

PAPER

Adaptive Recommendation of Teaching Content in Higher Education Using Mobile Interaction Technology

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With the rapid advancement of mobile interaction technology, teaching methodologies in higher education are increasingly moving toward personalization and intelligence. The use of mobile interaction technology for adaptive recommendation of teaching content has become a critical topic for enhancing educational effectiveness. Existing research in content recommendation, primarily based on collaborative filtering algorithms, often relies on single-dimensional data applications and lacks comprehensive consideration of both location information and temporal effects. Consequently, these approaches fall short in addressing the complex requirements of dynamic learning environments. This study proposes a multi-dimensional dynamic adaptive recommendation system for teaching content based on mobile interaction technology to address the limitations of existing methods. The research encompasses location-based collaborative filtering for teaching content, time-effect-based collaborative filtering, and an integrated multi-dimensional dynamic recommendation model that considers both location and temporal factors. This study is expected to provide a more precise and dynamically adaptive solution for personalized teaching in higher education.

KEYWORDS

mobile interaction technology, teaching content recommendation, collaborative filtering, location information, temporal effects, personalized teaching

1 INTRODUCTION

With the rapid advancement of information technology, the application of mobile interaction technology in higher education has deepened, resulting in significant transformations in teaching methodologies [1–4]. Through mobile devices such as smartphones and tablets, students can now engage in classroom interactions at any time and place, thus breaking the traditional constraints of classroom time and space [5–7]. However, with the increasing demand for personalized learning experiences, the question of how to deliver adaptive, personalized recommendations for teaching content using mobile interaction technology has become central to

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enhancing educational outcomes. Particularly as teaching scenarios diversify and student learning behaviors grow more complex, traditional, unified teaching models fall short in meeting individualized learning needs.

In this context, research on adaptive recommendation of teaching content based on mobile interaction technology not only enhances the utilization of educational resources but also actively fosters student engagement and motivation, thereby improving overall teaching quality [8–12]. By incorporating multi-dimensional data, such as students' location information and temporal effects, teaching content recommendations can better align with students' learning habits and behavioral patterns, thus driving both the intelligence and personalization of educational resources [13].

While related studies have explored teaching content recommendation methods using collaborative filtering algorithms, most remain confined to single-dimensional data applications, overlooking the combined influence of location information and temporal effects on the adaptiveness of teaching content [14–17]. Additionally, existing methods often lack an effective multi-dimensional dynamic adaptation mechanism when addressing dynamic teaching demands and complex interaction behaviors, leading to limitations in recommendation precision and overall teaching effectiveness [18–21].

Against this backdrop, a multi-dimensional dynamic adaptive recommendation system for teaching content based on mobile interaction technology was proposed in this study. The main research components include: first, collaborative filtering based on location information, aimed at enhancing the influence of geographic location on the recommendation of educational resources; second, collaborative filtering based on temporal effects, optimizing the role of learning time on recommended content; and finally, a multi-dimensional dynamic recommendation model that integrates location information and temporal effects. By combining location information with temporal effects, this study is expected to improve the precision and adaptability of teaching content recommendations, providing a more scientific solution for personalized education in higher education.

2 COLLABORATIVE FILTERING OF TEACHING CONTENT BASED ON LOCATION INFORMATION

With the widespread adoption of mobile devices and intelligent technologies in education, students increasingly rely on smartphones, tablets, and other devices for learning. This trend has not only made learning locations and schedules more flexible but has also led to more personalized and diversified student learning needs. To accommodate this shift, adaptability in teaching content recommendation systems has become essential, ensuring that recommended content promptly reflects changes in students' learning demands. Student learning behaviors and interests exhibit high temporal dynamics, especially within mobile learning environments where the study time may be fragmented and unpredictable. Consequently, recommendation systems must account not only for students' historical behavior but also dynamically adjust recommendation strategies to ensure that the suggested content aligns with current learning contexts. To address these requirements, a dynamic collaborative filtering recommendation algorithm based on three elements—time, location, and ratings—was developed in this study. The incorporation of temporal effects enables the recommendation system to perform timely adjustments, such as decaying or amplifying the relevance of teaching resources based on different learning times, thereby avoiding the suggestion of outdated content. Additionally, seasonal factors

were considered to ensure that recommended content aligns with students' learning plans and revision needs at specific times, such as at the beginning of a term, before midterm exams, or during summer break. Figure 1 provides a visual overview of the principle enhancing the dynamic adaptability of teaching content recommendations based on mobile interaction technology.

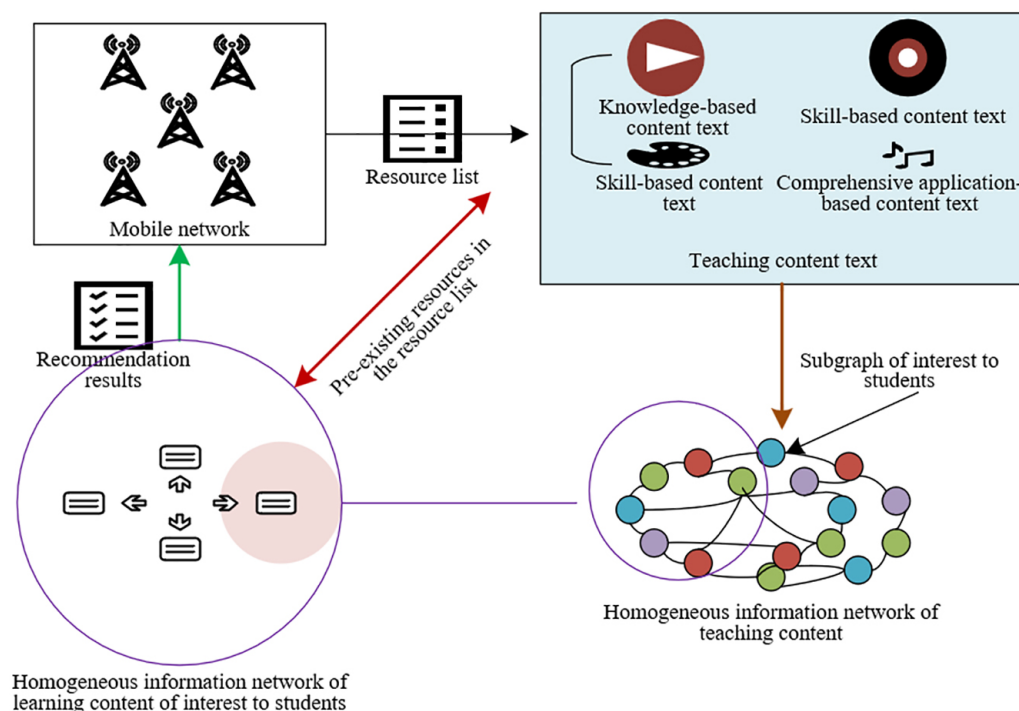


Fig. 1. The principle enhancing the dynamic adaptability of teaching content recommendations based on mobile interaction technology

The construction of the collaborative filtering recommendation model for teaching content based on location information is motivated by the varying impacts of different learning environments on students. By capturing students' learning habits across diverse geographic locations, it is possible to infer their learning preferences within specific settings. For example, students may concentrate more on textbook material in classrooms, while in libraries, they might prefer consulting reference resources. Based on these patterns, a location preference matrix was proposed in this study to quantify students' demand for learning content across various locations. Furthermore, specific location rating rules were designed, assigning different weights to the relevance between each student and the teaching content. Using a location information filtering algorithm, the recommended content can be dynamically adjusted in line with students' actual learning environments, ensuring that the suggested educational resources align with students' current states and thereby enhancing the adaptability of their learning experiences.

The location information model based on mobile interaction technology proposed in this study, which integrates multi-dimensional data such as check-ins, location sharing, general packet radio service (GPRS) data traffic, and location ratings, establishes a scoring mechanism capable of effectively capturing students' learning behaviors and preferences across different geographical locations. By consolidating these behavioral data, the system dynamically adjusts recommended teaching content to accommodate students' specific learning needs within particular locations

and contexts. For instance, in a library, the system may prioritize the recommendation of in-depth learning materials, while off-campus, content related to independent and less intensive study may be more suitable. This dynamic modelling of location information enhances both the adaptability and precision of content recommendations, thereby providing strong support for personalized learning in higher education.

Specifically, the application of check-in functionality in teaching content recommendation resembles the check-in features commonly used on social platforms or in lifestyle services. When students enter particular learning environments, such as classrooms, libraries, or cafes, they can check in through the mobile application, and the system automatically records their location. By analyzing students' check-in data, the system can infer their learning preferences within certain environments. For example, a student checking in at a classroom may require more formal course content, while check-ins in recreational areas may indicate a need for light revision or preview materials. Based on check-in frequency and the number of visits, a scoring mechanism can be established for each location, determining students' preferences for particular environments and thus providing a basis for teaching content recommendations.

Throughout the learning process, students may share their current study locations or resources through the mobile application. This sharing behavior serves not only as feedback on content but also as feedback on learning contexts. The system assigns weights to specific study locations based on location-sharing behaviors, as such actions often signify that these locations are perceived by students as effective learning spaces. Consequently, the system can prioritize content recommendations for these high-efficiency locations in the future. If the longitude of a student's location is denoted as x , the latitude as y , and the abstract location as $@$, then the location information is represented by the following model:

$$LOCATION = M(x, y, @) \quad (1)$$

The use of GPRS data traffic similarly reflects students' learning behavior preferences across different locations. For instance, when students utilize a significant amount of mobile data for accessing online learning resources within environments such as libraries or study rooms, the system can infer a higher level of study focus at these locations. By analyzing data usage, the system assigns higher scores to these locations, optimizing future teaching content recommendations. Conversely, in locations associated with lower learning efficiency, the system may lower the intensity or difficulty of recommended content based on lower data usage, thereby aligning with students' learning states at these locations.

A location rating mechanism further enhances the accuracy of the location information model. Students may rate specific study locations via the mobile application, and these ratings not only reflect students' satisfaction with these locations but also provide direct feedback for the recommendation system. For instance, students may rate whether a particular location is suitable for certain types of study, such as self-study, group discussions, or lab work. The system can utilize these ratings to adjust location scores and dynamically tailor recommended teaching content for each location. This mechanism personalizes recommendations and allows for continuous optimization of recommendation strategies based on students' real-time feedback.

To achieve more precise recommendations, each rating in the location-rating matrix can be computed through a weighted summation, with the weights of different behaviors adjusted based on their impact on learning behavior. Specifically, let the multi-dimensional vector T represent the four factors of location sharing, check-ins, GPRS data usage, and location ratings, such that $T = (t_1, t_2, t_3, t_4)$, where t_1

represents location sharing, $t2$ denotes check-ins, and $t3$ reflects GPRS data usage. The calculation formula is as follows:

$$T = 0.25(t1 + t2 + t3 + t4) \quad (2)$$

By calculating the similarity of students' location information, the system further optimizes the effectiveness of recommendations. Data within the location-rating matrix was used to analyze learning behaviors of different students at similar locations, enabling recommendations that better align with individual learning habits. Specifically, the collection of location information serves as the foundation, with mobile devices acquiring real-time location data via global positioning system (GPS), Wi-Fi, and similar technologies. Then location similarity among students was computed. Let T_{lv} represent the location similarity between students l and v ; O_{lv} denote the set of jointly rated locations by students l and v ; e_{al} represents student l 's rating of location a ; e_{av} represent student v 's rating of location a ; and \bar{e}_l and \bar{e}_v represent the average location ratings for students l and v , respectively. The similarity calculation formula is as follows:

$$T_{lv} = \frac{\sum_{n \in O_{lv}} (e_{a,l} - \bar{e}_l)(e_{a,v} - \bar{e}_v)}{\sqrt{\sum_{n \in O_{lv}} (e_{a,l} - \bar{e}_l)^2 \sum_{n \in O_{lv}} (e_{a,v} - \bar{e}_v)^2}} \quad (3)$$

Upon identifying similar students, the most representative student can be selected by setting an appropriate K value. To enhance recommendation accuracy, the filtering recommendation algorithm was combined with the location filtering recommendation. By analyzing students' learning needs within specific locations, a deeper understanding of their learning objectives can be attained, facilitating the recommendation of content that meets these needs. For instance, within a particular learning environment, students may prefer courses or resources relevant to that environment, and the system can make intelligent recommendations based on this preference.

3 TIME-EFFECT-BASED COLLABORATIVE FILTERING OF TEACHING CONTENT

In constructing the time-effect-based collaborative filtering recommendation model for teaching content, this study draws on a detailed analysis of how study time influences students' learning outcomes. Time not only affects students' energy distribution but also causes fluctuations in their learning interests. Therefore, based on factors such as the persistence of interest, patterns of decay, resource popularity, and seasonality, a dynamic time-effect model was proposed in this study. Different time periods may be better suited to different types of teaching content. For example, students may be more inclined to focus on complex or abstract concepts during morning study sessions, while in the evening, lighter revision or preview tasks may be more appropriate. Through the filtering recommendation algorithm of the time-effect model, the system dynamically adjusts content recommendation strategies according to the temporal distribution of students' study behaviors, ensuring that students receive the most suitable content at optimal time periods.

In this algorithm, the time effect can be understood as the dynamic change in students' interests over time. Unlike static content recommendations, students' learning needs and interests tend to exhibit cyclic or sporadic patterns. For example, students may develop a heightened interest in certain teaching content as exams approach, only for this demand to decrease rapidly post-exam. Traditional recommendation

algorithms, by disregarding this time sensitivity, often fail to update recommendations in a timely manner, leaving students' learning needs unmet. Hence, in the multi-dimensional dynamic teaching content recommendation algorithm, the time effect encompasses more than simple timestamp records; it includes capturing the decay, amplification, or periodic fluctuations of student interest over time.

Let S_{MAX} denote the time of the last rating, S_{CU} represent the actual rating time for the learning resource, and S_0 denote the starting time for the student. The following formula represents the consideration of rating intervals:

$$d(S_{CU}) = 84.21 \cdot \left(S_{MAX} - \frac{(S_{CU} - S_0)}{2} \right)^{-0.2383} + 15.66 \quad (4)$$

The similarity calculation formula for learning resource ratings, incorporating a time function, is given as follows:

$$SIM_l(x, y) = \frac{\sum_{t \in T_{xy}} (e_{(x,t)} * d(S_{CU}) - \bar{e}_x) (e_{(x,t)} * d(S_{CU}) - \bar{e}_y)}{\sqrt{\sum_{t \in T_x} (e_{(x,t)} * d(S_{CU}) - \bar{e}_x)^2 \times \sum_{t \in T_y} (e_{(x,t)} * d(S_{CU}) - \bar{e}_y)^2}} \quad (5)$$

By integrating four temporal attributes—persistence, decay, popularity, and seasonality—the algorithm is enabled to more accurately predict students' learning needs and recommend content that aligns with their current time and learning status.

- a) Persistence attribute: This attribute reflects the degree of sustained interest a student has in a particular teaching content item. It is measured by the formula $PE(v, SJ, DQ)$, where v represents the student's historical view count for the content, SJ denotes the most recent viewing time, and DQ signifies the current time.
- b) Decay attribute: Decay reflects the gradual decrease in a student's interest in a given teaching content item over time. The formula $AT(a1, a2, \dots, an)$ is used to calculate the frequency of views within a specific period. Assuming a weekly cycle, let xu represent the daily view frequency; the calculation formula is $v/7$, where v indicates the number of days within the week that the student viewed the content.
- c) Popularity attribute: This attribute captures the overall popularity of the teaching content among the entire student cohort. It is calculated by the formula $PO(l)$, where l ranges from 1 to 5, representing the average rating of the content. Higher values signify greater popularity.
- d) Seasonality attribute: Seasonality considers the alignment between the teaching content and the student's current season. This is computed by the formula $SE(a, b)$, where a denotes the optimal season for the content, and b represents the current season. If a and b are the same, then $SE(a, b) = 1$; otherwise, it is 0.

4 MULTI-DIMENSIONAL DYNAMIC COLLABORATIVE FILTERING RECOMMENDATION OF TEACHING CONTENT

The integration of the location information model and time-effect model constitutes the core innovation of this study. Single-dimensional recommendation algorithms are often inadequate for addressing complex teaching scenarios. However, by combining location information with temporal effects, personalized

recommendations can be dynamically adapted to meet students' learning needs. For example, the system may consider both a student's geographical location and the current time to determine the optimal recommendation strategy. During an afternoon break, content related to relaxed learning may be suggested, while during the formal study time in a classroom setting, the system can recommend resources for in-depth study relevant to the course. Figure 2 illustrates the principle of the multi-dimensional dynamic collaborative filtering recommendation model for teaching content. The detailed steps for implementing this algorithm are as follows:

Step 1: Location similarity calculation: The first step involves calculating similarity based on the location information of mobile students. Unlike conventional recommendation systems, mobile students' learning environments and needs vary with location. For instance, students may have different learning needs depending on the setting, such as at school, in a library, or at home.

Step 2: Selection of location neighbors and formation of the neighbor set: After calculating location similarity, students whose locations are similar to that of the target student can be selected to form a location neighbor set. These location neighbors represent a geographically proximate group whose shared learning environments or teaching resource needs offer significant referential value for the target student's learning behavior.

Step 3: Calculation of learning resource rating similarity: Beyond location similarity, the system also calculates learning resource rating similarity based on students' ratings of teaching content. Rating data from the traditional collaborative filtering algorithm was used in this study. By computing the similarity between the target student's ratings and those of other students for the same teaching resources, interest similarity can be determined. Let T_{lv} represent the interest similarity between students l and v ; let O_{lv} denote the set of jointly rated learning resources for students l and v ; let $e_{n,l}$ represent student l 's rating of learning resource n ; and let $e_{n,v}$ represent student v 's rating of learning resource n . The average rating of learning resources by individual students is denoted by \bar{e}_l and \bar{e}_v . In calculating rating similarity, a perturbation factor x was introduced.

$$T_{lv} = \frac{\sum_{n \in O_{lv}} (x \cdot e_{n,l} - \bar{e}_l)(x \cdot e_{n,v} - \bar{e}_v)}{\sqrt{\sum_{n \in O_{lv}} (x \cdot e_{n,l} - \bar{e}_l)^2 \sum_{n \in O_{lv}} (x \cdot e_{n,v} - \bar{e}_v)^2}} \quad (6)$$

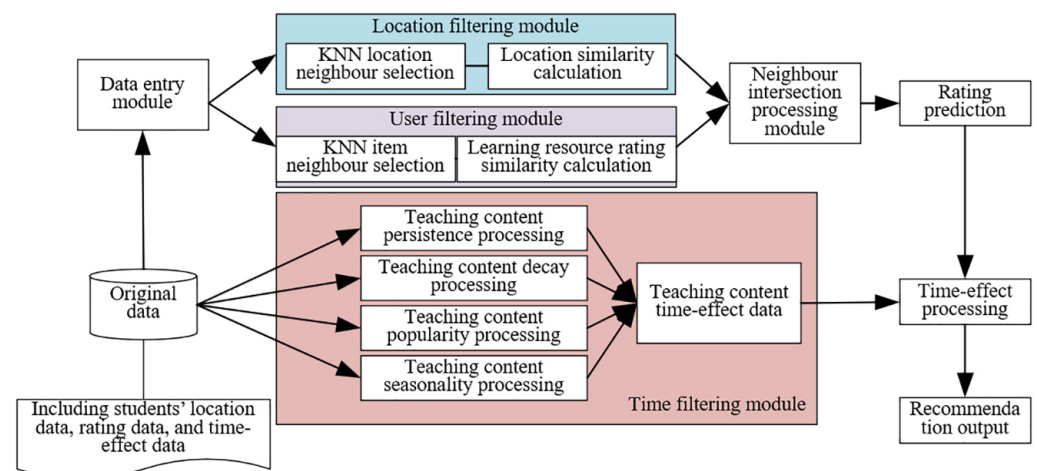


Fig. 2. Multi-dimensional dynamic collaborative filtering recommendation model for teaching content

Step 4: Neighbor selection to form the rating neighbor set: Based on the similarity in learning resource ratings, students whose ratings are similar to those of the target student can be selected to form the rating neighbor set U_2 . This set represents a group of students whose interests in teaching content align closely with those of the target student, thereby providing strong support for the recommendation system.

Step 5: Intersection of location and learning resource ratings: At this step, the algorithm calculates the intersection of the location neighbor set and the rating neighbor set, forming the final neighbor set. Students within this set share similarities with the target student in both location and rating preferences. Specifically, let $SIM(i,x)$ represent the similarity between the target student i and a similar student x ; let e_{xu} denote the actual rating of student x for the predicted learning resource u ; let $\bar{e}(x)$ denote the average rating of the similar students, and $\bar{e}(i)$ the average rating of the target students. The location similarity student set is denoted by Ma , and the learning resource similarity student set by Ua , with their intersection E represented by the following formula:

$$E = Ma \cap Ua \quad (7)$$

Step 6: Rating prediction: By synthesizing the behavior of these neighbor students, the system predicts a rating for each candidate teaching content based on the historical ratings of students who are similar to the target student in both location and rating. This predicted rating is intended to accurately reflect the target student's potential interest in specific teaching content. The rating formula is given as follows:

$$e_{MI-ZD}(i,u) = \bar{e}(i) + \frac{\sum_{x \in V(i)} SIM(i,x) \cdot (e_{xu} - \bar{e}(x))}{\sum_{x \in V(i)} |SIM(i,x)|} \quad (8)$$

Step 7: Ranking and selection of the top V predicted ratings for learning resources: Based on predicted ratings, the system ranks all teaching content and selects the top V highest-rated items as recommended candidates. The value of V can be dynamically adjusted according to the actual needs of the system.

Step 8: Seasonality assessment for each learning resource: The selected candidate teaching content undergoes seasonal filtering. The system assesses the appropriateness of each resource for recommendation based on the current time period and the seasonality attribute of the content. For example, during summer break, content related to summer activities may be prioritized, while during the academic term, more emphasis might be placed on exam review materials. The judgment formula $SE(a,b)$ was applied to filter out content that does not align with the current season, ensuring timeliness in recommendations.

Step 9: Rating adjustment: After the seasonal filtering, the teaching content undergoes a final rating adjustment. The formula for the final rating of a learning resource is as follows:

Final rating of learning resource = seasonality + popularity + persistence – decay

Step 10: Reordering of learning resources based on final ratings: All teaching content was then re-ranked according to the adjusted final ratings. This step ensures that the combined score, reflecting both time effects and location information, accurately represents the content most relevant to the student's

current interests, thereby enhancing the personalization and precision of the recommendations.

Step 11: Recommendation of the top-rated learning resource: In the final step, the top-rated learning resources were selected from the re-ranked content and recommended to the student. This recommendation process incorporates not only the student's interests and location information but also integrates time effects, ensuring that the recommended content is suitable for the current learning scenario and aligns with both the student's immediate and long-term learning needs.

5 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1 reveals distinct differences in the weight distributions for seasonality, popularity, persistence, and decay across different teaching resources. For example, the first teaching resource, which includes keywords such as “micro-lesson” and “live class,” exhibits a high persistence weight of 0.378, indicating sustained learning value over an extended period. However, its popularity weight is relatively low at 0.148, reflecting a lower current demand. In contrast, keywords such as “e-homework” and “cloud classroom” in the second resource are associated with a high seasonality weight (0.789), suggesting that this content may be more effective during specific time periods. Similarly, the weights assigned to different time attributes for other resources highlight distinct adaptability patterns. For instance, “interactive design” and “collaborative learning” show high weights in popularity and persistence, at 0.956 and 0.787, respectively, indicating suitability for scenarios where sustained engagement is desired. The experimental results clearly illustrate the application of each type of resource across different time attributes. Based on the findings, it is evident that teaching resource recommendations need to be adaptively adjusted according to time attributes. Specifically, for content with high persistence but low popularity, the recommendation system may benefit from extending its display cycle to maximize its long-term educational value. Conversely, for resources with high seasonality and popularity, such as “e-homework” and “cloud classroom,” prioritized recommendations within targeted timeframes can better fulfil users' short-term learning needs.

Table 1. Representative keywords in the top five teaching resources

ID	Keywords for Each Teaching Resource					Weight			
	Word 1	Word 2	Word 3	Word 4	Word 5	Seasonality	Popularity	Persistence	Decay
17	Micro-lesson	Live class	Online discussion	Real-time feedback	Learning check-in	0.312	0.148	0.378	0.214
72	E-homework	Cloud classroom	Mobile learning	Virtual lab	AR	0.789	0.789	0.132	0.556
11	VR	Adaptive learning	Data analytics	Gamified learning	Learning path	0.326	0.445	0.924	0.243
32	Quiz system	Online assessment	Social learning	Voice recognition	Video courseware	0.214	0.057	0.124	0.084
44	Interactive design	Collaborative learning	Knowledge graph	Online Q&A	Flipped classroom	0.665	0.956	0.787	0.011

Table 2. Performance of different recommendation methods on teaching content adaptability in terms of MAP and NDCG

Resource Type	Metric	MF	FM	NCF	CAR	BPR	Proposed Method
Knowledge	MAP	0.0016	0.3879	0.0016	0.0033	0.32154	0.4415
	NDCG	0.0124	0.1895	0.0091	0.0165	0.1874	0.2654
Skills	MAP	0.0012	0.2895	0.0002	0.0142	0.3521	0.4231
	NDCG	0.0092	0.1542	0.0001	0.0312	0.1789	0.3215
Attitudes & values	MAP	0.0001	0.3874	0.0002	0.0092	0.2156	0.4125
	NDCG	0.0008	0.1956	0.0023	0.0214	0.1325	0.3789
Comprehensive application	MAP	0.0135	0.3125	0.0032	0.0063	0.0135	0.4126
	NDCG	0.0232	0.1874	0.0132	0.0214	0.0214	0.3546
All	MAP	0.0071	0.3213	0.0003	0.0221	0.3215	0.3326
	NDCG	0.0132	0.1658	0.0008	0.0278	0.2236	0.2245

From the data in Table 2, it is evident that the proposed method demonstrates superior performance in teaching content adaptability recommendations across various resource types, outperforming traditional recommendation methods in the key metrics of mean average precision (MAP) and normalized discounted cumulative gain (NDCG). Specifically, in knowledge-based content recommendations, the proposed method achieves a MAP of 0.4415, significantly higher than that of matrix factorization (MF) (0.0016) and Bayesian personalized ranking (BPR) (0.32154), with an NDCG of 0.2654, also notably better than other methods. Furthermore, in skills-based content recommendations, the proposed method achieves MAP and NDCG values of 0.4231 and 0.3215, respectively, showing a substantial advantage in adaptability recommendations, particularly in comparison to factorization machines (FM), which achieved MAP and NDCG scores of 0.2895 and 0.1542, respectively. Similarly, for attitudes & values and comprehensive application resources, the proposed method consistently leads, with MAP and NDCG values significantly higher than those achieved by other recommendation methods. Overall, the proposed model's average MAP and NDCG performance across all resource types is 0.3326 and 0.2245, respectively, outperforming traditional methods such as BPR and FM. Analysis of the experimental data shows that the multi-dimensional dynamic teaching content recommendation system based on mobile interaction technology effectively leverages the collaborative filtering advantages of geographic location and temporal effects, greatly enhancing the accuracy and adaptability of the recommendation system. The experimental results reveal that the proposed method exhibits an outstanding ability to adapt to high-dynamic resources, such as skills and comprehensive application types, and shows marked improvements in recommending persistent resources in knowledge-based and attitudes & values categories. This finding indicates that the recommendation model can be flexibly adjusted according to the temporal attributes and location information of different teaching content, thereby providing more personalized recommendation services. Compared to traditional methods, such as MF and FM, the proposed method demonstrates clear advantages in both MAP and NDCG metrics, further validating its interpretability and practical value.

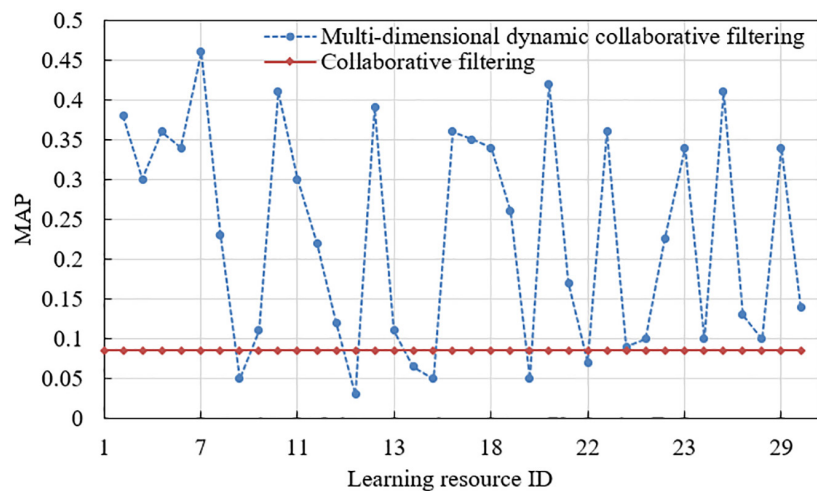


Fig. 3. MAP performance of teaching content recommendations using two types of collaborative filtering

Figure 3 presents MAP performance data for teaching content recommendations using multi-dimensional dynamic collaborative filtering versus traditional collaborative filtering. MAP values for each learning resource are significantly higher with multi-dimensional dynamic collaborative filtering than with traditional collaborative filtering. For example, in the case of Resource ID 1, the MAP value is 0.38 under multi-dimensional dynamic collaborative filtering, compared to only 0.085 with traditional collaborative filtering, demonstrating a substantial difference. For Resource ID 22, the MAP is 0.42 using multi-dimensional dynamic collaborative filtering, while the traditional method maintains a value of 0.085. This trend persists across other resources, notably for Resource IDs 11 (0.36 vs. 0.085) and 29 (0.34 vs. 0.085), further confirming the effectiveness of multi-dimensional dynamic collaborative filtering in enhancing recommendation accuracy. The experimental results clearly indicate that the multi-dimensional dynamic collaborative filtering method provides superior recommendation performance across various teaching resource types, exhibiting greater adaptability and specificity. Based on the experimental outcomes, it can be concluded that the proposed multi-dimensional dynamic collaborative filtering model, by incorporating location information and time effects to optimize recommendation strategies, can effectively enhance the adaptability and recommendation accuracy of teaching content. Unlike the fixed weights of traditional collaborative filtering, the proposed method dynamically adjusts recommendation parameters based on geographical and temporal variables, enabling personalized recommendations that better align with the practical needs of learning resources across diverse contexts.

As observed in Figure 4, the performance of different recommendation methods in terms of MAP and NDCG varies significantly based on the number of pre-existing resources in the recommendation list. Multi-dimensional dynamic collaborative filtering consistently demonstrates superior MAP and NDCG performance across all resource quantity scenarios.

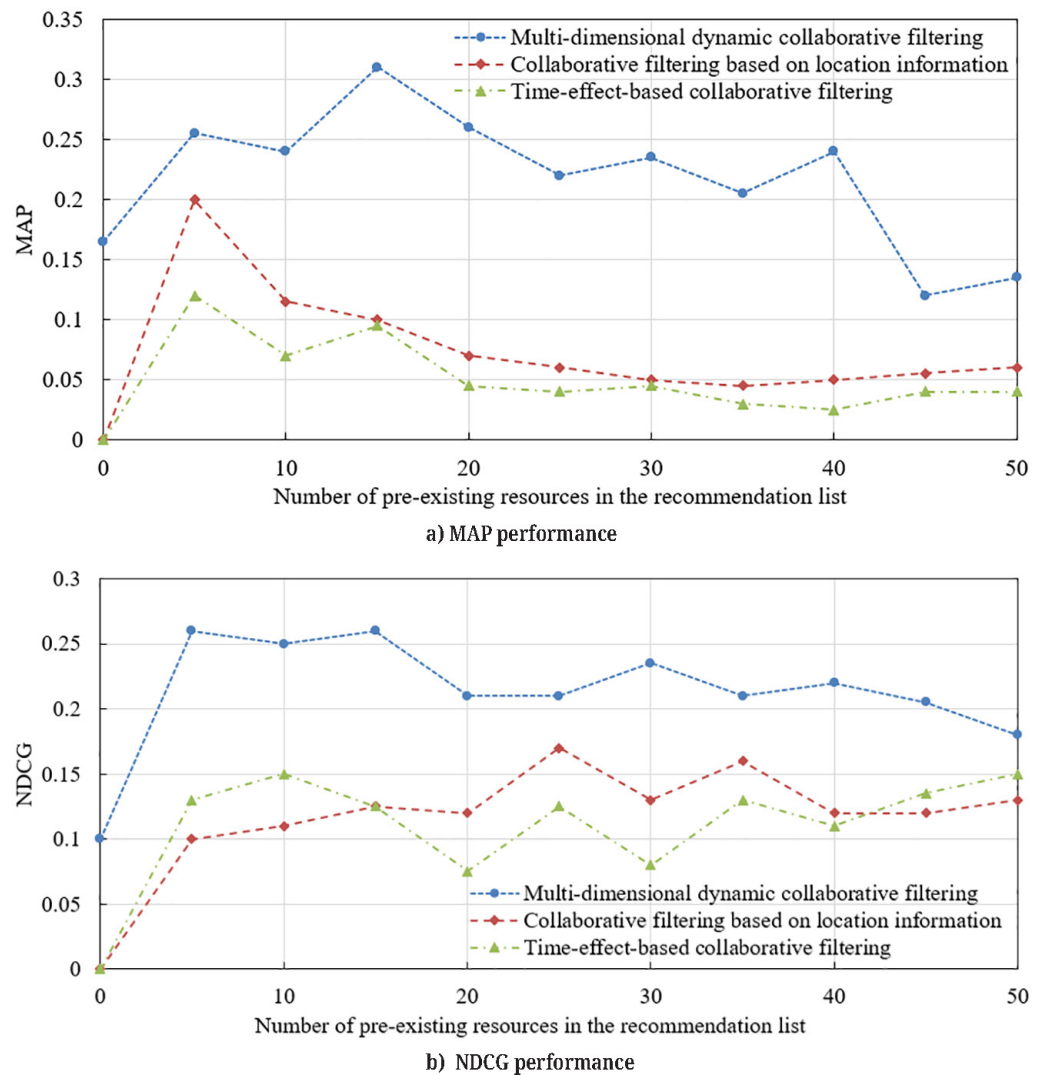


Fig. 4. Performance of different recommendation methods with varying numbers of pre-existing resources in the recommendation list

For instance, when there are no pre-existing resources in the recommendation list, its MAP reaches 0.165, which is substantially higher than that of collaborative filtering based on location information (MAP = 0.0) and time-effect-based collaborative filtering (MAP = 0.0). As the number of pre-existing resources increases to 30, the MAP for multi-dimensional dynamic collaborative filtering reaches a peak of 0.31, whereas collaborative filtering based on location information achieves a MAP of 0.1, and time-effect-based collaborative filtering attains 0.095 under the same conditions. A similar trend is observed for NDCG; with ten pre-existing resources, the NDCG for multi-dimensional dynamic collaborative filtering reaches 0.26, outperforming other methods. When the resource count reaches 40, time-effect-based collaborative filtering surpasses location-based collaborative filtering in NDCG, but it remains below the performance of multi-dimensional dynamic collaborative filtering. These results suggest that multi-dimensional dynamic collaborative filtering is particularly effective when the recommendation list contains a relatively small or moderate number of pre-existing resources.

Based on the analysis of experimental results, the proposed multi-dimensional dynamic collaborative filtering model exhibits stable and superior recommendation performance across various conditions regarding the number of resources in the recommendation list. In contrast, location-based and time-effect-based collaborative filtering methods show weaker performance when fewer resources are present and display greater variability as resource numbers increase. This finding indicates that the proposed method not only adapts recommendation weights flexibly according to geographic and temporal factors but also offers significant advantages in responding to dynamic changes in the recommendation list. This adaptability allows multi-dimensional dynamic collaborative filtering to effectively accommodate the richness and diversity of educational resources in personalized learning recommendations. In summary, the proposed method's high MAP and NDCG performance highlights its potential applicability in educational content recommendation systems, providing feasibility and theoretical support for enhancing precision in personalized teaching recommendations.

6 CONCLUSION

A multi-dimensional dynamic adaptive recommendation system for teaching content, based on mobile interaction technology, was proposed in this study. The primary innovation lies in the integration of location information and time effects into the collaborative filtering process to enable personalized recommendations for teaching content. Specifically, location information was used to improve recommendation accuracy by enhancing the geographic suitability of learning content. Additionally, time effects were incorporated to adjust recommendation strategies, aligning suggested content more closely with learners' study time. Experimental results demonstrate that the proposed method achieves superior MAP and NDCG performance in content adaptability compared to traditional recommendation methods, especially when resources are abundant or moderately available in the recommendation list. Furthermore, the multi-dimensional dynamic collaborative filtering model shows greater stability and adaptability across varying numbers of pre-existing resources. The experimental data illustrate the potential and effectiveness of multi-dimensional dynamic collaborative filtering in personalized dynamic learning environments, confirming its practical application value in educational content recommendation systems.

However, this study has certain limitations. Primarily, this study focuses on location information and time effects, without addressing other individual characteristics that could impact teaching content recommendations, such as learners' interests and cognitive levels. Additionally, the experimental data were derived mainly from simulated environments, which may not fully capture the complexity of dynamic factors present in real-world learning settings. Future research could explore multi-dimensional data sources, such as learners' interest preferences, knowledge mastery levels, and social network relationships, to construct more comprehensive and intelligent recommendation models. Field experiments are also an important direction for future improvement, aiming to validate the adaptability and scalability of the recommendation model in real educational scenarios. Such advancements would further enhance the accuracy and flexibility of recommendation systems, providing robust technical support for personalized and adaptive learning in education.

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