Recommendation of Online Learning Resources for Personalized Fragmented Learning Based on Mobile Devices

https://doi.org/10.3991/ijet.v17i03.29427

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Abstract—Fragmented learning aims to fully utilize fragmented time slices to learn and accumulate fragmented knowledge. The current mobile online learning apps fail to fully consider the preferences, demands, and adaptability of users. The content and difficulty of the recommended resources are not in match with user features. Therefore, this paper explored the issue of the recommendation of personalized online learning resources for fragmented learning based on mobile devices. Firstly, the authors developed an architecture for the adaptive recommendation model of online learning resources, modeled the learners and fragmented learning resources. Next, the recommendation model was constructed for personalized online learning resources, the flow of the recommendation engine was detailed, and the degrees of resource recommendation and matching were calculated. The proposed model was proved valid through experiments.

Keywords—mobile devices, fragmented learning, online learning resources, personalized learning resources

1 Introduction

In the education field, the application of fragmented learning based on mobile devices in various disciplines has been gradually valued by people [1-5]. College students generally face with heavy learning tasks and great academic pressure, and fragmented learning is a good way for them to fully utilize fragmented time slices to learn and accumulate fragmented knowledge [6-11]. However, currently, most online learning apps installed on mobile devices recommend learning resources centered on their e-learning platforms, they haven't really considered the preferences, demands, and adaptability of users [12-16]. Therefore, how to help learners acquire personalized learning resources during their fragmented learning in a timely manner to meet their respective learning preferences and demands has brought a new challenge to the resource recommendation function of existing e-learning platforms operating based on mobile devices.

Regarding this challenge, scholars Cheng and Wang [17] designed a five-dimensional model of learner features and a three-dimensional model of English reading resource features; to make the learning resources fit for the temporal and spatial characteristics of fragmented learning, they rationally designed and subdivided the reading resources of CET-4 (College English Test - Band Four) to meet learners' demands for fragmented learning. At present, research results of the efficiency of mobile fragmented learning generally have the problem of low evaluation efficiency, so Zhu [18] built an EIS (evaluation index system) to explore the impact of mobile devices on fragmented learning efficiency based on an analysis of the structure of mobile learning terminal systems, then after questionnaire survey and data sorting, the distribution of evaluation indexes was obtained and the final EIS was determined. Gao [19] introduced the connotation of fragmented learning of college English, researched the feasibility of fragmented learning of college English under the background of big data, and expounded the significance of fragmented learning of college English. Li [20] emphasized that with the continuous development of digital technology, using mobile terminals to conduct decentralized learning has become an effective supplementary means for extracurricular learning; then, staring from the concept of English learning fragmentation, the specific forms and content of English learning fragmentation were constructed, and a few matters that need attention were proposed for the content application resources. Since the quality of mobile learning resources can directly affect the efficiency of mobile learning, Li and Fang [21] applied the interactive concept map theory to the design of fragmented mobile learning resources, and verified its effectiveness through experiments.

Existing online learning resource recommendation systems generally mine and analyze the information of learners' learning behavior features and learning content interest preferences, and then make personalized recommendations based on these mining and analysis results. Language learning apps have conducted more explorations into the aspect of personalized resource recommendation, however most of them have the problem that the content and difficulty of recommended resources can hardly match with user features. The second chapter of this paper gave an architecture of the adaptive recommendation model of online learning resources, and modeled the learners and fragmented learning resources. The third chapter constructed the recommendation model for personalized online learning resources, elaborated on the flow of the recommendation engine, and calculated the degrees of resource recommendation and matching. The fourth chapter verified the effectiveness of the constructed model using experimental results.

2 Modeling of learners and fragmented learning resources

In a fragmented learning environment based on mobile devices, the online learning resources should be recommended to learners according to their learning demands and preferences to meet their personalized learning requirements. Firstly, this paper explored a few aspects such as the evaluation of fragmented learning ability, knowledge memory methods, learning resource design, and the architecture of adaptive online learning systems; then, during the research process, according to the feature information of three dimensions of mobile device-based fragmented learning, namely knowledge level, cognition ability, and demand preference, the feature information of three dimensions of difficulty, quality, and recognition of the online learning resources was extracted; at last, the relationship between learner model and learning resource model was constructed. Taking the above analysis results as the reference of the recommendation decisions of personalized online learning resources, an adaptive recommendation model of fragmented online learning resources was constructed, Figure 1 gives the architecture of the model.

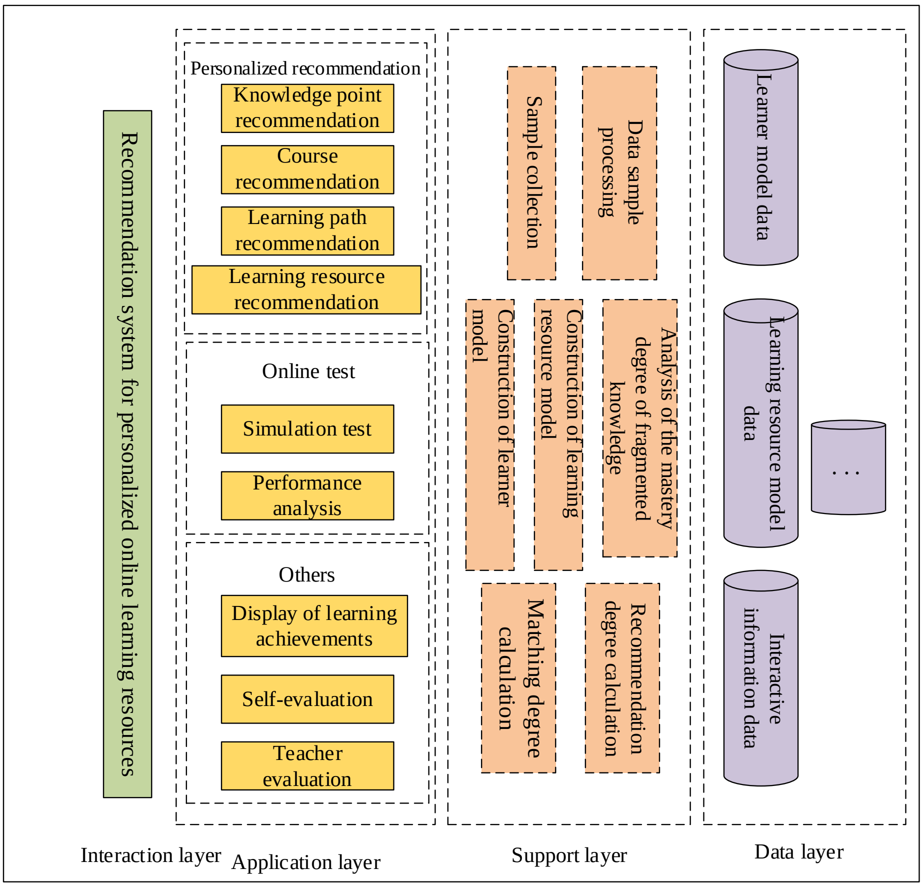

Fig. 1. Architecture of the adaptive recommendation model of fragmented online learning resources

2.1 Construction of learner model

Figure 2 shows the execution process of learner model. As can be seen from the figure, the features of learner model include knowledge level, cognition ability, learning demands, and learning preferences. The specific description is as follows.

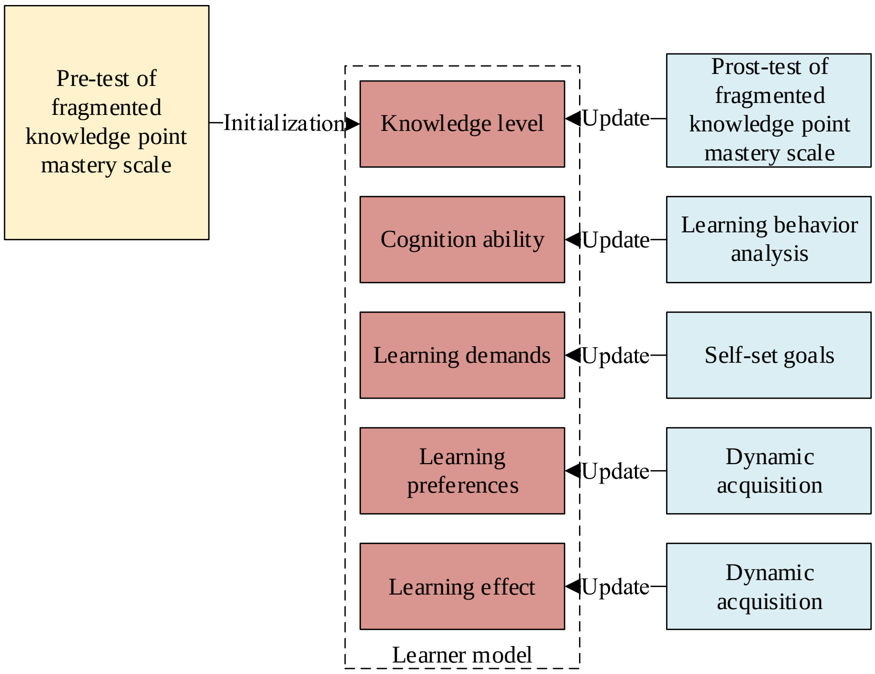

Fig. 2. Execution process of the learner model

During fragmented learning based on mobile devices, learners' knowledge level could be improved, that is, their mastery of relevant professional knowledge could be strengthened. From low to high, the knowledge level of learners could be divided into 6 degrees: knowing, understanding, application, analysis, integration, and evaluation. Suppose H_i represents the i-th fragmented knowledge point, ψ_i represents the mastery degree of the i-th fragmented knowledge point, $\psi_i \in \Psi$, Ψ={0,1,2,3,4,5,6}, then a set of two-tuples could be defined as $L=\{(l_1, \psi_1),\ldots,(l_i, \psi_i),\ldots,(l_m, \psi_m)\}$; if the i-th fragmented knowledge point is a blind point for learners, then $\psi_i=0$. To figure out learners' mastery of a certain fragmented knowledge point, namely the knowledge level, Q&A tests could be performed; 1 and -1 respectively represent correct and wrong answers; $Of_i(1)$ and $Of_i(-1)$ respectively represent the numbers of correct and wrong answers. Formula 1 gives the formula for calculating the correct rate $\eta(f_i)$ of learners' knowledge level f_i for each fragmented knowledge point:

$$\eta\left(f_i\right)=\frac{Of_i\left(1\right)}{Of_i\left(1\right)+Of_i\left(-1\right)},i=1,2,3,...,6 \quad (1)$$

Further, based on Formula 2, the eigen vector L of learners' mastery degree of fragmented knowledge points is:

$$L=\left\langle\eta\left(f_1\right),\eta\left(f_2\right),\eta\left(f_3\right),...,\eta\left(f_6\right)\right\rangle \quad (2)$$

During fragmented learning based on mobile devices, learners' cognition ability could be enhanced as well, that is, their ability to learn new knowledge could be strengthened, too. Cognition ability could be divided into 8 types: induction ability, memory ability, observation ability, abstract ability, analysis ability, calculation ability, imagination ability and logical understanding ability. Suppose d_i represents a learner's cognition ability for the i-th fragmented knowledge point, k_i represents the level of the cognition ability for the i-th fragmented knowledge point, then a set of two-tuples could be defined as $D=\{(d_1, k_1),\ldots,(d_i, k_i),\ldots,(d_8, k_8)\}$. In order to accurately measure learners' cognition of fragmented knowledge points, suppose: CO represents the type of the cognition ability of the Q&A test, MA represents the standard answers, α represents the difficulty coefficient of the questions, τ_1 and τ_2 respectively represent the time it takes for learners to think and answer the questions, and the learners' learning time; then, the question types of the Q&A test could be designed as follows:

$$CE=\left(CO,MA,\alpha,\tau_1,\tau_2\right) \quad (3)$$

For each question CE, learners need to give an answer MA_i to complete the Q&A test. Formula 4 gives the expression of the set of learners who have completed the test:

$$HD=\left\{\left(CE_1,MA_1\right),...,\left(CE_i,MA_i\right),...,\left(CE_m,MA_m\right)\right\} \quad (4)$$

The learners' cognition ability for a certain fragmented knowledge point could be expressed as:

$$k\left(CO\right)=\frac{1}{m}\sum_{i=1}^{m}\frac{\left(MA_i\cap MA\right)\alpha}{\tau_1\tau_2} \quad (5)$$

Further, the expression of the eigen vector of learners' cognition ability could be obtained:

$$HC=\left\langle k\left(CO_1\right),k\left(CO_2\right),k\left(CO_3\right),...,k\left(CO_8\right)\right\rangle \quad (6)$$

The recommendation decisions of personalized online learning resources need to be formulated according to learners' learning preferences and demands, namely their personalized preferences and demands for online learning resources. According to the features of research objectives of the adaptive recommendation of fragmented online learning resources, learners' learning demand preference features can be divided into demonstrative, exploratory, and cooperative strategy features, including formal features such as video, PPT, and text, and implicit features describing the interactive effect between learners and learning resources and the feedback. Formula 7 gives the expression of the eigen vector of learners' demand preferences:

$$WU = \langle TA, LB, HC \rangle \tag{7}$$

Suppose "○" is the connecting symbol, then the constructed learner model could be expressed as Formula 8:

$$LEA = L \circ HC \circ WU \tag{8}$$

Combining Formulas 2, 6, and 7, there is:

$$LEA = \langle \eta(f_1), \eta(f_2), ..., \eta(f_6), k(CO_1), k(CO_2), ..., k(CO_8), TA, LB, HC \rangle \tag{9}$$

2.2 Fragmented learning resource model

The features of online learning resources for fragmented learning on mobile devices contain two aspects: intrinsic features and evaluation features. Figure 3 lists all features of the fragmented online learning resource model. According to the figure, the intrinsic features of online learning resources refer to the knowledge point content and resource types they cover, and the evaluation features of online learning resources refer to experience perception generated in learners during their interaction with learning resources, which can be described from three dimensions of difficulty, quality, and recognition. Suppose: *GU* represents the intrinsic features of online learning resources, and *SU* and *LB* respectively represent the covered knowledge point content and resource types, then, there is:

$$GU = \langle SU, LB \rangle \tag{10}$$

Suppose: *PJ* represents the evaluation features of online learning resources; *NA*, *CH* and *RE* respectively represent the difficulty, quality, and learner's recognition for the resources, then there is:

$$PJ = \langle NA, CH, RE, HC \rangle \tag{11}$$

The constructed online learning resource model is given by Formula 12:

$$SR = GU \circ PJ \tag{12}$$

Combining Formulas 10 and 11, then there is:

$$SR = \langle \mathrm{SU, LB, NA, CH, RE, HC} \rangle \tag{13}$$

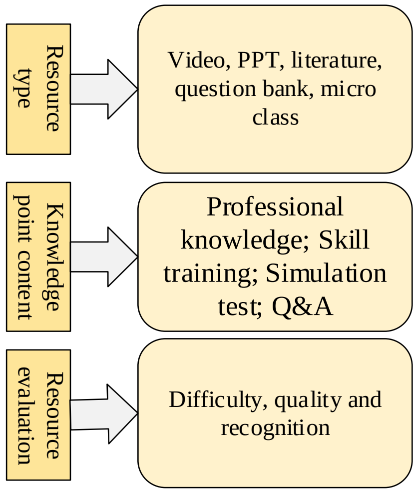

Fig. 3. Features of the fragmented online learning resource model

3 Construction of the recommendation model of personalized learning resources for fragmented online learning

After obtaining the learner model and learning resource model, the final task is to recommend the corresponding online learning resources according to the learners' learning demand preferences, and adaptively adjust the recommended online learning resources according to the ever-changing knowledge level, cognition ability, and demand preferences of learners. Figure 4 shows the relationship between the learner model and the fragmented learning resource recommendation model. Since the key to the function realization of the personalized online learning resource recommendation system is that the recommendation algorithm should be able to meet the requirements of practical applications, this paper took recommendation engine as the correction link in the automatic control function module of the proposed recommendation system. The recommendation system can form feedback on the detection of knowledge level, cognition ability, and demand preference of learners, and input it into the recommendation engine of correction link for calculation. Then, under the impact of the generated learning correction adjustment parameters, the learners' personalized online learning process could get better learning effect, and gradually achieve the optimal output of knowledge level, cognition ability, and demand preference of learners.

As the biggest functional component in the personalized online learning resource recommendation system, the recommendation engine proposed in this paper has independent operation rules; its operation process includes five links: startup, analysis of key knowledge mastery, calculation of recommendation degree, calculation of matching degree, and resource recommendation. Finally, according to the matching degree, the screened online learning resources could be arranged and output according to the specific learning demands of learners.

In the personalized online learning resource recommendation system, for each learner, a learn model and an online learning resource model will be generated after each Q&A test, the parameters are the features of the models involved in the tests, which will then be taken as objective features of the subsequent online learning resource recommendation.

The changing process of learners' three features of knowledge level, cognition ability, and demand preference is continuous. Under the conditions that the feature attributes, namely the classification items are determined, this paper used the probability distribution of each feature to construct the online learning resource recommendation model and solve the maximum probability of possible features.

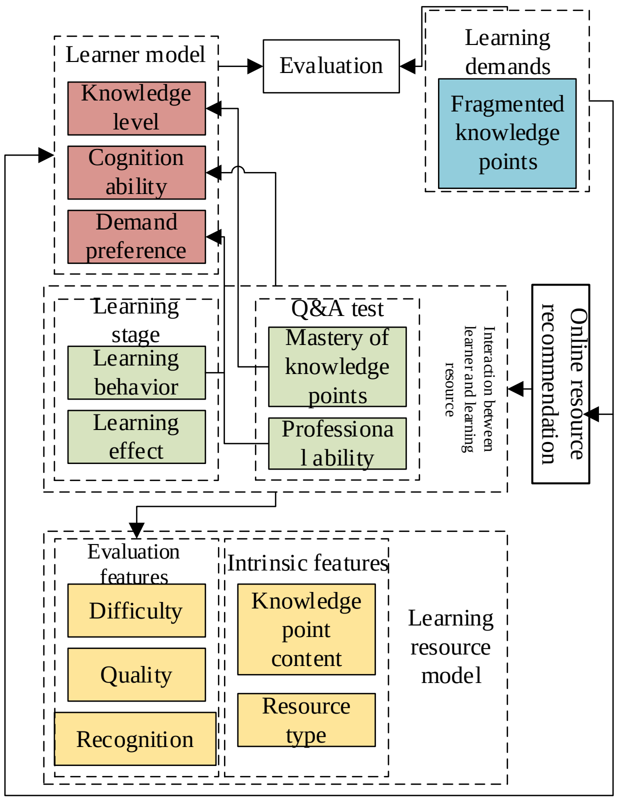

Fig. 4. Relationship between the learner model and the fragmented learning resource recommendation model

To analyze learner's mastery of key knowledge, firstly, it's assumed δ represents the evaluation results of learners' ability value for the fragmented knowledge point H; $FD(H)=\{FD_1,...,FD_i\}$ represents the set of precursor knowledge points, $B(H)=\{B_1,...,B_j\}$ represents the set of successor knowledge points; in this paper, the learner's mastery of fragmented knowledge points was divided into three degrees: completely mastered (*FG*), basically mastered (*BU*), and not mastered (*NM*).

When analyzing learner's mastery of a fragmented knowledge point *H*, the following parameters should be comprehensively considered:

a) The priori probabilities $QV_{FG}(H)$, $QV_{BU}(H)$, $QV_{NM}(H)$ of the mastery degree of fragmented knowledge point *H*;
b) The posteriori probabilities $QV_{F\text{-}FG}(H)$, $QV_{F\text{-}BU}(H)$, $QV_{F\text{-}NM}(H)$ of the mastery degree of fragmented knowledge point *H* under the influence of precursor knowledge points;
c) The posterior probabilities $QV_{B\text{-}FG}(H)$, $QV_{B\text{-}BU}(H)$, $QV_{B\text{-}NM}(H)$ of the mastery degree of fragmented knowledge point *H* under the influence of successor knowledge points.

Formulas 14, 15 and 16 respectively give the expressions of the posterior probabilities of learner's mastery of fragmented knowledge point *H*:

$$QV_{FG}^{'}\left(H \mid B, FD\right) = QV_{FG}\left(H\right) QV_{F-FG}\left(H\right) QV_{B-FG}\left(H\right) \tag{14}$$

$$QV_{BU}^{'}\left(H \mid B, FD\right) = QV_{BU}\left(H\right) QV_{F-BU}\left(H\right) QV_{B-BU}\left(H\right) \tag{15}$$

$$QV_{NM}^{'}\left(H \mid B, FD\right) = QV_{NM}\left(H\right) QV_{F-NM}\left(H\right) QV_{B-NM}\left(H\right) \tag{16}$$

The learner's mastery degree of fragmented knowledge point H can be calculated through the following steps:

1. Check whether the learner has a history of taking the Q&A test of fragmented knowledge point *H* or not, if there is, then calculate $QV_{FG}(H)$, $QV_{BU}(H)$, and $QV_{NM}(H)$; if there isn't, then their values take 0.1624, 0.5988 and 0.1457, respectively.
2. Calculate $QV_{F\text{-}FG}(H)$, $QV_{F\text{-}BU}(H)$, and $QV_{F\text{-}NM}(H)$, if there are precursor knowledge points, then their values all take 1.
3. Calculate $QV_{B\text{-}FG}(H)$, $QV_{B\text{-}BU}(H)$, and $QV_{B\text{-}NM}(H)$, if there are successor knowledge points, then their values all take 1.
4. According to Formulas 14-16, calculate the final values of posteriori probabilities and output the learner's mastery degree of fragmented knowledge points corresponding to the maximum value of the posteriori probabilities.

In the process of personalized online learning resource recommendation, the relationship between learners and online learning resources depends on the degree of learning demands, not just the learning interest, and this means that learners' demands for each personalized online learning resource recommendation are changing dynamically, and they are un-markable, we can only rely on the Q&A test results to identify which learning resource feature elements are required by learners.

Besides learners' evaluation on the three dimensions of learning resources (difficulty, quality, and recognition), the recommendation degree, describing the degree of learners' needs for reinforcing a certain fragmented knowledge point, also has a great impact on the improvement of the learners' overall learning ability, and its calculation process is detailed as follows:

- *Step 1*. Suppose: there're x fragmented knowledge points in a Q&A test, HG and ZW respectively represent the set of corresponding knowledge points and the set of the mastery degree of each knowledge point; after the calculation of the learner model, the fragmented knowledge points that are not mastered and basically mastered by learners could be extracted to further generate the candidate knowledge point evaluation sets of basically mastered and not mastered knowledge points, which are respectively represented by $HG_{NM}=\{HG_1,\dots,HG_x|HG(ZW)='NM'\}$ and $HG_{BU}=\{HG_1,\dots,HG_x|HG(ZW)='BU'\}$.
- *Step 2*. Suppose: in a Q&A test, it contains both the professional ability evaluation questions and fragmented knowledge point mastery degree evaluation questions, the two evaluation value sets are respectively represented by $W=\{W_1,...,W_y\}$ and $L=\{L_1,...,L_y\}$, wherein the evaluation questions of learners' current learning ability are consisted of the fragmented knowledge points in HG and the professional abilities in W, therefore, the learners' current learning ability could be represented by L_{nm}, and it is consisted of professional abilities and the mastery degree of fragmented knowledge points.
- *Step 3*. Count the mastery degree of relevant fragmented knowledge points in HG_{NM} and HG_{BU} in the Q&A test, and record them as a set L_A; count the evaluation of professional abilities related to the mastery degree of these fragmented knowledge points, and record them as a set W_A.
- *Step 4*. Extract the values of all relevant feature parameters in HG_{NM}, HG_{BU}, L_A, and W_A, and calculate the final recommendation degree TJ_H of fragmented knowledge point HG.

Formula 17 gives the calculation method of recommendation degree based on the mastery degree of fragmented knowledge points:

$$TJ_L = \gamma \cdot \frac{1}{l+1} \cdot \frac{w_L+1}{l+1} \cdot \frac{h_L+1}{l+1} \cdot D_{h_L} \left(l \in L_A \right) \tag{17}$$

Suppose: l represents the evaluation value of the mastery degree of a target fragmented knowledge point, w_L represents the evaluation value of professional abilities related to l, h_l represents the evaluation value of fragmented knowledge points related to w_L, HE_{HG} represents the centrality of fragmented knowledge points, h represents evaluation value of the target fragmented knowledge point, γ represents the importance coefficient of fragmented knowledge point, then Formula 18 gives the calculation method of the recommendation degree of fragmented knowledge points:

$$TJ_{HG} = \gamma \cdot \frac{1}{h+1} \cdot HE_{HG} \left(h \in H_{NM}, H_{BU} \right) \tag{18}$$

The value of γ is greatly affected by the probabilities of the three mastery degrees, and Formula 19 gives the calculation formula:

$$\gamma = 0.1 \cdot QV_{FG}(h) + 0.3 \cdot QV_{BU}(h) + 0.6 \cdot QV_{NM}(h) \tag{19}$$

The final output of the recommendation engine is the recommended online learning resources. After obtaining TJ_L and TJ_{HG}, the matching degree of the resources could be calculated based on the values of TJ_L and TJ_{HG} and the labels of fragmented knowledge points in the online learning resources to further realize the recommendation of online learning resources based on matching degree. Suppose: PI_ε represents the matching degree of learners to online learning resource ε, h represents the fragmented knowledge points contained in learning resource ε, l represents learners' mastery degree of the fragmented knowledge points contained in learning resource ε, γ_{HG} and γ_L respectively represent the importance coefficients of the corresponding fragmented knowledge point and the mastery degree of the knowledge point, TJ_{Max} and TJ_{Min} respectively represent the maximum and minimum values of the fragmented knowledge point contained in learning resource ε and the mastery degree of knowledge point, then Formula 20 gives the calculation formula of matching degree PI:

$$PI_\varepsilon = \left(\sum_h \gamma_{HG} TJ_{HG}\right) \cdot \left|TJ_{HG-Max} - TJ_{HG-Min}\right| + \left(\sum_l \gamma_L TJ_L\right) \cdot \left|TJ_{L-Max} - TJ_{L-Min}\right| \tag{20}$$

4 Experimental results and analysis

This paper also analyzed the correlation between the learner model, the fragmented learning resource model, and the online learning effect of learners. At first, the attribute values of knowledge level, cognition ability, and demand preference in the learner model, and the correct rates of answers and self-evaluation results of learners after learning were subject to correlation analysis. Table 1 gives the correlation analysis results of the learner model. Then, the attribute values of knowledge point content, resource type and resource evaluation in the fragmented learning resource model, and the correct rates of answers and self-evaluation results of learners after learning were subject to correlation analysis, and Table 2 gives the correlation analysis results of the fragmented learning resource model. Test on the Pearson correlation coefficient showed that, the correlation coefficients of knowledge level and demand preference in the learner model and the correct rate of answers were 0.152^{**} and 0.187^{**}, respectively, the significance level was less than 0.01. The correlation coefficient between the resource type in the fragmented learning resource model and the correct rate of answers was -0.012^{**}, the significant level was less than 0.01, indicating that knowledge level, demand preference, and resource type were significantly positively correlated with the correct rate of answers.

By unifying the value range of the features of different dimensions of the learner model, a radar map of the feature distribution of typical learners was obtained, as shown in Figure 5.

Table 1. Correlation analysis of the learner model

	Correct rate of answers		Self-evaluation results	
	Correlation coefficient	***Significance***	***Correlation coefficient***	***Significance***
Knowledge level	0.152**	0.002	-0.126**	0.003
Cognition ability	-0.085*	0.003	-0.021	0.076
Preferences and demands	0.187**	0.001	-0.127**	0.007

Table 2. Correlation analysis of the fragmented learning resource model

	Correct rate of answers		Self-evaluation results	
	Correlation coefficient	***Significance***	***Correlation coefficient***	***Significance***
Knowledge point content	-0.224**	0.013	0.015	0.325
Resource type	0.024	0.002	0.024	0.635
Resource evaluation	-0.015	0.375	0.367**	0.001

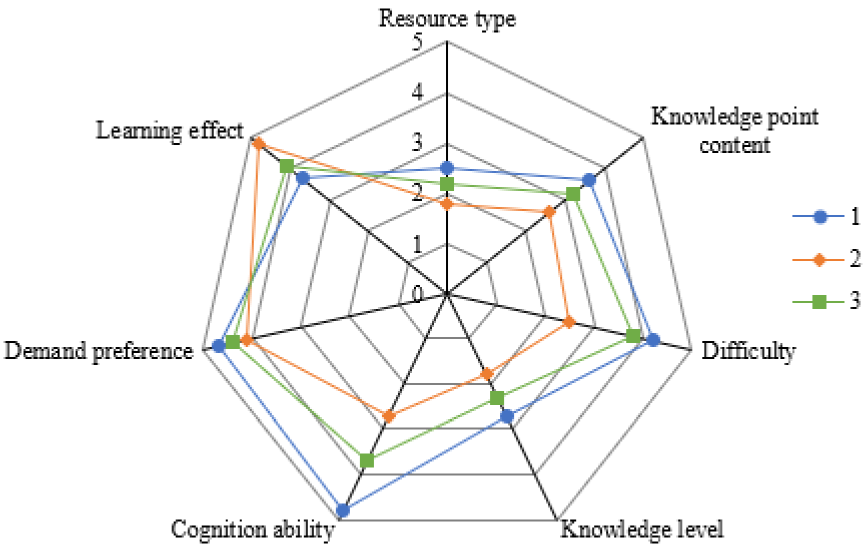

Fig. 5. Radar map of feature distribution of different dimensions of the learner model

Figure 5 clearly shows the attribute values of the knowledge level, cognition ability and demand preference of different learners, and the requirements of fragmented learning resources in terms of knowledge point content, resource type, and resource evaluation. The learning effect of all learners improved constantly during the process of personalized fragmented online learning, and the change value of the constantly-changing learning effect of learners can reflect that, the learner and fragmented learning resource features determined in the resource recommendation model constructed in this paper and the set eigen values were reasonable. For different learners, the constructed model can quickly adjust the recommended online learning resources, and the adaptability was good.

Learners with a fragmented online learning time of more than three months were selected, and their correct rates of answers in half a month were counted. Figure 6 shows the statistical results of the correct rates of learners. As can be seen from the figure, the learning effect of learners who conducted fragmented online learning continuously showed an overall increasing trend, which had verified the effectiveness of the recommendation model constructed in this paper.

Table 3 compares the resource recommendation effect of different models, specifically, these models are the cosine similarity recommendation model, the singular value matrix recommendation model, the artificial neural network model, and the proposed model. According to the table, through online learning, learners' knowledge level and cognition ability had improved to varying degrees. Several resources were output according to learners' specific learning demands, and post-learning tests were carried out. By comparing the pre-learning and post-learning effect, we can see that the proposed model outperformed other recommendation models in terms of learning effect improvement, and it got the highest scores in the statistics of learners' satisfaction with the recommended learning resources. Therefore, the experiments had proved that applying the constructed model to the resource recommendation scenarios of personalized fragmented online learning based on mobile devices was feasible and effective.

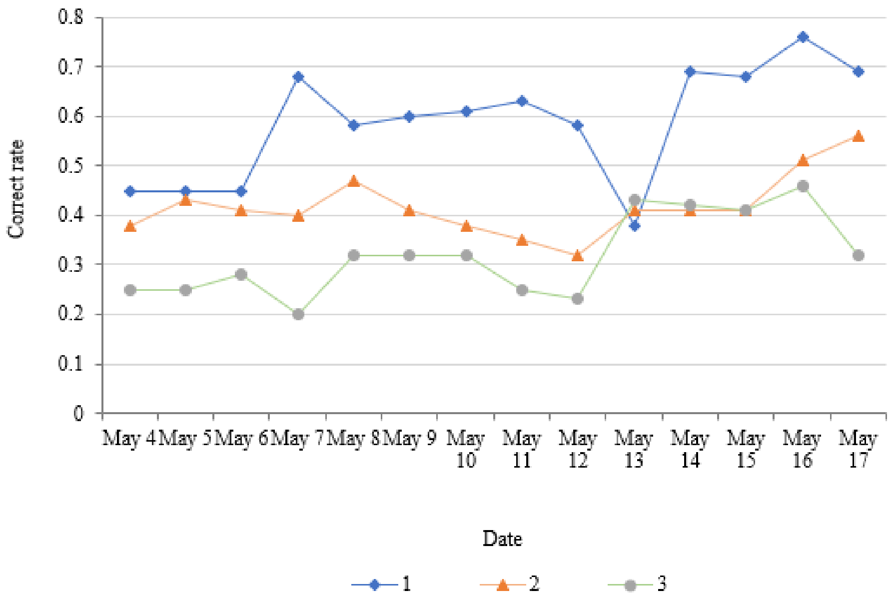

Fig. 6. Statistics of the correct rates of learners

Table 3. Comparison of the resource recommendation effect of different models

Model No.		1	2	3	4
Preliminary evaluation		62.4(7.5)	61.3(8.1)	63.7(7.3)	62.3(7.6)
Post-learning evaluation		66.3(5.2)	62.9(6.2)	65.4(8.4)	71.7(4.5)
Change effect		3.9	1.6	1.7	9.4
Satisfaction (Full Score: 5)	***top1***	3.2	3.4	3.1	3.5
	top2	3.1	3.4	3.2	3.6
	top3	2.8	2.4	3.2	3.4

5 Conclusion

This paper studied the resource recommendation for personalized fragmented online learning based on mobile devices. At first, the paper designed the architecture of the adaptive recommendation model of online learning resources, and constructed the learner model and the fragmented learning resource model. Then, it built the resource recommendation model for personalized fragmented online learning, elaborated on the flow of the recommendation engine, and calculated the recommendation degree and matching degree of resources. After that, through experiments, this paper analyzed the correlation between learner model, fragmented learning resource model, and the online learning effect of learners, plotted a radar map of the feature distribution of different dimensions of the learner model, and counted the correct rates of learners. Moreover, this paper also compared the resource recommendation effect of different models, and used experiments to prove that applying the constructed model to the resource recommendation scenarios of personalized fragmented online learning based on mobile devices was feasible and effective.

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Article submitted 2022-01-02. Resubmitted 2021-02-03. Final acceptance 2022-02-06. Final version published as submitted by the author.