Features and Influencing Factors of Mobile Learning Behavior of Employees in Accounting Profession

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Abstract—Data mining of the mobile learning behavior of learners can help researchers understand the underlying association rules of such behavior and the internal mechanism of the development of their thinking during the learning process, thereby giving the true and accurate evaluations on the thought and status of mobile learners. However, existing models established for mobile learning behavior recognition cannot give satisfactory enough explanations to the changes in the cognition level of learners, so this paper took employees in accounting profession as subjects to analyze the features and influencing factors of their mobile learning behavior. At first, this paper built a neural network model based on the attention mechanism and used it to classify and recognize the input data of mobile learning behavior via original data learning, and feature extraction and analysis. Then, this paper created evaluation scenarios for subjects participating in mobile learning, designed economic management tasks applicable for actual application scenarios, and proposed several evaluation indexes for assessing their learning performance. After that, the explicit learning behavior of the subjects was taken as the criterion for judging whether their learning performance has achieved the desired learning goals or not. At last, the effectiveness of our analysis model was verified by the experimental results.

Keywords—accounting, employee, mobile learning, behavior recognition, learning performance, attention mechanism

1 Introduction

Frontier technologies such as cell phone chips and 5G make cell phone no longer a communication gear but a multi-functional mobile terminal that can assist users in learning, shopping, working, and entertaining with diverse application software installed on it [1–7]. Such technological advancement lays a foundation for the emergence of mobile learning platforms, and mobile learning quickly becomes a learning method in style. Now these platforms have covered large populations, their user group expands from on-campus students to nearly everyone in the society, and a huge amount of learning behavior data have accumulated on the platforms during such expansion [8–14]. The data mining of the mobile learning behavior of learners can help researchers understand the underlying association rules of such behavior and the internal mechanism of the development of thinking during the learning process, thereby giving the true and accurate evaluations on the thought and status of mobile learners [15–20].

Common mobile terminals refer to cell phones, smartphones, and tablets, together with online education, they have been gradually introduced into colleges and universities in the past decades. Questions such as whether using mobile device in distance learning can trigger learning initiative in students and affect learning process were proposed a decade ago but haven't been answered yet. Scholar Eom [21] attempted to answer this question in his study, he used the Smart PLS v.3.3.2 to verify structural model based on 323 valid and non-repeated online responses given by students from a Midwestern university in the U.S., and the paper proved that the use of mobile devices has positive effects on students' intrinsic and extrinsic learning motivations. Neffati et al. [22] researched a smart device that can incorporate visual simulation into e-learning and developed an augmented reality platform for e-learners to expand the coursebook with graphics and virtual multimedia applications. Chen et al. [23] proposed a Chinese language learning application Persona for mobile terminals, in which two characters were set based on the understanding of current products and previous research; the paper also discussed and assessed other translation and learning apps for mobile devices. Kilty and Burrows [24] introduced how researchers integrate mobile devices into outdoor science learning, and evaluated the learning activities and the consistency of purpose, integration, and assessment; they concluded that the benefit of such integration is to support the development of scientific inquiry skills, and the consistency of purpose and assessment provides important evidence for the learning of students to meet accountability standards. Although there're a lot of researches on the application of mobile technologies in promoting language learning and the educational practices that foster such learning approach, there's few empirical evidence of learners' acceptance and utilization situations of the mobile learning platforms in developing countries. Scholar Hoi [25] sought to fill in this research gap by applying a modified version of the unified theory of acceptance and use of technology and adopted a Rasch-based path model to analyze the survey data of 293 Vietnamese college students, and the results proved the important roles of attitude and performance expectancy in predicting learners' behavior intention and their use of MALL.

After carefully reviewing existing relevant literatures, it's found that researchers have gained certain outcomes in terms of online learning behavior and cognition theory, but most of these results are relevance study or learning performance prediction, and the existing models established for the purpose of mobile learning behavior recognition cannot give satisfactory enough explanations to the changes in the cognition level of learners. Therefore, to make up for these shortcomings, this paper took the mobile learning of several subjects (employees in the accounting profession) as examples, and integrated mobile learning behavior feature extraction and learning effect evaluation information with data processing technologies to realize the recognition of the mobile learning behavior of our subjects and analyze and the influencing factors. At last, the experimental results verified the validity of our analysis method.

2 Mobile learning behavior feature extraction

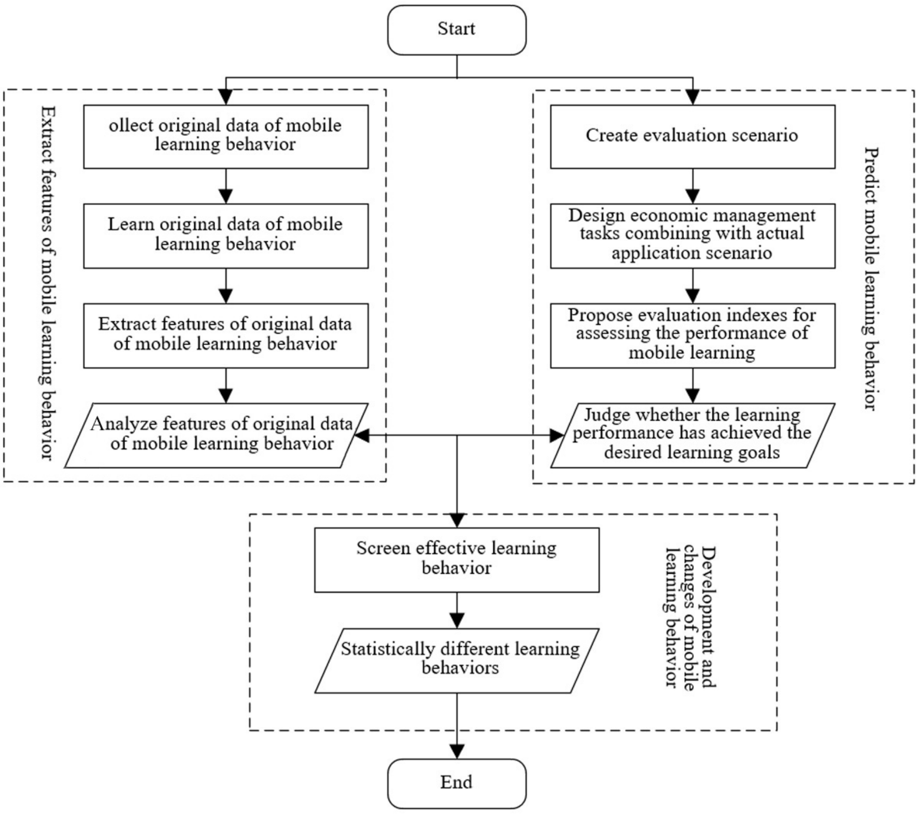

Fig. 1. Analysis process of the mobile learning behavior of subjects

In the mobile learning environment, it's not accurate enough to analyze and predict the mobile learning behavior based only on the history data of the subjects' professional accounting knowledge, so this paper took the feature extraction of history behavior data as support to design evaluation scenarios and economic management tasks to realize the evaluation of the learning performance of our subjects. The analysis flow is shown in Figure 1, and the text below introduces the mobile learning behavior feature extraction model constructed in this paper.

The neural networks built for deep learning can classify and recognize the input data of mobile learning behavior through learning, feature extraction, and features analysis of the original data of mobile learning behavior. In order to quickly get terminal information from the large amount of original input data of mobile learning behavior, neural networks are often applied together with the attention mechanisms.

There're three types of attention mechanisms: spatial domain attention, channel domain attention, and mixed domain attention, wherein the spatial domain attention is differentiable. Assuming: U represents the information after transformation; V represents the information before transformation; l represents the kernel function;

then the original data information of mobile learning behavior that needs to be subject to spatial transformation can be expressed in the form of kernel function as shown in Formula 1:

$$U_i^d = \sum_m^F \sum_n^Q V_{nm}^d l(a_i^r - n; \psi_a) l(b_i^r - m; \psi_b) \tag{1}$$

The generation of channel attention needs to go through three operations: squeeze, excitation, and scale. The squeeze function G_{rw} is given by Formula 2:

$$c_d = G_{rw}(V_d) = \frac{1}{F*Q} \sum_{i=1}^F \sum_{j=1}^Q v_d(i,j) \tag{2}$$

G_{rw} can be equivalent to a global average pooling operation which superimposes and sums the eigenvalues of mobile learning behaviors. Assuming: ε represents the *sigmoid* activation function; Q_1 and Q_2 represent two functions of channel attention, then, the activation function G_{oa} was processed as shown in Formula 3:

$$r = G_{oa}(c,Q) = \varepsilon(h(c,Q)) \tag{3}$$

The scale function G_{scale} is:

$$A_d = G_{scale}(v_d, r_d) = v_d \cdot r_d \tag{4}$$

The mobile learning behavior recognition model proposed in this paper based on the attention mechanism contains two parts: depth-wise separable convolution, and feature extraction of mixed attention. In this paper, at first, the original data stream of the mobile learning behavior on the mobile learning platform was filtered and segmented to create grayscale image, then, based on the constructed recognition model, the grayscale image data were processed to realize the recognition of the mobile learning behavior of subjects.

The channel attention was calculated by the model, that is, the input feature map was subject to the pre-processing of global maximum pooling operation to realize the extraction of new features after feature enhancement, the calculation formula is:

$$SBM_d(G) = \varepsilon(Q_1(Q_0(GAP(G)))) \tag{5}$$

Then, the feature map of mobile learning behavior was created based on spatial domain attention, and its calculation formula is:

$$SBM(G) = \varepsilon(G^{7*7}([AP(G); MP(G)])) \tag{6}$$

This paper optimized the conventional channel attention, Formula 7 gives the formula of Discrete Cosine Transform (DCT):

$$g_l = \sum_{i=0}^{K-1} a_i cos\left(\frac{\pi l}{K}(i+0.5)\right), s.t. l \in \{0,1,\ldots,K-1\} \tag{7}$$

The formula of two-dimensional (2D) DCT is:

$$g_l = \sum_{i=0}^{F-1}\sum_{j=0}^{Q-1} a_{i,j}^{2e} cos\left(\frac{\pi f}{F}(i+0.5)\right) cos\left(\frac{\pi q}{Q}(j+0.5)\right), \\ s.t. f \in \{0,1,\ldots,F-1\}, q \in \{0,1,\ldots,Q-1\} \tag{8}$$

The corresponding direct 2D-DCT is given by the following formula:

$$a_{i,j}^{2e} = \sum_{f=0}^{F-1}\sum_{\theta=0}^{Q-1} g_{f,q}^{2e} cos\left(\frac{\pi f}{F}(i+0.5)\right) cos\left(\frac{\pi q}{Q}(j+0.5)\right), \\ s.t. f \in \{0,1,\ldots,F-1\}, q \in \{0,1,\ldots,Q-1\} \tag{9}$$

The lowest frequency part of the 2D-DCT is the case when the subscript of g is 0,0, that is:

$$\begin{aligned} g_{0,0}^{2e} &= \sum_{i=0}^{F-1}\sum_{j=0}^{Q-1} a_{i,j}^{2e} cos\left(\frac{0}{F}\left(i+\frac{1}{2}\right)\right) cos\left(\frac{0}{Q}\left(j+\frac{1}{2}\right)\right), \\ &= \sum_{i=0}^{F-1}\sum_{j=0}^{Q-1} a_{i,j}^{2e} = gap(a^{2e})FQ \end{aligned} \tag{10}$$

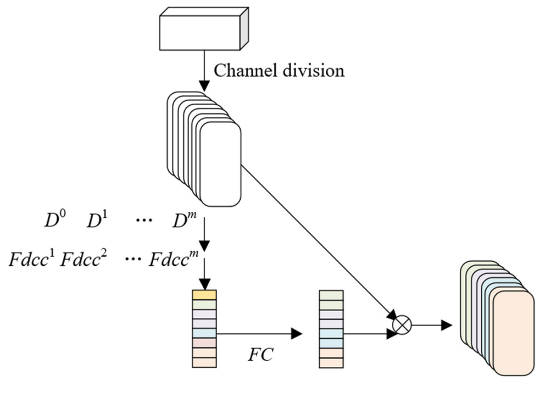

Fig. 2. Corrected channel attention

According to above analysis, attention mechanism can process other frequency domain information, but the preprocessing of the original learning behavior data by channel attention based on global maximum pooling will lead to serious frequency domain information missing, so this paper corrected the *GAP* of channel attention, and the correction form was the combination of frequency domain components. Figure 2 presents a schematic diagram of the corrected channel attention. First, the *D* channels were divided into [D^1, D^2, …, D^m], and the following formula gives the corrected channel attention formula:

$$Fdcc^{i} = 2D - DCT^{\alpha,\beta}(A^{i}) \tag{11}$$

$$Fdcc = cat([Fcdd^{0}, Fdcc^{1}, \ldots, Fdcc^{m-1}]) \tag{12}$$

$$ms_{x}pp = sigmoid(g_{d}(Fdcc)) \tag{13}$$

3 Analysis and prediction of influencing factors of mobile learning behavior

The cognition level of subjects is constantly improving during mobile learning. If a subject wants to finish the learning tasks of high cognition level professional accounting knowledge, he or she must have the ability to learn low cognition level professional accounting knowledge; if the subject wants to become a qualified accountant, during the mobile learning process, he or she needs to recall and reorganize the professional knowledge points accumulated, and complete a series of procedural economic management tasks such as bookkeeping, accounting, and reimbursement, and solve various issues they encountered.

Current discussions on factors affecting the mobile learning behavior are generally carried out from objective aspects such as teachers and platforms, and qualitative judgments are mainly made based on survey results, thus they are often prone to problems such as unsuitable survey scenarios or inconsistent evaluation criteria. This paper attempts to create evaluation scenarios for subjects participating in mobile learning, design economic management tasks combining with actual application scenarios, and propose evaluation indexes for assessing subjects' learning performance, thereby judging whether their learning performance has achieved the desired learning goals based on their explicit learning behavior. The evaluation indexes include four aspects: information volume of learning behavior evaluation, relevance degree of learning behavior evaluation, professionalism of learning behavior evaluation, and credibility of learning behavior evaluation.

Assuming: $N_p(d)$ represents the vocabulary size of learning behavior comment text d; $EA_p(d)$ represents the comprehensiveness of the evaluation angles included in d, then the formula for calculating the information volume is:

$$IF(d) = ln(N_{P}(d)) * EA_{P}(d) \tag{14}$$

Assuming: n represents the number of evaluation angles of learning behavior; m represents the number of evaluation angles included in a piece of comment, then Formula 15 give the formula for calculating the comprehensiveness of the evaluation angles of subjects' mobile learning behavior, and Figure 3 shows the calculation of the comprehensiveness of learning behavior evaluation angles:

$$EA_{P}(d) = \frac{m}{n} \tag{15}$$

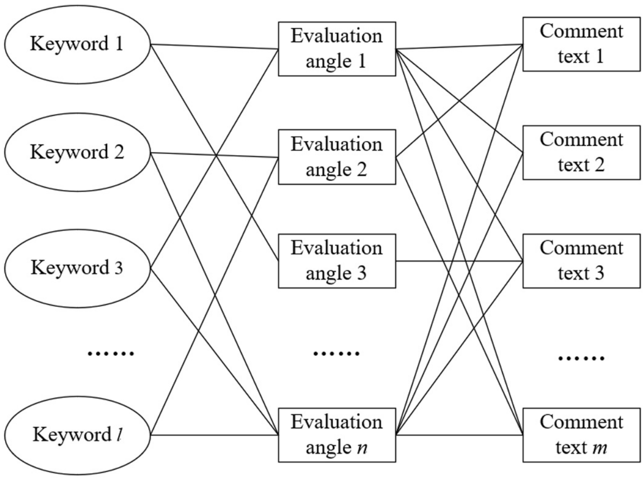

Fig. 3. Calculation of the comprehensiveness of learning behavior evaluation angles

For economic management task document and the corresponding learning behavior evaluation text, this paper built the eigenvector of learning behavior evaluation text based on *TF-IDF* weights, and the formula below was adopted to quantify the relevance degree between the two, which was defined as *ER*(*d*), the relevance degree of learning behavior evaluation of our subjects. Assuming: *TF* and *d* represent the eigenvector of economic management task documents and learning behavior evaluation text, then there is:

$$ER(d) = cos\omega = \frac{\sum_{i=1}^{m}(TF_i * d_i)}{\sqrt{\sum_{i=1}^{m}(TF_i)^2}\sqrt{\sum_{i=1}^{m}(d_i)^2}} \tag{16}$$

Evaluation indexes mainly measure the professionalism of learning behavior from three aspects: keyword content, feature word content, and feedback score, and they represent the suggested text word size, content validity, and evaluation reference proposed based on the task completion situation of other learner users.

Assuming: $N_P(D_{CA})$ and $N_P(D_{SU})$ represent the text word size compared with the task completion situation of other learner users and that of suggested part, then the quantification of keyword content can be expressed as:

$$KIC(d) = N_P(D_{CA}) + N_P(D_{SU}) \tag{17}$$

Assuming: *CW*(*d*) represents the number of feature words that can be matched in the learning behavior comment; *m* represents the total length of the comment, then the quantification of feature word content can be expressed as:

$$CWC(d) = o^{\frac{CW(d)}{m}} \tag{18}$$

Assuming: $FS(d)$ represents the feedback score, then the professionalism index of learning behavior evaluation is given by the following formula:

$$EP(d) = ln(KIC(d)+1) * CWC(d) + FS(d) \tag{19}$$

The subjective-objective degree of comment text and feedback score of economic management tasks determines the credibility of subjects' credibility evaluation, which is denoted as $AUT(d)$, assuming $SOD_{FS}(d)$ represents the subjective-objective degree of feedback score; $SOD_{CT}(d)$ represents the subjective-objective degree of comment text, then there is:

$$AUT(d) = SOD_{FS}(d) + SOD_{CT}(d) \tag{20}$$

The subjective-objective degree of feedback score $SOD_{FS}(d)$ was determined by the absolute error of scores of all teachers participating in the evaluation of economic management tasks. Assuming: m represents the number of teachers participating in the evaluation of economic management tasks, then there is:

$$SOD_{FS}(d) = \left| \frac{1}{m} \sum_{i=1}^{m} FS_i - FS_d \right| \tag{21}$$

The subjective-objective degree of comment text $SOD_{CT}(d)$ was quantified by taking the proportion of the number of positive and negative emotional words contained in the learning behavior comment text in the total number of words contained in the entire comment text, then the calculation formula is:

$$SOD_{CT} = \frac{m}{N_P(d)} \tag{22}$$

According to above analysis of the evaluation indexes of subjects' learning performance, indexes of four aspects (information volume of learning behavior evaluation, relevance degree of learning behavior evaluation, professionalism of learning behavior evaluation, and credibility of learning behavior evaluation) can affect the quality of the comment text of learning behavior to varying degrees. In order to predict the mobile learning behavior of subjects, this paper performed linear regression analysis on above indexes to complete learning behavior evaluation. Assuming: $\gamma = (\gamma_1, \gamma_2, \gamma_3, \gamma_4)$ represents the weights of the four indexes, then a multiple regression model could be constructed as:

$$LBE(d) = \beta + \gamma_1 IF(d) + \gamma_2 ER(d) + \gamma_3 EP(d) + \gamma_4 AUT(d) \tag{23}$$

4 Experimental results and analysis

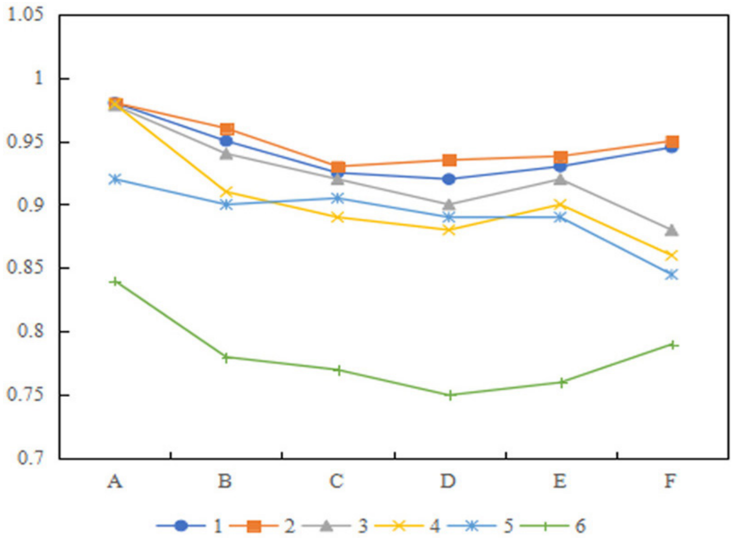

Fig. 4. Comparison of the experimental results of attention modules with different structures

For each economic management task, the data samples of multiple evaluation indexes of various mobile learning behaviors of subjects were experimented, taking six typical learning behaviors as examples (topic discussion A, resource utilization B, teaching activity participation C, self-testing D, task execution E, review F), the experimental results of 6 attentions models with different structures are given in Figure 4. According to the figure, the spatial attention mechanism has a greater impact on the feature extraction of various mobile learning behaviors of our subjects, the main reason lies in that the spatial attention mechanism is more effective in processing the texture of the grayscale images created after the mobile learning behavior data stream is filtered and segmented, thus this paper selected and combined spatial domain attention and channel domain attention to build the mobile learning behavior feature extraction model.

The types of mobile learning behaviors of subjects to be studied in this paper include: topic discussion (A), resource utilization (B), teaching activity participation (C), self-testing (D), task execution (E), review (F), continuity of log in to the mobile learning platform (G), teacher-student interaction (H), preview (I), and question proposal (J). As for our subjects, the employees in the accounting profession, their cognition of professional learning contain eight levels: accounting definitions and objects (1), accounting equations and calculation (2), accounting functions (3), accounting procedures (4), accounting vouchers (5), accounting books (6), accounting statements (7), and accounting and financial analysis indicators (8). Table 1 shows the statistics of the differences in the mobile learning behaviors of subjects under eight cognition level dimensions. According to the data shown in the table, there're statistical differences in the mobile learning behaviors of subjects under all eight dimensions, and this indicates that there's a relationship between the different mobile learning behaviors and the cognition level of subjects, which has important influence on the improvement of their economic management ability. Therefore, subjects' mobile learning behaviors with statistical differences under various cognition levels were retained and taken as the attention focus of learning methods for improving the cognition ability of this level.

Table 1. Statistics of the differences in mobile learning behaviors under eight cognition level dimensions

Cognition Level	A	B	C	D	E	F	G	H	I	J
1	√		√		√		√		√	
2	√	√		√		√		√		√
3		√		√	√		√		√	
4	√		√		√	√		√		√
5		√		√		√		√	√	
6	√		√		√		√			√
7		√	√	√		√	√	√	√	
8	√	√		√	√		√			√

Table 2. Performance evaluation of the prediction model

Cognition Level	1	2	3	4	5	6	7	8
Correct rate (%)	63.15	62.47	68.20	71.59	68.52	62.54	68.31	82.49
Accuracy (%)	64.28	61.38	60.27	74.51	62.18	60.35	62.57	82.35
Recall rate (%)	69.48	62.51	63.73	74.61	69.37	66.02	64.85	87.13
$F1$ value (%)	62.42	63.19	61.48	73.95	62.58	69.31	61.27	85.48

According to a certain scale, test sample set and training sample set of the constructed model were created based on the original data set of mobile learning behavior, and Table 2 gives the performance evaluation of the prediction model. According to the table, the constructed model showed ideal prediction effect on the subjects' cognition level of professional learning, wherein the prediction accuracy of Level-4 (accounting procedure) exceeded 74%, and the prediction accuracy of Level-8 (accounting and financial analysis indicator) was over 80%, which proved the feasibility of judging whether the learning performance of subjects has reached the desired learning goals based on their explicit learning behavior. Table 3 shows the possibility matrix of comment texts and evaluation angles, which gives a detailed reflection of the possibility of each evaluation angle contained in the comments of the professional learning performance of some subjects.

Table 3. Possibility matrix of comment texts and evaluation angles

Serial Number of Comment Texts	1		2		3		4		5	
*Topic*1	0.0251	6415	0.0145	6924	0.0625	7142	0.3125	8471	0.2143	1528
*Topic*2	0.0367	6259	0.0362	3526	0.0485	925	0.0148	3269	0.0251	8475
*Topic*3	0.0248	6358	0.0152	4175	0.0152	7415	0.0261	7481	0.0485	8263
*Topic*4	0.0619	4021	0.0481	3628	0.0496	3629	0.0329	7526	0.0629	4517
*Topic*5	0.0284	6396	0.0695	7419	0.0157	1257	0.0481	5124	0.0214	9586
*Topic*6	0.0417	6851	0.0652	2516	0.0362	7051	0.0529	7195	0.0584	8152
*Topic*7	0.0625	6248	0.0695	3481	0.0484	7546	0.0517	3625	0.0623	6140
*Topic*8	0.0518	6021	0.0326	3625	0.0519	3529	0.0629	7142	0.0419	8473
*Topic*9	0.0246	8592	0.0417	1958	0.0526	6414	0.413	1251	0.0511	5516
*Topic*10	0.0958	2037	0.0584	4126	0.0413	7582	0.0425	7958	0.2487	1284

Table 4. Prediction results of different models

Model	Accuracy (%)	Recall Rate (%)	*F*1 Value (%)
SVM	74.51	66.29	65.27
Random forest	72.39	79.58	73.19
The proposed model	71.52	73.26	70.55

The ability level of subjects in each cognition level could be judged based on their cognition of professional learning behavior, and subjects could use the evaluation results to infer the situation of their learning goal achievement of each cognition level, thereby attaining references for the learning behavior selection of the next step, so the evaluation results could be regarded as a binary classification prediction problem based on comment texts. The prediction results of different models are given in Table 4 and Figure 5. The reference models are support vector machine (SVM) and random forest.

As can be seen from the experimental results, the proposed model outperformed the reference models in terms of accuracy, recall rate, and F1 value, which had verified the feasibility of using the evaluation scenarios constructed for the constructed model and the and economic management tasks designed combining with actual application scenarios to evaluate subjects' learning performance, besides, the model structure and parameters were set reasonably, and the evaluation indexes were selected scientifically.

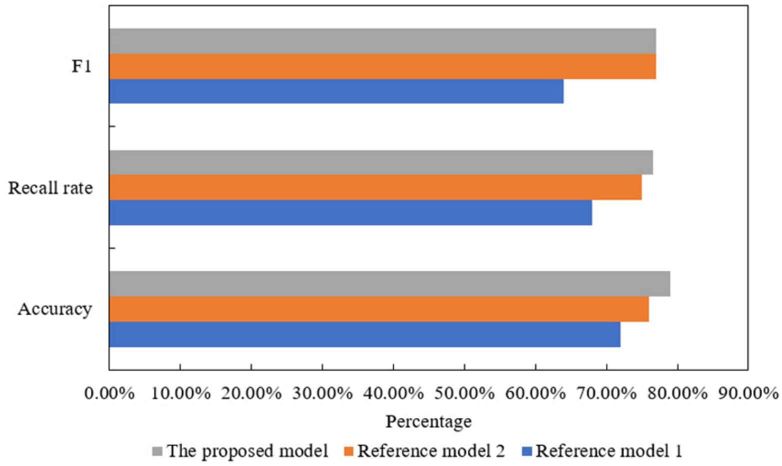

Fig. 5. Comparison of prediction results of different models

5 Conclusion

Taking employees in accounting profession as subjects, this paper analyzed the features and influencing factors of their mobile learning behavior, constructed a neural network model based on the attention mechanism, and classify and recognize the input data of mobile learning behavior via original data learning, and feature extraction and analysis. By creating evaluation scenarios for subjects participating in mobile learning and designing economic management tasks applicable for actual application scenarios, this paper proposed evaluation indexes for assessing subjects' learning performance and judged whether their learning performance has achieved the desired goals based on their explicit learning behavior. In the experiment, the experimental results of attention modules with different structures were compared, which verified the scientificity of selecting and combining spatial domain attention and channel domain attention to construct the behavior feature extraction model for mobile learning. Then, differences in the mobile learning behaviors of subjects under eight cognition level dimensions were counted, and this paper proposed to retain and take subjects' mobile learning behaviors with statistical differences under various cognition levels as the attention focus of learning methods for improving the cognition ability of this level. Moreover, the performance evaluation of prediction model demonstrated the feasibility of using subjects' explicit learning behavior to judge whether their learning performance has achieved the desired learning goals. At last, this paper gave the prediction results of different models and verified the effectiveness of the proposed analysis method.

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