculation method is shown below.

$$d_{GF}\left(i,H_s\right)=\frac{\frac{1}{|I_s|-|H_s|}\sum_{u\in I_s,u\notin H_s}O\left(i,u\right)+1}{\frac{1}{|H_s|}\sum_{u\in H_s}O\left(i,u\right)+1} \tag{7}$$

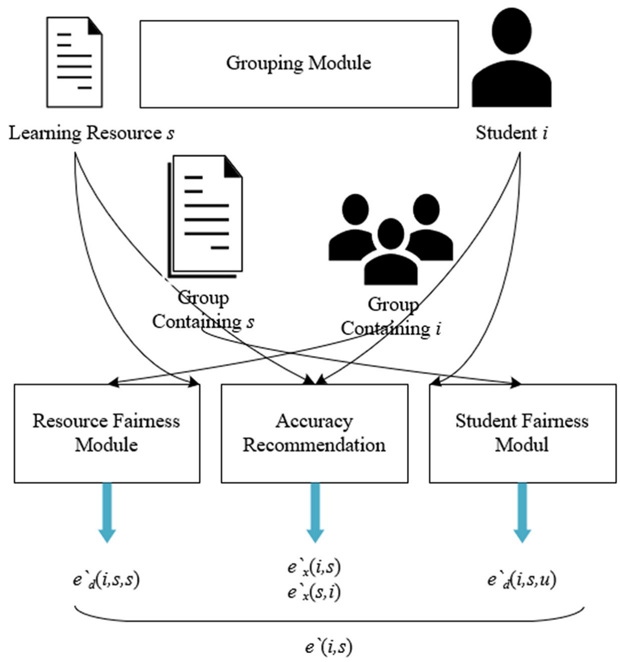

Fig. 3. Recommendation model process

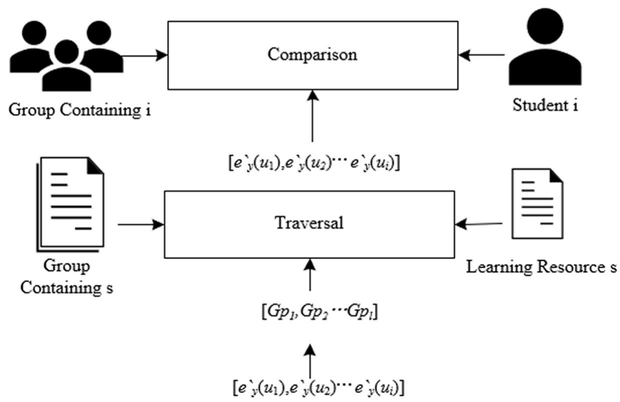

Fig. 4. Comparison of grouping methods in the grouping module

4 EXPERIMENTAL RESULTS AND ANALYSIS

Based on the data in Table 1, the algorithm combination proposed in this paper is competitive in terms of accuracy compared to traditional recommendation algorithms. In the table, the sum of the three weight coefficients for student satisfaction with learning resources for enhancing SRL abilities (positive accuracy), the estimation of uniformity and diversity for learning resources, and the estimation of uniformity and diversity for students remain constant at 1. The ratios are 1:1:1, 2:1:1, 1:2:1, 1:2:2, and 2:2:1, corresponding to algorithm-combination 1 and algorithm-combination 5, respectively. Specifically, the SVD-CF algorithm performs optimally on both MAE and RMSE metrics, achieving 0.178 and 0.225, respectively. This demonstrates the powerful capability of SVD in handling sparse data and revealing latent features. The transformer algorithm closely follows, demonstrating high accuracy, particularly in handling intricate sequence data. However, the algorithm combination 5 proposed in this paper achieved an MAE of 0,201, outperforming most traditional algorithms, albeit slightly inferior in RMSE performance. This indicates that this combination algorithm has achieved certain effects in balancing the estimation of preference degree, resource uniformity. and diversity, as well as student uniformity and diversity. Although other combination algorithms may not perform as well as SVD-CF or Transformer on certain metrics, overall, they demonstrate acceptable accuracy for providing fair recommendations. Based on the above data analysis, the recommendation method proposed in this paper is effective, particularly algorithm-combination 5. This algorithm considers the uniformity and diversity of learning resources, as well as the uniformity and diversity of students, which are crucial for enhancing SRL abilities among higher education students. By providing students with personalized and diverse learning resources, recommendation algorithms help facilitate students in discovering and utilizing resources that suit their personal learning styles and needs. This enhances the effectiveness of learning and supports independent and on-demand learning needs.

Table 1. Accuracy results of different mobile learning equitable recommendation methods

Method	*MAE/eMAX*	*RMSE/eMAX*
SVD-CF	0.178	0.225
ALS-CF	0.189	0.235
Bothway-CF	0.193	0.248
LSTM	0.225	0.256
Transformer	0.187	0.234
The proposed algorithm-combination 1	0.223	0.245
The proposed algorithm-combination 2	0.215	0.248
The proposed algorithm-combination 3	0.208	0.236
The proposed algorithm-combination 4	0.231	0.258
The proposed algorithm-combination 5	0.201	0.236

Table 2 presents the performance of various mobile learning recommendation algorithms in relation to uniformity and diversity. Observing the Coverage@50 and Recommendation Counts@50 metrics, we can see that the LSTM algorithm and algorithm combinations 4 and 5 exhibit higher uniformity, with Coverage@50 exceeding 40%. This means that these algorithms can encompass learning resources more broadly, providing students with more choices. Especially algorithm-combination 5, which was accessed 48569 times in Recommendation Counts@50, significantly outperformed any other algorithm. This indicates the highly uniform distribution of recommendations across different resources. When considering Diversity@K, the diversity of the recommendation list and algorithm combinations 1 and 4 show the highest diversity in the table, at 0.169 and 0.189, respectively. This indicates that the recommendation system can provide a wide range of learning resources. Algorithm-combination 4 maintains a high level of both uniformity and diversity, indicating its ability to balance these aspects and offer students a wide and diverse range of learning materials. It can be concluded that the mobile learning equitable recommendation method proposed in this paper, especially algorithm combinations 4 and 5, performs better in terms of uniformity and diversity compared to traditional algorithms. This is crucial for enhancing the SRL abilities of higher education students. Uniform recommendations of learning resources ensure that students are exposed to a wide range of learning materials. Diversity stimulates students' interest and motivation to learn, helping them explore new learning areas, which are key components of SRL abilities.

Table 2. Uniformity and diversity results of different mobile learning equitable recommendation methods

Algorithm	*Coverage@50*	Recommendation Counts @50	*Diversity@K*
SVD-CF	3.21%	185.23	0.071
ALS-CF	17.562%	112.03	0.123
Bothway-CF	18.569%	89.365	0.145
LSTM	41.236%	51.231	0.156
Transformer	35.698%	52.488	0.152
The proposed algorithm-combination 1	38.547%	51.369	0.169
The proposed algorithm-combination 2	37.521%	52.682	0.167
The proposed algorithm-combination 3	37.236%	53.691	0.152
The proposed algorithm-combination 4	41.236%	48.988	0.189
The proposed algorithm-combination 5	41.236%	48569	0.178

Table 3. Diversity and SRL facilitation results of different mobile learning equitable recommendation methods

Algorithm	Diversity@50/*eMAX*	Degree of facilitation/*eMAX*
SVD-CF	0.112	0.214
ALS-CF	0.124	0.215
Bothway-CF	0.126	0.189
LSTM	0.112	0.223
Transformer	0.089	0.189
The proposed algorithm-combination 1	0.124	0.214
The proposed algorithm-combination 2	0.112	0.225
The proposed algorithm-combination 3	0.114	0.214
The proposed algorithm-combination 4	0.118	0.206
The proposed algorithm-combination 5	0.126	0.236

Table 3 presents a performance comparison of various mobile learning recommendation methods in terms of diversity and their facilitation of SRL abilities. In the Diversity@50 metric, we observe that algorithm combination 5 scores 0.126, performing the best among all algorithms, demonstrating the highest diversity. This indicates the algorithm's effectiveness in recommending various types of learning resources, enriching students' learning experiences. In terms of facilitating SRL abilities, algorithm combination 5 also stands out with a score of 0.236, representing the most effective algorithm in helping students enhance their SRL abilities. Other algorithm combinations, such as combinations 2 and 4, also demonstrate strong performance in these two metrics but do not exceed combination 5. In comparison, while SVD-CF and LSTM algorithms perform reasonably well in facilitating accuracy, they fall short in diversity. These data suggest that the recommendation method proposed in this paper has a clear advantage in motivating student self-learning and providing personalized learning resources. According to the data analysis in Table 3, the algorithm, especially combination 5 proposed in this paper, performs excellently in enhancing students' SRL abilities, which is crucial for student learning in higher education environments. Algorithm combination 5 considers the uniformity and diversity of learning resources and students, aiming to achieve a strong alignment between learning content and learner needs with a weight ratio of 2:2:1. This approach ensures that the recommendation system can offer a diverse range of learning resources to meet the personalized needs of individual students, effectively promoting the development of students' SRL abilities.

Figure 5's data on recommendation coverage shows that as the group size increases, recommendation coverage grows from 37.80% with 25 groups to 42.80% with 200 groups. This indicates that as the recommendation system considers a larger user group, it can access more learning resources, thereby being able to recommend suitable learning content to a broader audience. Regarding the standard deviation of recommendation counts, it decreases from 56.40% to 47.50%, indicating that as group size increases, the distribution of resource recommendations becomes more uniform. For recommendation diversity, there is a slight decline as group size increases, from 0.1808 with 25 groups to 0.1750 with 200 groups. Although the decline is minimal, it suggests that the system slightly sacrifices recommendation diversity while expanding coverage and balancing recommendation counts. The conclusion can be drawn that the proposed recommendation algorithms effectively increase recommendation coverage. This means the algorithms can access and recommend more learning resources, benefiting different students' learning needs. With the expansion of group size, the decrease in standard deviation indicates a more equitable distribution of resources among different users by the recommendation system. This balanced recommendation strategy encourages students to explore a variety of learning materials, thereby promoting the enhancement of SRL abilities.

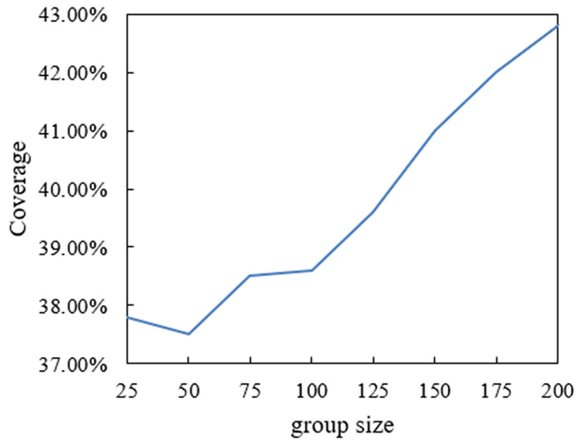

Fig. 5. *(Continued)*

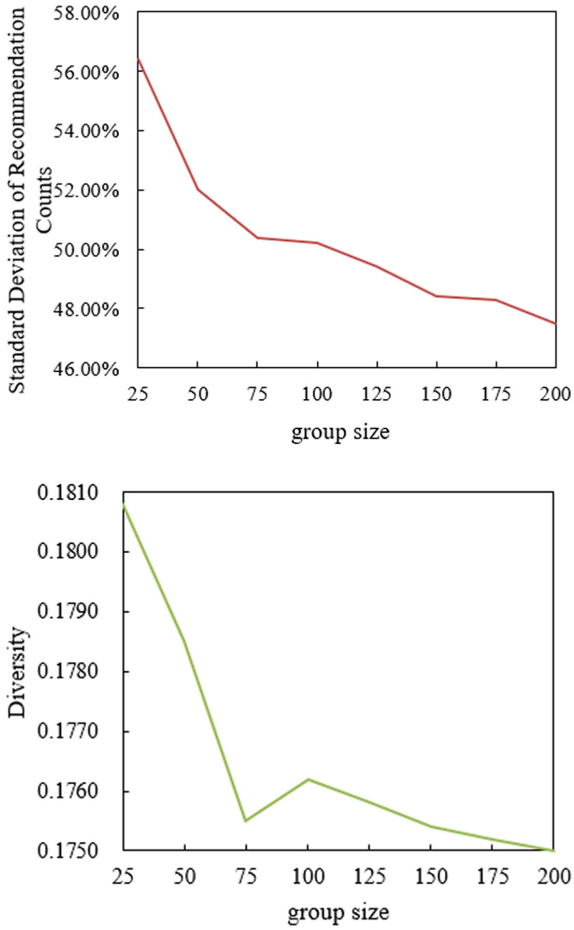

Fig. 5. Changes in algorithm recommendation coverage, standard deviation of recommendation counts, and recommendation diversity across different group sizes

5 CONCLUSION

This paper primarily focuses on analyzing higher education students' preferences for mobile learning resources and developing recommendation algorithms. Through quantitative research methods, this study first analyzed students' preferences for mobile learning resources. Based on these preferences, researchers designed a new recommendation method aimed at providing students with more uniform and diverse learning resource recommendations. This recommendation system not only considers personalized needs but also strives for balance in the breadth and depth of recommendations to enhance students' SRL abilities.

Experimental results show that the recommendation method proposed in this paper performs excellently in terms of accuracy, uniformity, and diversity. It can effectively enhance the diversity of recommended resources, indirectly aiding students' SRL abilities. Furthermore, this study also demonstrated changes in the algorithm's recommendation coverage, standard deviation of recommendation counts, and recommendation diversity through varying group sizes. These finding validate effectiveness and adaptability of the new recommendation method.

In summary, the research outcomes of this paper provide new theoretical and practical guidance for the design of recommendation systems for mobile learning resources in higher education. This research is particularly valuable for supporting students' personalized learning and enhancing their SRL abilities. However, this study also has certain limitations. For instance, the recommendation algorithm may need to be tested and optimized in more real-world application scenarios to verify its universality and stability. Future research could be conducted on larger datasets to explore the applicability of the algorithm across different cultural backgrounds and educational systems. Additionally, further refinement of the recommendation algorithm is needed to adapt to the dynamic changes in students' learning preferences. Moreover, future work could also explore how to combine students' learning outcome feedback to continuously adjust the recommendation algorithm, achieving a truly personalized learning path design.

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